AN INTELLIGENT WAREHOUSE POSTPONEMENT DECISION SUPPORT SYSTEM FOR EFFICIENT E-COMMERCE ORDER FULFILLMENT

LEUNG KA HO

PhD

The Hong Kong Polytechnic University

2019

THE HONG KONG POLYTECHNIC UNIVERSITY

DEPARTMENT OF INDUSTRIAL AND SYSTEMS

ENGINEERING

An Intelligent Warehouse Postponement Decision Support

System for Efficient E-Commerce Order Fulfillment

LEUNG Ka Ho

A thesis submitted in partial fulfillment of the requirements

for the Degree of Doctor of Philosophy

December 2018

CERTIFICATE OF ORGINALITY

I hereby declare that this thesis is my own work and that, to the best of my knowledge and belief, it reproduces no material previously published or written, nor material that has been accepted for the award of any other degree or diploma, except where due acknowledgement has been made in the text.

(Signed)

Leung Ka Ho (Name of Student)

Abstract

The rise of omni-channel and e-commerce online shopping has reshaped the entire retail and logistics industry. Though numerous benefits are brought by such e-shopping trend, the e-retailers and logistics service providers (LSPs) now face noticeable challenges to meet the tight requirements of e-commerce order processing as demanded by e-retailers and end consumers. To capture the market pie of e-commerce logistics business, LSPs are struggling to transform their business from handling traditional large lot-sized shipment orders to e-commerce parcel-based, discrete orders. The fundamental differences among traditional and e-commerce logistics orders (e-orders), in terms of arrival frequency, delivery requirement, urgency, and the number of stock-keeping-units (SKUs), have created enormous handling difficulties for LSPs in processing e-orders efficiently in their distribution centres using conventional order processing flow.

In view of the need for LSPs to improve their internal core competence in processing e-orders so as to grasp today's e-commerce logistics business opportunities, this research is performed with an objective of improving LSPs' e-order handling efficiency through re-engineering of their e-order operational flow in distribution centres. The re-engineering of e-order processing flow is achieved by the implementation of "Warehouse Postponement Strategy" (WPS), a proposed operational strategy in this research, having an aim to "delay the execution of logistics operations until the last possible moment". By consolidating the e-orders and subsequently releasing the consolidated orders at the right timing, a LSP would be able to deploy the WPS in distribution centres for handling e-orders efficiently. However, the re-engineering of e-order operational flow through the introduction of WPS in strengthening the internal competence of LSP is effective only if the decision-makers can manage to (i) consolidate similar e-orders logically, and (ii) release the consolidated orders at the most appropriate timing.

As neither of the above-mentioned decisions can be made manually, an E-commerce Fulfillment Decision Support System (EF-DSS) is proposed in order to provide LSPs with decision support in determining (i) “How to group the e-orders”, and (ii) “When to release the grouped e-orders”. The issue of “How to group the e-orders” is tackled with a GA-rule-based approach to group e-orders based on the similarity of storage locations of ordered items, whereas the problem of “When to release the grouped e-orders” is solved by a novel autoregressive-momentum-moving average-based Adaptive Network-Based Fuzzy Inference System (AR-MO-MA-ANFIS) approach, integrating the autoregressive, momentum and moving average elements of time series data into the modeling of ANFIS. The feasibility of the proposed system is validated through three case studies conducted in third-party LSPs based in Hong Kong. The system reveals a significant improvement in terms of the order handling efficiency and resource management.

Though there has been a noticeable growth in both business-to-customers (B2C) and business-to-business (B2B) e-commerce retail activities in recent decades, the mainstream literature in dealing with e-commerce operating activities has been lacking. The major contribution of this research is in the design and application of an e-commerce operations-oriented decision support system that integrates the wider concept of the proposed Warehouse Postponement Strategy for effective e-order fulfilment in distribution centres. A practical roadmap of WPS implementation is provided in this research, enabling logistics practitioners to deploy WPS effectively as well as opening up a new area for researchers to take e-commerce operating inefficiencies into account in research on warehouse decision support.

Publications Arising from the Thesis

(**4** international journal papers have been published, accepted or under review. **2** book chapters have been published. **8** conference papers have been published or under review.)

List of International Journal Papers

1. **Leung, K.H.**, Luk, C.C., Choy, K.L., Lam, H.Y., & Lee, Carman K.M. (2019). A B2B flexible pricing decision support system for managing the request for quotation process under e-commerce business environment, *International Journal of Production Research*, DOI: 10.1080/00207543.2019.1566674.

2. **Leung, K.H.**, Choy, K.L., Siu, Paul K.Y., Ho, G.T.S., Lam, H.Y., & Lee, Carman K.M. (2018). A B2C E-commerce Intelligent System for Re-engineering the E-Order Fulfilment Process, *Expert System with Applications*, 91, 386-401.

3. **Leung, K.H.**, Choy, K.L., Ho, G.T.S., Lam, H.Y., Luk, C.C. & Lee, Carman K.M. (2018). Prediction of B2C e-commerce order arrival using hybrid autoregressive-adaptive neuro-fuzzy inference system (AR-ANFIS) for managing fluctuation of throughput in e-fulfilment centre, *Expert System with Applications*, 134, 304-324.

4. Hui, Yasmin Y.Y., Choy, K.L., Ho, G.T.S., **Leung, K.H.**, Lam, H.Y. (2016), A cloud-based location assignment system for packaged food allocation in e-fulfillment warehouse, *International Journal of Engineering Business Management*, 8, 1-15.

List of Book Chapters

1. **Leung, K.H.**, Luk, C.C., Choy, K.L. & Lam, H.Y. (2018). The integration of big data analytics, data mining and artificial intelligence solutions for strategic e-commerce retail and logistics business-IT alignment: a case study. In Albert Tavidze (Eds.), *Progress in Economics Research* (Vol. 41, pp. 141-165). New York: Nova Science Publishers Inc.

2. **Leung, K.H.**, Cheng, W.Y., Choy, K.L., Wong, W.C., Lam, H.Y., Hui, Y.Y., Tsang, Y.P., & Tang, Valerie (2016). A Process-Oriented Warehouse Postponement Strategy for E-Commerce Order Fulfillment in Warehouses and Distribution Centers in Asia. In Patricia Ordóñez de Pablos (Eds.), *Managerial Strategies and Solutions for Business Success in Asia* (pp.21-34). Hershey, PA: IGI Global.

List of Conference Papers

1. **Leung, K.H.**, Choy, K.L, & Lam, H.Y. (2018). An intelligent order allocation system for effective order fulfilment under changing customer demand, *Engineering Applications of Artificial Intelligence Conference 2018 (EAAIC 2018)*. Sutera Harbour, Kota Kinabalu, Malaysia, 3-5 Dec, 2018.

2. Lee, Jason C.H., Choy, K.L. and **Leung, K.H.** (2018), An intelligent fuzzy decision support system for flexible adjustment of dye pricing to manage customer-supplier relationship. *In: International Symposium on Semiconductor Manufacturing and Intelligence (ISIMI2018) & IEEE International Conference on Smart Manufacturing, Industrial & Logistics Engineering (IEEE SMILE2018)*. Hsinchu, Taiwan, 7-9 Feb, 2018, 7-11.

3. **Leung, K.H.**, & Leung M.T. (2017). An E-Commerce Order Handling System for E-Logistics Process Re-Engineering, *In: Data Driven Supply Chains. Ljubljana, Slovenia: The 22nd International Symposium on Logistics (ISL 2017)*. Ljubljana, Slovenia, 9-12 Jul, 2017, 328-335.

4. Lee, Jason C.H., Choy, K.L. and **Leung, K.H.** (2017), Development of a Fuzzy Decision Support System for Formulating Adaptive Flexible Pricing Strategy for Dye Machinery Utilization. *In: Data Driven Supply Chains. Ljubljana, Slovenia: The 22nd International Symposium on Logistics (ISL 2017)*. Ljubljana, Slovenia, 9-12 Jul, 2017, 123-130.

5. Tsang, Y.P., Siu, Paul K.Y., Choy, K.L., Lam, H.Y., Tang, Valerie, **Leung, K.H.** (2017), An Intelligent Route Optimization System for Effective Distribution of Pharmaceutical Products. *In: Data Driven Supply Chains. Ljubljana, Slovenia: The 22nd International Symposium on Logistics (ISL 2017)*. Ljubljana, Slovenia, 9-12 Jul, 2017, 394-401.

6. **Leung, K.H.**, Choy, K.L., Tam, M.M.C., Hui, Y.Y.Y., Lam, H.Y., & Tsang, Y.P. (2016). A Knowledge-based Decision Support Framework for Wave Put-away Operations of E-commerce and O2O Shipments, *6th International Workshop of Advanced Manufacturing and Automation*, Manchester, United Kingdom, 10-11 Nov, 2016, 86-91.

7. **Leung, K.H.**, Choy, K.L., Tam, M.C., Cheng, Stephen W.Y., Lam, H.Y., Lee, Jason C.H., & Pang, G.K.H. (2016). Design of a case-based multi-agent wave picking decision support system for handling e-commerce shipments. In: *Technology Management for Social Innovation*. United States of America, Portland: Portland International

Conference on Management of Engineering and Technology (PICMET), 2248 – 2256.

8. **Leung, K.H.**, Choy, K.L., Tam, M.C., Lam, C.H.Y., Lee, C.K.H., & Cheng, Stephen W.Y. (2015). A Hybrid RFID Case-based System for Handling Air Cargo Storage Location Assignment Operations in Distribution Centers, In: *Management of the Technology Age*. United States of America, Portland: Portland International Conference on Management of Engineering and Technology (PICMET), 1859 - 1868.

Acknowledgements

I would like to express my deepest gratitude to my supervisor, Dr K.L. Choy for his excellent supervision, valuable advice, and on-going guidance and support throughout the research period. Above all, I appreciate his support, motivation, and encouragement at every stage of this research, and I have to thank him for allowing me a great deal of independence. Sincere thanks also go to my co-supervisor, Dr George Ho for his valuable comments and support throughout the research.

I would also like to thank all the staff of the three case study companies for providing the practical cases for this research. Appreciation also goes to my colleagues and friends, especially Dr Cathy Lam, for providing valuable comments and support for my research.

During the course of this research, I have been very fortunate to have the help and support from many friends. Special thanks go to Yick, Yoyo, Karin, Sum, Ball and his family for their friendship.

The financial assistance support by the Innovation and Technology Commission from the Hong Kong Government and CAS Logistics Limited under the Teaching Company Scheme, and, the Research Office of the Hong Kong Polytechnic University through the award of research studentship, are greatly appreciated.

Finally, I am truly grateful to my father, mother, sister, aunts, and grandma for their love and faith in me over the years. I am deeply grateful, above all, to them.

Table of Contents

List of Figures

List of Tables

List of Abbreviations

3PL	Third-party Logistics
AHP	Analytic Hierarchy Process
AI	Artificial Intelligence
ANN	Artificial Neural Network
AR	Autoregressive
ARIMA	Autoregressive Integrated Moving Average
ARMA	Autoregressive Moving Average
AR-MO-MA-ANFIS	Autoregressive-momentum-moving average-based Adaptive Network-Based Fuzzy Inference System
B2B	Business-to-business
B2C	Business-to-customer
CBR	Case-based Reasoning
DM	Data Mining
E-order	E-commerce Order
EBRM	E-order Batch Releasing Module
EDI	Electronics Data Interface
EF-DSS	E-commerce Fulfillment Decision Support System
ECM	E-order Consolidation Module
EGM	E-order Grouping Module
ERP	Enterprise Resource Planning
FIS	Fuzzy Inference System
GA	Genetic Algorithm
GDP	Gross Domestic Product
IT	Information Technology
ICT	Information Communication Technology
IOT	Internet-of-things
LIS	Logistics Information System
LSP	Logistics Service Provider
MA	Moving Average
MO	Momentum
MCDM	Multiple Criteria Decision-Making

NNR	Nearest Neighbor Retrieval
O2O	Online-To-Offline
OMS	Order Management System
RFID	Radio Frequency Identification
SaaS	Software-As-A-Service
SARIMA	Seasonal Autoregressive Integrated Moving Average
SKU	Stock-Keeping Units
TMS	Transportation Management Systems
WPM	Weighted Product Model
WPS	Warehouse Postponement Strategy
WMS	Warehousing Management System
WSM	Weighted Sum Model

Chapter 1 – Introduction

1.1 Research Background

The wider applications of the Internet for online shopping in recent decades have brought enormous growth potential for international business-to-business (B2B) and business-to-customers (B2C) trading. Shopping via multiple channels has become a rapidly growing phenomenon. On one hand, companies continually add new sales channels. On the other hand, end consumers and business entities can make purchases using any of their mobile devices at any time. Since the beginning of 21st century, the idea of "online shopping" that was expanded globally has already brought a series of benefits for the stakeholders, especially the end consumers, wholesalers and retailers. However, some drawbacks are perceived by the stakeholders under the e-commerce business environment, as suggested in Table 1.1. B2B and B2C e-commerce have had a profound impact on stakeholders along a supply chain, such as manufacturers, retailers and logistics service providers (LSPs) (Gunasekaran & Ngai, 2004; Johnson & Whang, 2002). In the perspective of manufacturers, the trend of online shopping opens up the opportunity for them to directly sell their finished goods to end consumers via their e-commerce shopping sites. This, in turn, threatens the position of wholesalers and retailers as manufacturers are no longer required with wholesalers and retailers as the middleman (Abhishek et al., 2015). As for LSPs, the e-commerce logistics business is a huge market to capture. However, successful transformation of the traditional logistics business to e-commerce for gaining the market share can be achieved only if LSPs strengthen their internal order processing capability to handle e-commerce orders (e-orders).

The motivations for LSPs to improve their core competence in order handling under the e-commerce logistics business is twofold. First, the market for the traditional logistics business is to a certain extent quite mature. The e-commerce logistics business is a new market segment in recent decades that has a large growth potential, with the fact that consumers have started perceiving online sales platforms as one of the major channels for making a purchase (Carlson et al., 2015; Falk & Hagsten, 2015). In light of the continuous B2B and B2C e-commerce growth, the underlying logistics e-order processing operations, such as e-order fulfillment in distribution centres and last-mile delivery of parcels, are in great demand. Second, the rise of such online-to-offline (O2O) retailing and e-commerce business has revamped the entire order fulfilment process along supply chains (Lekovic & Milicevic, 2013). At the operational level, LSPs are struggling with the problem of e-commerce order handling inefficiencies in warehouses or distribution centers (Lang & Bressolles, 2013), which is largely attributed to the difference between e-commerce orders and traditional orders. As shown in Table 1.2, i.e. a summary of a comparison between the characteristics of traditional logistics orders and e-commerce orders, there are vast differences between these orders in terms of the nature of the order, size per order, stock-keeping units involved in each order, number of orders received within a timeframe, arrival frequency, time availability for processing, and the delivery schedule. Traditionally, logistics orders processed in warehouses are mainly initiated from retailers who require stock replenishment for specified physical stores. Each of these traditional orders involves only a few types of stock-keeping units (SKUs), but in large quantity. In contrast, e-commerce orders are placed by end consumers worldwide via e-commerce selling platforms, which exhibit very different order characteristics as each e-order involve a large number of SKUs, but with each SKU demanding only a very small quantity. Also, these e-orders are significantly more wide-spread in terms of delivery location. Adding the requirement of same-day or next-day delivery for e- orders, the e-commerce logistics business model is now more complex and dynamic than the traditional one. Previous studies have already addressed the difficulty for LSPs to manage warehouse operations and last-mile order fulfilment without strategic and operational transformation (Hultkrantz & Lumsden, 2001; Cho et al., 2008; Lang & Bressolles, 2013). Therefore, taking the above-mentioned motivations into account, there is a crucial need for LSPs to strength their core competencies for e-order handling in order to capture the e-commerce logistics market pie. On the other hand, however, they can no longer follow the conventional order fulfilment process in handling e-commerce orders due to the fundamental differences between conventional and e-commerce logistics orders.

Table 1.1. The impact of e-commerce business on various stakeholders

End consumer	
Positive impacts	*Negative impacts*
• *Convenience, better prices, and wider range of products and services* – Ease of performing benchmarking in the selection of retailers or products due to the higher degree of product information and pricing	• *Fake or low-quality products* – The inability of physical inspection of products by consumers • *Privacy concerns* – Purchasing habits, delivery address, personal details are all stored at the database of e-commerce sites
Retailers	
Positive impacts	*Negative impacts*
• *Maximizing revenue while reducing the operating expenses* – smaller operating space requirements, less staff • *Enlarged consumer base* - the opportunity to be visible and visited by more customers	• *Intense competition* – Ease of entering the market indicates the existence of a large number of direct competitors • *Decline of being a middleman between manufacturers and end consumers* – The emerging e-commerce business models close the

• *Low barriers to entry* – Ease of entering the e-commerce market at low operating costs	gap between manufacturers and end consumers
Manufacturers	
Positive impacts	*Negative impacts*
• *Forward integration* – By extending its role from manufacturer to retailer in the supply chain through e-commerce • *Better cost control and inventory management* – Reduce the bullwhip effect with the shortened supply chains	• *Lack of knowledge* – Diversified focus on core business, hard to take the role as distributor
Logistics service providers	
Positive impacts	*Negative impacts*
• *E-commerce logistics business as a new market segment to target* – Opportunity to capture new e-commerce logistics market • *A greater role to play in e-commerce marketplace* – Last-mile delivery and e-commerce order handling are the keys to customer satisfaction in online shopping	• *Strict delivery requirements phasing out traditional LSPs with low operating efficiency* – Requires LSPs to keep up with the pace of e-commerce development by enhancing internal order handling efficiency • *Difficulty in business transformation from traditional LSPs to e-commerce based LSPs* – A gap exists between enormous e-commerce order volume and logistics order handling ability

Table 1.2. A comparison between the nature of traditional logistics orders and e-commerce orders (Leung et al., 2016)

Order characteristics	**Traditional logistics orders**	**E-orders placed by end customers electronically**
Nature of order	Mostly stock replenishment	Fragmented, discrete
Size per order	In bulk	In small lot-size
SKUs involved in each order	Very few or even identical	Many
Number of orders pending for processing	Less, relatively easy to predict	More and unlimited, relatively difficult to predict
Arrival frequency of order	Regular	Irregular
Time availability for fulfilment	Less tight	Very tight
Delivery schedule	Relatively more time buffer	Next-day or even same-day delivery

1.2 Problem Statement

- *The need for an introduction of Warehouse Postponement Strategy*

Given the huge market potential of the e-commerce logistics business, the existing operational inefficiencies in e-order handling in warehouses and distribution centres lead to major bottleneck for LSPs to capture the e-commerce business opportunities (Mangiaracina et al., 2015). Therefore, in this research, the need for LSPs to re-engineer their order processing flow for streamlining e-commerce order handling is addressed. Without the re-engineering of the order fulfillment process for today's e-commerce business, there are two significant problems in the existing operations, as shown in Fig. 1.1, they are:

(i) Inefficiency of e-commerce order handling due to frequent and discrete arrival of orders

In today's e-commerce retail industry, customers are guaranteed in advance to be able to receive the items before a specified date or within the timeslot they selected. Facing the tight delivery requirements, LSPs are required to handle e-orders extremely efficiently. 'Efficient e-order handling', 'speed' and 'accuracy' are the critical performance indicators of LSPs (Krauth et al., 2005; Gunasekaran et al., 2004). Not only do they have to be capable of processing a large number of e-orders accurately within the specified time constraints to meet the customers' or retailer's delivery requirements, but they are also required to be agile enough in handling the fluctuating arrival of incoming e-orders. In turn, effective resource management can be achieved through better utilization or allocation of available resources, such as manpower and material handling equipment, in various order arrival periods throughout the working hours. For instance, as depicted in Fig. 1.1, during the peak period of e-order arrivals, customer service representatives process the received e-orders accordingly and send the order details to the distribution centres for actual order fulfilment, which involves warehouse workers picking the ordered items from the corresponding storage locations and packing the items according to the customer order. The problems of such a conventional order handling process lie in the difficulty for warehouse workers to handle a large number of discrete e-orders individually. It is almost impossible for the workers handle fragmented e-orders one-by-one.

(ii) Lack of mechanism for data pre-processing of e-commerce orders

In the case of Hong Kong, being a global transhipment hub, LSPs are shifting their business to an e-commerce orientation owing to the fast growing trend of e-business in Asia. However, most of the logistics practitioners lack an effective mechanism for e-commerce order pre-processing, as their operations are still manual and without IT support. E-commerce orders are handled in the same conventional way as for traditional logistics orders.

(iii) Lack of cost effective decision support tools to facilitate e-commerce logistics operating procedures

The frequent and discrete arrival of e-commerce orders, one of the biggest differences as compared to the traditional logistics orders, has resulted in e-commerce order handling in e-fulfilment centres being inefficient. There is a lack of lightweight, cost effective IT solutions that are specifically designed to handle e-commerce orders which are received from the Internet. The core reason for this is the lack of domain know-how by IT solution developers in the e-commerce supply chain field, thereby being unable to identify the B2C e-commerce order handling difficulties currently faced by the logistics practitioners.

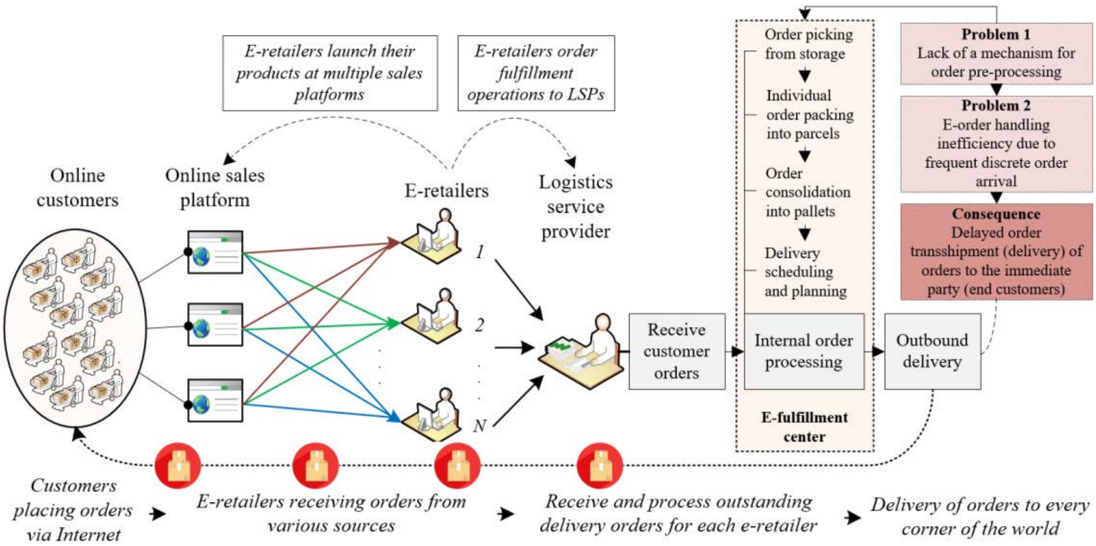


Fig. 1.1. Order fulfillment bottlenecks under today's e-commerce operating environment

Consequently, the absence of a mind-set from the managerial perspective and an effective mechanism in the operational perspective for order pre-processing has created barriers for logistics practitioners to engage in the e-commerce logistics business. Further, not only does the internal incapability of efficient e-order handling become the major obstacle in business expansion, but it is also a bottleneck in the entire e-commerce supply chain which affects the efficiency of e-fulfilment of the downstream supply chain partners. This explains why the last-mile delivery in e-commerce, the final leg of the complete journey of a parcel before it reaches the customer, is regarded as one of the biggest challenges in today's e-commerce business.

In view of the necessity of logistics process re-engineering under the emerging e-commerce logistics business environment, this research identifies the need to extend the wider concept of "postponement strategy" to the warehouse operational level, by not only conventionally delaying the configuration and assembling of a product in the manufacturing perspective, but also at the warehouse operational level "delaying the execution of a logistics process until the last possible moment". The "delay of a logistics process execution until the last possible moment" is defined as "warehouse Postponement Strategy" (WPS) in this study. In theory of WPS, the throughput rate in a distribution centre from a fluctuating pattern is rearranged to one that follows a regular wave pattern, as presented in Fig. 1.2.

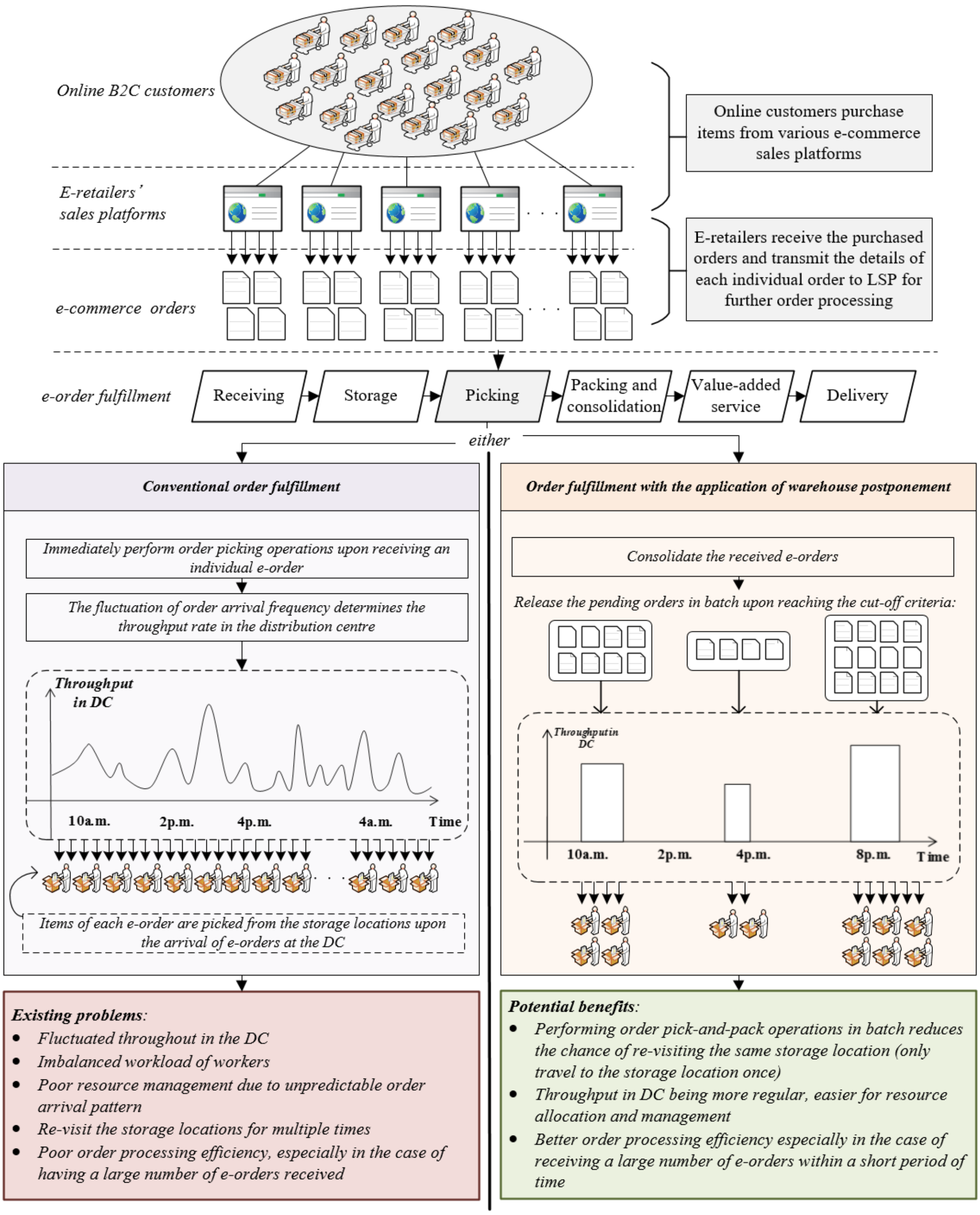


Fig. 1.2. An order fulfilment process comparison with and without the application of warehouse postponement strategy

- *The current research and practical gap in deploying WPS*

The concept of WPS can be achieved by grouping e-orders in a consolidation pool, and then subsequently releasing the grouped e-orders for processing at the same time. By means of bulk processing, different e-orders that consist of the same item(s) can be picked from the designated storage location(s) of the distribution centre at the same time. Such practice best suits the nature of e-order handling, as these frequently arrived e-orders are fragmented, discrete and smaller lot-sized. Therefore, deploying WPS for bulk e-order handling not only rearranges the throughput rate in a distribution centre, but also benefits logistics practitioners in terms of order processing efficiency, resource management and workforce level adjustment. A noticeable advantage of the deploying WPS is the reduction of the possibility for a worker to re-visit the same storage location throughout the working hour. In the absence of WPS deployment, order pickers are required to process each e-order individually. Hence, the order pickers are very often required to visit the same storage locations for those popular items which are frequently ordered by individual consumers. Traveling to repetitive storage locations is a type of operating inefficiency due to improper order planning. Therefore, a logistics practitioner can perform better order planning through the introduction of WPS. However, for effective deployment of WPS, the following two conditions are critical:

(1) How e-orders are grouped for later batch processing; and

(2) When should a decision-maker stop consolidating e-orders and release the consolidated e-orders for actual batch processing.

While the above WPS deploying conditions determine the success of logistics re-engineering for the e-commerce operating environment, the decision support proposed in the mainstream literature in facilitating e-commerce logistics operations has been lacking. A majority of the expert systems proposed in previous studies in the domain of warehousing and transportation process improvement, such as Oliveira et al. (2015), Patriarca et al. (2016), Gu et al. (2016), Yang et al. (2015), Accorsi et al. (2014), Lam et al. (2011), Poon et. al. (2011), Yao et al. (2010), Zacharia & Nearchou (2010), Taniguchi & Shimamoto (2004), Chan et al. (2009) and Chen et al. (2008), focus only on tackling a specific operational issue in warehouses or distribution centers in handling general logistics orders. However, without consideration of the differences in the nature and handling requirements between e-commerce orders and conventional logistics orders, previous expert systems might not be applicable to the scenario of today's e-commerce order handling process. Furthermore, Nguyen et al. (2018) suggested that very little research in the mainstream literature has been conducted to manage e-commerce order fulfilment activities better. Mangiaracina et al. (2015) also suggested that, the environmental implications of the related logistics activities have not yet been studied in detail, despite logistics practitioners playing an emerging role of multichannel strategies in e-commerce.

1.3 Research Objectives

In view of the crucial necessity to re-engineer the logistics operational flow for improved e-order handling in warehouses and distribution centers, this research proposes an operational strategy, namely "Warehouse Postponement Strategy". For successful implementation of WPS in a real production environment of LSPs, it is suggested that two conditions, i.e. (1) How e-orders are grouped for later batch processing *(How to group)*, and (2) When should a decision-maker stop consolidating e-orders and releasing the grouped e-orders must be deeply considered, as shown in Fig. 1.3. Therefore, this research develops a decision support system for assisting the

LSPs in making prompt decisions regarding (1) How to group, and (2) When to release. The specific objectives of this research are:

(i) To re-engineer the internal order processing flow for LSPs to improve their core competencies in e-order handling;

(ii) To provide decision support solutions to properly deal with the issue of "How to group" and "When to release" for successful deployment of the proposed Warehouse Postponement Strategy; and

(iii) To present a generic system architecture so as to enable a LSP to implement WPS based on their specific size of e-commerce logistics business.

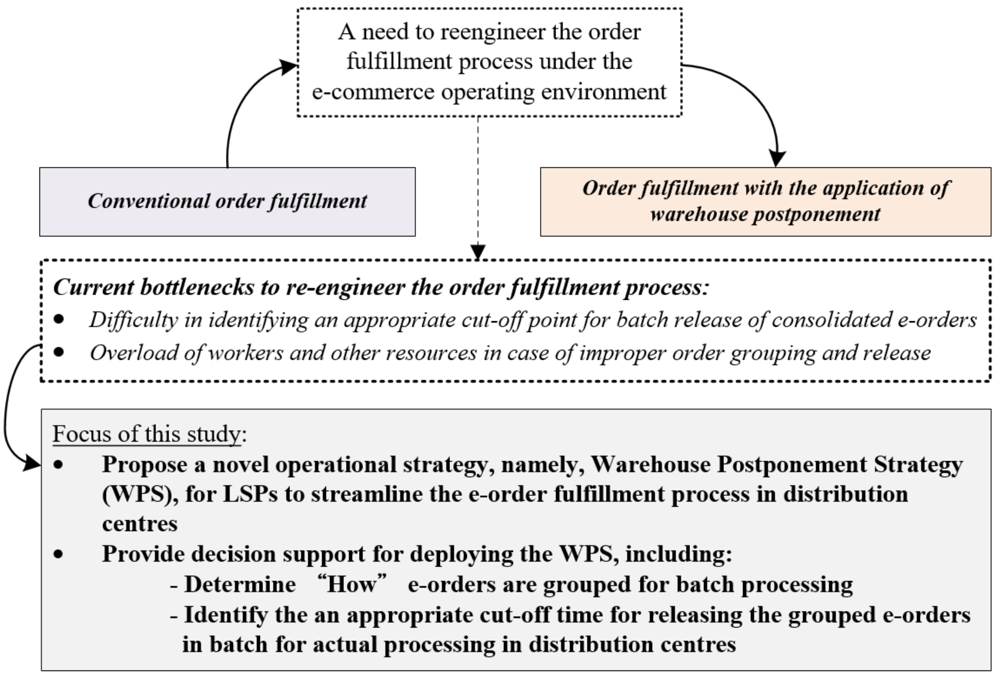


Fig. 1.3. The focus of this research

1.4 Significance of the Research

Traditional approaches proposed in the literature rarely took the e-commerce logistics environment into account, rendering the previous proposed expert systems inapplicable to the current e-commerce logistics business. Moreover, previous studies attempted to manage productivity in warehouses and distribution centres by means of resource management and effective order planning, such as the development of IOT-based or RFID-based solutions for logistics order and resource track and trace in warehouses, and heuristics solutions using artificial intelligence, data mining approaches, or mathematical modelling approach for streamlining the conventional order processing flow. Resource management and order planning in conventional logistics warehouses have been widely and adequately researched. Under the ever complex and dynamic order handling environment in today's e-fulfilment centre, productivity management in logistics can be performed not only by means of resource management and order planning, but also through logistics order arrival prediction.

Logistics order arrival prediction is a new subject that has attracted sparse attention by both researchers and industry practitioners as conventional logistics orders arrive at the warehouses in a regular time interval. However, under the dynamic e-commerce logistics business, forecasting the irregular arrival pattern of fragmented and discrete e-orders becomes an essential subject for LSPs to identify "When to release the grouped e-orders", one of the conditions of deploying WPS. Thus, this research fills the existing gap in the literature and opens up a new research area in the field of e-commerce-based order management under today's customer-driven supply chain, by addressing the need to forecast e-order arrival for formulating a proper Warehouse Postponement Strategy for improved order planning and execution. This research is a new study that introduces a novel autoregressive-momentum-moving average-based Adaptive Network-Based Fuzzy Inference System (AR-MO-MA-ANFIS) approach, integrating the nature of autoregressive feature of time series data into an ANFIS model for improving the operating efficiency in the context of supply chain management, by means of forecasting the arrival of e-commerce orders.

In addition to the integrated AR-MO-MA-ANFIS approach for the prediction of e-order arrival figures, the framework of the proposed system in this research provides a step-by-step implementation flow of WPS, enabling logistics practitioners to efficiently manage a large number of discrete, small lot-sized e-orders in distribution centers, which is a phenomenon that commonly exists in today's order fulfilment operations. In turn, the re-engineering of logistics operational flow in handling e-commerce orders can be achieved. This would be beneficial for various stakeholders along the supply chains. LSPs would become more capable in capturing the logistics of the e-commerce business due to higher efficiency in e-order handling. Retailers can build brand images and loyalty by satisfying the consumers' needs and expectations, especially considering the timeliness of the last-mile e-order delivery, one of the most critical e-fulfilment processes. End consumers can receive their purchased items without a long waiting time.

1.5 Thesis Outline

The thesis is divided into seven chapters, as described below.

(i) Chapter 1 introduces the background of the research. The problem definitions under the e-commerce operating environment of LSPs, the motivations and significance of this research are also discussed.

(ii) Chapter 2 provides an academic review of the related research, including a comprehensive review of the current e-commerce logistics operating environment, and the existing bottlenecks of e-order handling activities in warehouse and distribution centres. The analysis of decision support systems and existing approaches, such as the application and integration of artificial intelligence and data mining techniques, and time-series data analytical tools, adopted in warehouse activities are discussed and reviewed.

(iii) Chapter 3 is divided into two main sections. The first section introduces the architecture of the proposed system, namely the E-commerce Fulfillment Decision Support System (EF-DSS). The second section describes the infrastructure of EF-DSS, which consists of an E-order consolidation module (ECM), an E-order grouping module (EGM), and an E-order batch releasing module (EBRM). The development of these system modules realizes the proposed concept of "Warehouse Postponement Strategy" by "delaying the logistics process execution until the last possible moment", so as to enable logistics practitioners to improve the internal core competencies in e-order handling activities.

(iv) Chapter 4 provides a generic implementation guide of EF-DSS from the design stage, through the structural formulation of each module, to the implementation and evaluation stage. This framework allows industry practitioners to deploy the WPS according to their size of e-commerce logistics business.

(v) Chapter 5 presents three case studies in which EF-DSS is developed and implemented in three different Hong Kong-based third-party logistics service providers, in order to demonstrate the feasibility of the proposed methodology in managing e-commerce orders. An EF-DSS software prototype is developed and the related operating mechanism for supporting the decision-making process is also discussed.

(vi) Chapter 6 discusses the results and major findings of the research. The system performance and parameter settings for obtaining the best system parameters are presented, followed by a discussion of the overall operating performance of the case companies after the pilot implementations of EF-DSS.

(vii) Chapter 7 concludes the work undertaken in the research. Contribution made by the research and key areas for future research are highlighted.

Chapter 2 – Literature Review

2.1 Introduction

The focus of this research is on the design of a E-fulfilment decision support system for re-engineering the operational flow of e-commerce operations in distribution centres. To achieve this, a comprehensive review on the background of supply chain management under e-commerce business environment and the data mining and artificial intelligence techniques for heuristics problem-solving is required. The aim of this chapter is to examine the previous literature related to the current research areas. Figure 2.1 depicts the roadmap for reviewing the related literature. In this chapter, there are four phases of the review of the literature. The purpose of the first two phases is to comprehensively review the background and scope of the research areas of this research, i.e. supply chain management and warehousing operations under e-commerce operating environment. Through the background studies, the existing challenges of logistics, distribution, and warehousing operations under e-commerce operating environment are discussed and identified, so as to identify the existing research gaps in the literature. For instance, Phase I, i.e. Recent Developments in E-commerce-based Supply Chain Management, covers three sections: Section 2.2.1 - Evolution of B2B and B2C E-commerce, Section 2.2.2 - Effects of E-commerce Business Towards Supply Chain Management, and Section 2.2.3 - Existing Approaches in Managing E-commerce Business Activities. For Phase II, i.e. Overview of Logistics and Warehousing Operations, it covers two sections: Section 2.3.1 - The Differences between Conventional and E-commerce-based Logistics and Warehousing Operations, and Section 2.3.2 - Existing Decision Support Solutions for Facilitating Conventional and E-commerce-based Logistics and Warehousing Operations.

A comprehensive review of the existing tools for improving the decision-making process in warehouses and distribution centers and for time-series data prediction is performed in Phase III and IV. Through the review of the literature, appropriate tools can be selected and suggested in this chapter for achieving the objectives of this research, i.e. developing a decision support system to improve the operating efficiency of LSPs in handling e-commerce orders in distribution centers. In Phase III - Existing DM and AI techniques Used in Improving Decision-Making in Warehouses and Distribution Centers, in total there are seven techniques reviewed, including case-based reasoning, multi-agent technology, analytical hierarchy process, genetic algorithms, fuzzy logic, association rule mining, and adaptive network-based fuzzy inference system (Section 2.4.1 to Section 2.4.7). Apart from reviewing these data mining and artificial intelligence techniques, approaches for forecasting time-series data are also reviewed, so as to select proper tools for forecasting the e-order arrival pattern to assist LSPs' in determining the "when to release grouped e-orders" decision, one of the objectives of this research. Therefore, in Phase IV - Existing approaches for time series data prediction, stochastic modelling approaches including linear regression, moving average (MA), exponential smoothing, auto regressive (AR), and autoregressive integrated moving average (ARIMA) model, are reviewed in Section 2.5.1. Machine learning techniques for time series data prediction including ANN-based and ANFIS-based forecasting models, are reviewed in Section 2.5.2. Lastly, conclusions are drawn in Section 2.6 – Summary, to provide insight on the research direction and discuss the traits of the E-fulfilment decision support system proposed in this research study.

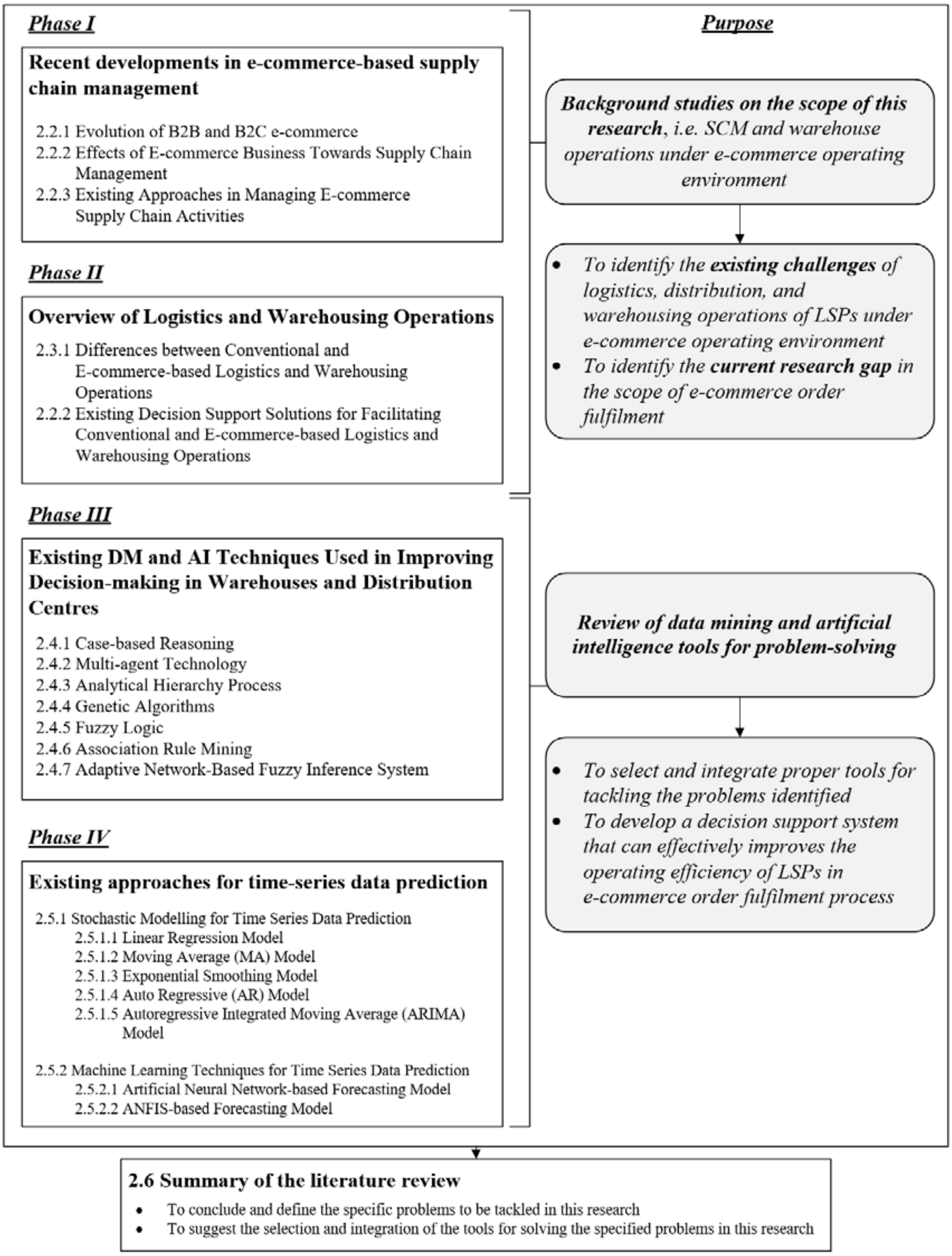


Fig. 2.1. Roadmap for reviewing the literature

2.2 Recent Developments in E-commerce-based Supply Chain Management

The development of supply chain management has been drastically affected by the emerging shift of consumer buying behavior, owing to an increasing trend of online shopping experience in which retailers around the globe are struggling to deliver to consumers worldwide. In this section, a review of the evolution of B2B and B2C e-commerce, the effects of e-commerce business activities towards modern supply chain management, and the existing approaches in managing e-commerce supply chain activities, are presented.

2.2.1 Evolution of B2B and B2C E-commerce

From the perspective of B2B e-commerce, business transactions are conventionally made through face-to-face meetings, phone calls and emails. The advancement of information technology (IT) enables enterprises to place orders via the Internet. Such contactless transactions made via the Internet have become a major sales channel for suppliers. In 2017, the gross merchandise volume of business-to-business e-commerce transactions amounted to 7.66 trillion U.S. dollars, up from 5.83 trillion U.S. dollars in 2013 (Statista, 2017). While the rise of B2B online retail stores creates more potential business opportunities due to the increase of brand exposure of suppliers to the potential customers worldwide, suppliers are forced to improve their efficiency in the internal business process, such as the Request for Quotation process (García-Crespo et al., 2009; Hvam et al., 2006), that supports the front line management of e-commece.

Over the past decade, e-commerce has bought a whole new era to the retail business. The drastic growth of e-commerce is attributed to the evolution of hardware and the internet, with both having a direct correlation with today's e-commerce. The emerging e-commerce not only revolutionised the retail industry, the way sellers sell their products and the way we buy and source products, but also the way we communicate with each other and the way companies perform marketing activities, especially making advertising. Social media, a computer-based technology that facilitates the sharing of ideas and information, is one of the hottest trends in the past decade. The use of social media has been extended from individual's use of communication and interaction with others to the use by business entities. With an enormous base of active users, social media platforms create a large base for marketers to utilize these platforms for achieving their marketing purposes, such as increasing brand exposure, building customer relationship, and implementing target marketing strategies. Social media has evolved to be a new hybrid element of the promotion mix (Mangold & Faulds, 2009).

The current directions of the e-commerce retail and logistics industry development are summarized below.

(i) *New product categories for e-commerce business* – The most popular product category for selling through online sales channels is computer and consumer electronics. Industry reports and statistics indicate that food and beverage is an upcoming trendy product category for e-commerce, which will drive e-commerce growth in the near future (Food Dive, 2016). The delivery of food and beverage products requires different skill sets and technologies as compared to the handling of traditional fast moving consumer goods (FMCGs). The food produce must be monitored closely along the entire cold supply chain. Higher requirements in terms of delivery timeliness, hygiene conditions in delivery, and temperature control are also expected.

(ii) The mobility trend for mobile and social commerce – Marketing research conducted by Global Web-Index (GWI) (2017) underscored how mobile applications (Apps) and Internet users in the Asia-Pacific region are taking a lead in social commerce. In contrast to only 67% of the Facebook users being interested in online shopping, 81% of WeChat users and 79% of Sina Weibo users have been participating in online shopping. In Asia, affluent audiences embrace new technologies at a fast pace. Technologically, mobile apps for mobile and social commerce are also being rapidly developed in Asian countries as one of the motivators of Internet users participating in online shopping via apps. With the “Buy now” option available on more social media platforms, such a mobile and social commerce trend is promising.

(iii) The convergence trend – Global internet companies are at a stage of enterprise cooperation, mergers and reorganizations. Examples in mainland China include Dangdang being merged with Taobao Mall, and Alibaba integrated with Meituan. Due to the similar marketing positioning of the e-commerce sites, mergers and reorganizations reduce the number of competitors in the market, reduce any potential duplication of resources, and jointly enhance the overall competitiveness and bargaining power.

2.2.2 Effects of E-commerce Business Towards Supply Chain Management

In the past decades, the logistics industry has been facing numerous operational challenges. First, the mode of production has been transformed from the traditional mass production into the mass customization production mode to facilitate increasing global market competition (Chow et al., 2006). In order to adapt to such change to achieve competitive advantage, warehouses need to be redesigned and automated to achieve higher productivity and throughput, thereby reducing the order processing cost (Harmon, 1993). The adoption of new philosophies such as Just-In-Time (JIT) and lean production has brought dramatic changes in the functions and operations of warehouses to minimize stock with tighter inventory control policies and shorten the response time (Gu et al., 2007). Second, the emerging trend of e-commerce business also poses serious challenges in the field of logistics. As e-commerce shipments require an entirely new distribution infrastructure to handle online business (Cho et al., 2008), warehouses must be able to efficiently pick and pack single items and small volume orders, and deliver them in small parcel shipments at a higher frequency to consumers. In this sense, traditional order fulfillment which encompasses receiving, put-away, picking, transport through the warehouse or distribution center, might not be able to fully meet the requirements of e-commerce.

The supply chain network is becoming increasingly complex as e-commerce and omni-channel retailing has opened up the retail industry to new customer demands and market segments. Manufacturers who conventionally sell their products to wholesalers, i.e. the middleman between manufacturers and retailers, can sell their finished products directly to end consumers via launching online retail stores. Such vertical integration of manufacturers reshapes not only the traditional product flow within a supply chain, but also logistics practices in handling these online orders. The development of the e-commerce retail segment has been brought to the next level with the rise of mobile payment (Narang & Arora, 2018). The convenience brought by seamless mobile payment allows consumers to shop and pay at anytime and anywhere. As worldwide consumers are able to purchase items online, the success of B2C and B2B e-commerce trading requires the full cooperation between the e-retailers and the logistics service providers. LSPs are required to handle underlying logistics, warehousing and distribution process for the purchased items to cross borders and deliver to the destinations.

2.2.3 Existing Approaches in Managing E-commerce Supply Chain Activities

In the real logistics business environment, supply chain and logistics information management systems, also referred to as logistics information systems (LISs), are engineered and designed for logistics service providers to manage the available information in the supply chain for effective resource allocation and management of the physical flow of goods. They accommodate not only functions such as purchasing, warehousing and transportation, but also extensive connections with external partners (Sahin & Robinson, 2002), and engage customers to compete in the volatile and interconnected economy (Luo, 2013). Replacing phone, fax and e-mail to an increasingly degree, electronics data interface (EDI) automatically exchanges data between transactional parties. EDI is considered an indispensable capability for logistics functions to be coordinated with the operations of their partners and customers.

Typical LISs are warehousing management systems (WMS), transportation management systems (TMS), enterprise resource planning (ERP), etc. They substitute manual work or eliminate inefficient human effort and improve managerial decision making processes (Helo & Szekely, 2005). They streamline business processes (Faber, 2002), significantly reduce operation errors and enable the review of past performance, monitoring of current performance and prediction of future demand (Liu et al., 2005). With the integration of artificial intelligence technologies, LISs have the potential to help managers make complicated decisions by providing processed data of past cases. According to the annual analysis of the global WMS market conducted by the ARC Advisory Group (2014), retailers and manufacturers are "exerting demand on the WMS market whether from direct purchase of WMS solutions or through the extension of contracts with third-party logistics (3PL) providers so as to support their fulfillment operations". The ARC Advisory Group expects continuous expansion of omni-channel commerce and fulfillment in the coming years. WMS solutions are identified as a core enabler of omni-channel fulfillment.

However, the existing LIS solutions in the market, such as WMS, have little or no functionality that is integrated with AI technologies for enabling users in the decision-making of resources allocation and optimization (Accorsi et al., 2014; Poon et al., 2009). WMS are incapable of real-time information capturing or the actual working status visualization (Huang, 2007). Hence, data input must be done manually by operators, either via direct input into the system or by using handheld devices to capture data using barcodes, and then transfer the data via wireless network connections. As a result, the absence of decision-support functionality and a real-time information capturing ability reduces the overall efficiency of the order fulfillment process at the distribution centre or warehouse.

- ***The essence of information and communication technology for the supply chains***

In the global marketplace, the internet facilitates enormous business opportunities and is a prerequisite to develop technology-driven competitive advantage (Liu & Orban, 2008). With the maturity of Internet technology and the growing presence of WiFi and 4G-LTE wireless Internet access, the evolution towards ubiquitous information and communication networks is apparent. This leads to a paradigm shift from the use of traditional on-premise software systems to internet-based cloud computing model (Gubbi et al., 2013; Sasikala, 2011). On-demand software, referred to as software-as-a-service (SaaS), a completely innovative software application model, started to become popular at the beginning of the 21st century. End-users can choose and subscribe the software according to their actual needs so as to have the permission to use the software in a specified period of time (Buyya et al., 2013).

Gartner (2013) defined SaaS as "Software delivered remotely and managed by a third party as a one-to-many service through subscription or pay for use." Being widely recognized as a monumental enabler for business collaboration (Chen et al., 2007), the use of information technology and systems across diverse fields for routine operations and its reliance is growing (Shaikh & Karjaluoto, 2015). According to the 'Information Technology (IT) Spending Forecast' published by Gartner (2014), worldwide dollar-valued IT spending will grow 3.2% in 2014, reaching USD 3.8 trillion. 'Trends and Directions of SaaS in Asia/Pacific', another report published by Gartner (2013), addressed that SaaS for supply chain management including warehouse management, transportation management, sourcing and e-procurement, is within the top 10 SaaS applications in Asia pacific region in terms of the current usage.

As flexibility is known to be a decisive element of effective supply chain management (Duclos et al., 2003; Fredericks, 2005; Swafford et al., 2006), the cloud's scalability, ease of deployment and lowered cost of ownership enable cloud-based software solutions for supply chain and logistics industry to be more useful in the collaborative supply chain context (Boyer & Hult, 2005). The "pay per use" feature of SaaS which allows users to pay according to the actual usage, is an advantage for logistics operators due to cost reduction perspective they tend to focus on. Nevertheless, the uncertainties of IT implementation (Autry et al., 2010; Prater, 2005) and the slow pace of new technology adoption and innovation (Crum et al., 1996; Evangelista & Sweeney, 2006; European Commission, 2012; McKinnon, 2009) have been the obstacles faced by logistics operators. McDivitt, vice president and supply chain technologies leader for Capgemini North America, suggested that the cloud makes the most sense for shippers that intend to collaborate with external entities. However, the apprehension still lies in the thought of sharing data in the public cloud (McCrea, 2014). According to findings of Logistics Management's 11^{th} Annual

Software User Survey (McCrea, 2013), there are still companies that are either evaluating their cloud-based options or are not interested in the delivery method at all. Security concerns, privacy issues, system reliability and data integrity topped the list of cloud-related concerns. In most cases, shippers are worried about the loss of control that could come when an on-premise solution is replaced by a subscription-based model (McCrea, 2014).

- ***Technology adoption in logistics industry and the emerging trend of cloud-based ICT solutions for supply chain and logistics operations***

In the context of technology adoption in the supply chain and logistics industry, the mainstream literature deals with a myriad of subjects, varying from the factors influencing the adoption of LIS (Patterson et al., 2003; Barbosa & Musetti, 2010; Lin, 2007), the use of LIS in organizations (Huang et al., 2001; Ngai et al., 2008; Ketikidis et al., 2008), the impact of ICT adoption in logistics industry in various aspects (Lai et al., 2006, 2007; Wang et al., 2008), the factors affecting the adoption of technology innovation in 3PLs (Pokharel, 2005; Lin, 2007, 2008; Lin and Jung, 2006), as well as in small and medium-sized LSPs (Kilpala et al., 2005; Evangelista et al., 2013), the emerging trend of cloud logistics and how cloud-based logistics solutions or platforms benefit logistics practitioners (Autry et al., 2010; Hall et al., 2012; Liu et al., 2010). Nevertheless, none of the above studies have focused exclusively on investigation of the receptiveness, motivators and barriers of both LSPs and supply chain partners (SCPs) in various company sizes and ages so as to integrate supply chain and logistics-related cloud applications.

While the logistics processes are ever becoming more complex due to the shift in value creation in logistics from basic logistics services to value-added logistics services, logistics practitioners require extensive support from information technology systems. For ease of coordination and collaboration, logistics operators systematically manage a large amount of available information and share the information with the responsible parties internally and externally. With the emerging trend of cloud computing, the internal and external operational flow, communication channels and the means of information sharing, could be intervened and disrupted by the upcoming cloud-based ICT solutions. Nevertheless, the reluctance of logistics practitioners around the unproven idea of sharing sensitive and proprietary data online and the fear about the loss of control and ownership of cloud solutions are viewed to be the logistics practitioners' implementation concerns on cloud-based solutions.

2.3 Overview of Logistics and Warehousing Operations

2.3.1 The Differences between Conventional and E-commerce-based Logistics and Warehousing Operations

Logistics is a collection of functional activities that converts raw materials into finished goods (Ballou, 1999). As discussed by Stefansson (2006), in comparison to the first definition from the early 1960s made by Bowersox and colleagues (Smykay et al., 1961), the definitions of the term "logistics" have a much broader scope nowadays. The most leading definition is given by the Council of Logistics Management (CLM, 2004):

"Logistics is part of the supply chain process that plans, implements, and controls the efficient, effective forward and reverse flow and storage of goods, services, and related information between the point of origin and the point of consumption in order to meet customers' requirements."

Basically, traditional logistics and supply chain management is about the efficient planning and control of the movement of goods in supply chains. However, managing information flow along the supply chain is of equal importance to managing the physical flow of goods. For better coordination and collaboration with related parties within a supply chain, information technology (IT) serves as the enabler of efficient and effective information sharing and communication. As IT adoption and the capabilities of information sharing have a direct effect on the supply chain collaboration ability among supply chain partners (Li et al., 2009), the adoption of supply chain and logistics information management systems (LIS) in the logistics industry was regarded by many authors as one of the influential factors in achieving logistics operations excellences (Global Logistics Research Team, 1995; Bowersox et al., 1999). To reduce repetitive manual work and human error in the heavy information flow environment in logistics operations, the warehouse management system (WMS), transportation management system (TMS), and order management system (OMS) are among the Supply chain and logistics information management systems (LIS) that are mostly implemented by logistics service providers (LSPs) and supply chain partners (SCPs) (Helo & Szekely, 2005).

In a traditional supply chain, goods are processed in a multi-level supply chain in order to transport the goods from the factory to physical retail stores. End consumers make purchases and receive the products at physical stores. In today's Omni-channel retailing, the buying process of the end consumer involves various sources from online to offline. End consumers' orders can be received anytime and anywhere by the e-retailer. As orders are placed via the Internet, the downstream of the e-commerce B2C supply chain consists of a large number of unknown destinations spread around the world that require direct home delivery or consumer-direct delivery. The underlying fulfilment operations for e-commerce shipments, also called e-fulfilment (Agatz et al., 2008), is a crucial driver of e-commerce growth (Morganti et al., 2014; Maltz et al., 2004). While logistics and distribution play essential roles in the e-commerce sector

(Chen & Lin, 2013, Esper et al., 2003), logistics practitioners engaged in e-business have been facing a variety of challenges in fulfilling online B2C customer orders due to the e-fulfilment process being fundamentally different from the traditional shipments handling process in terms of the order nature and handling requirements, inventory management, warehouse design and management, last-mile delivery, and returns management (Agatz et al., 2008; De Koster 2003; Fernie & McKinnon, 2009; Leung et al., 2016; Maltz et al., 2004).

The order fulfilment process in traditional warehouses includes four major aspects: order receiving, order storage, order picking and packing, and order delivery. Amongst the four categories of order handling operations, order-picking is the most labour intensive operation in the warehouse and induces the highest warehouse-associated costs (Accorsi et al., 2014). In e-fulfilment, the operating categories in warehousing and distribution are common with respect to traditional order fulfilment. However, order-picking operations in e-fulfilment centers are initiated by end consumers who placed orders requiring the e-retailers or the logistics service providers to fulfil the orders accordingly. Such a demand-driven distribution model in the era of e-commerce further increases the complexity of order picking operations, as the order arrival pattern in more difficult to predict, compared to conventional large lot-sized logistics orders for weekly or bi-weekly stock replenishment of designated retail stores. Therefore, the importance of logistics capability and outsourcing is likely to increase. An entirely new fulfilment infrastructure is necessary in order to handle e-commerce shipments (Morganti et al., 2014; Xing et al., 2011; Chan et al., 2012; Cho et al., 2008).

- *Order-picking oeprations in warehouses and distribution centres*

Regardless of the type of logistics orders, i.e. conventional logistics orders and e-commerce orders, order-picking has been identified as one of the most labour intensive operations in warehouses and induces the highest warehouse-associated costs (Accorsi et al., 2014). Improved order-picking processes can significantly enhance warehouse operating efficiency. Research suggested that order-picking is estimated to be as much as fifty-five percent of the total warehouse operating expenses (Rene de Koster, 2006). Underperformance of the order-picking process can lead to unsatisfactory service levels and high operation costs in the warehouse. This could even induce a higher cost to the whole supply chain. The complexity of order-picking process is shown in Fig. 2.2 (Goetschalckx & Ashayeri, 1989), where the marketing channels, customer demand pattern, supplier replenishment pattern and inventory levels are the external factors that influence the order-picking choices. The internal factors include the characteristics of a system, organisation and operational policies of order-picking operation.

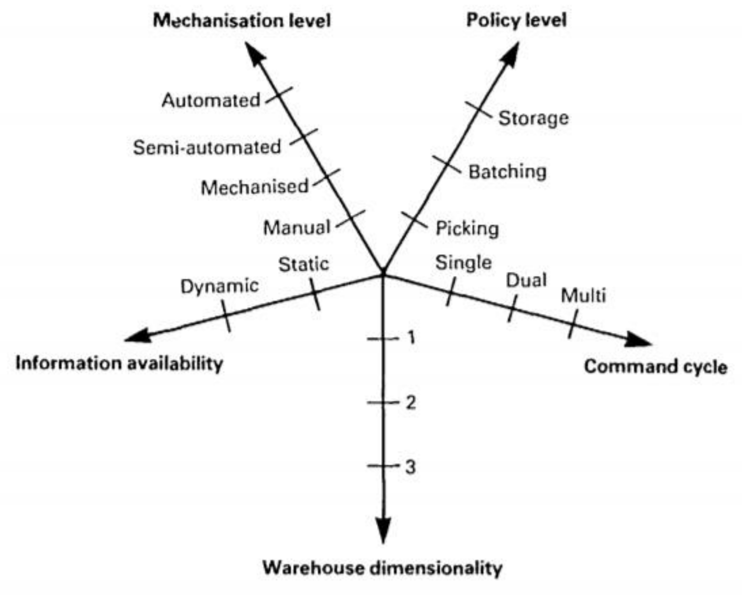


Fig. 2.2. Dimensions being considered in order picking process (Goetschalckx and Ashayeri, 1989).

For a manual-pick order-picking system which is commonly adopted in small-to-medium LSP warehouses, order-picking can further be classified into five operations: travel, search, pick, setup and others. The respective percentage of time used in each operation are shown in Fig. 2.3. It has been found that order pickers spent 70% of their time in traveling and searching for a specific item (Habazin et al., 2017). As travel distance is the major variable associating with travel time, therefore, if we can optimize the item listed on an order-picking list and the respective routing, we could make significant impact to half the total picking time. Besides, zoning can also minimize the effort of an order picker in searching for a particular item within the entire premises of the warehouse. Therefore, minimizing the order-picker travel distance and arranging products into zones are two major areas in order-picking that could be optimized.

In order to reduce the amount of redundant travelling time and travel distance to fulfil the required order-pick, batch order-picking, a process postponement strategy, can be applied because it evaluates multiple criteria before generating optimized result, which is a more systematic approach than human judgment based on an operator's experience. Postponement, a synonym of "delayed differentiation" is a strategy in a supply chain that delays the product configuration until the last possible moment (Choi et al., 2012). Postponement has been widely recognized as an effective strategy for managing uncertainties and variability in demand by improving the trade-off between cost and customer service in the face of diversifying products, and the need for quick response to customers' needs (Yang & Yang, 2010). Zinn and Bowersoz (1988) discussed five deferral strategies. The first four are related to the product, including labelling, packaging, assembling and manufacturing, whilest the fifth postponement strategy focuses on the process of logistics. It can further be classified as place postponement and time postponement. The former one emphasizes the storage location of finished products in a centralized logistics system, and the latter one emphasizes the time delay for slowing the movement of the transportation of a product until the last possible moment, rather than responding to customer order on demand. Decisions from the postponement strategy are significantly influenced by the total relevant logistics and transportation costs (Shao & Ji, 2008). However, discussion of logistics process postponement is currently lacking. Such postponement strategy can in fact apply to warehouse operation in better managing small lot-sized with wide variety of e-commerce order under this new trend of e-commerce predominated trading environment.

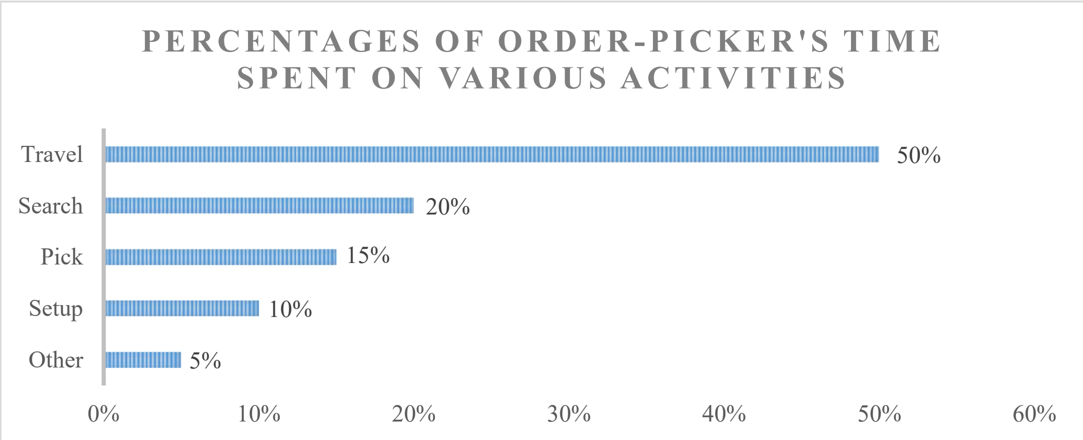


Fig. 2.3. Time usage distribution during order picking

2.3.2 Existing Decision Support Solutions for Facilitating Conventional and E-commerce-based Logistics and Warehousing Operations

A range of research activities regarding warehousing and transportation activities can be found in the mainstream literature. The areas specifically related to the design and process improvement in warehouses is summarized in Table 2.1. Concerning the warehouses and distribution operations, streamlining the traditional order fulfilment process through providing decision support for logistics practitioners has become one of the active research areas. Poon et al. (2011) integrated radio frequency identification (RFID) technology with the genetic algorithm (GA) technique for generating pick-up and delivery route planning for small batch replenishment orders. Lam et al. (2011) proposed a decision support system integrating the case-based reasoning (CBR) technique for supporting managers in making appropriate order fulfilling decisions. Though various aspects of the warehousing and transportation sector have been widely examined, previous research activities focused on traditional warehousing operations or transportation operations. The attention paid by researchers in consideration of today's e-commerce order fulfilment in the warehousing and transportation sector is very limited.

Numerous intelligent systems and approaches for providing order-handling decision support in warehouses have been developed. However, there is a scarcity in the literature on B2C e-commerce order fulfilment in distribution centers, which takes the e-order handling process and requirements into consideration. Only a limited range of papers related to B2C e-commerce can be found in the literature, such as assessing the level of B2C trust in e-commerce (Akhter et al., 2005), developing a negotiation model for B2C ecommerce (Huang et al., 2010), a prototype of e-commerce portal with a set of services provided by intelligent agents (Castro-Schez et al., 2011), and an evaluation model for ranking B2C websites in e-alliance (Yu et al., 2011). Hence, in this research, an e-order fulfilment pre-processing system is proposed, which highlights the importance of using the genetic algorithm approach as the core means of tackling the common operational bottlenecks found in e-fulfilment centers, with the integration of a rule-based inference engine for further providing a more comprehensive solution to assist e-commerce order fulfilment operations.

Table 2.1. A summary of the literature related to the conventional warehousing and transportation activities

Scope	Studies
Warehouse layout design	Yao et al., 2010; Hassan, 2002; Caron et al., 2000; Önüt et al., 2008
Storage location assignment in warehouses	Yang et al., 2015; Pan et al., 2015; Chew & Tang, 1999; Jane, 2000; Muppani & Adil, 2008
Order picking time reduction	de Koster et al., 2007; Petersen, 2000; Bindi et al., 2009
Resource management in warehouses	Chow et al., 2006
Design of warehouse scheduling system	Zacharia & Nearchou, 2016; Chan & Kumar, 2009; Park et al., 1996
Transportation routing and scheduling	Zegordi et al., 2010; Chen & Lee, 2008; Geismar et al., 2008; Taniguchi & Shimamoto, 2004

As for the existing approaches for order-picking optimization, studies related to order batching are mainly focused on the order batching layout that consists as single-aisle and two-dimensional. Due to the limitation of using integer programming to obtain the exact solutions with reasonable computation power for order-picking batching, researchers have developed other batching heuristics. Berg (1999) made a survey of these batching heuristics. Instead of directly minimizing the travel distance of operators, studies have considered different types of order proximity and distance approximation measures to cluster orders. With the development of complexity theory in the early 1970s, it became futile of ever finding an efficient exact solution by using the integer programming approach. New approaches using heuristic algorithms have proven to be effective in solving problems that have multiple constraints, multiple objectives and large dataset (Cabeza & Moilanen, 2001; Pressey & Possingham, 1997). Unlike integer programming, heuristics algorithms approach the problem by approximate solution techniques and identify the near optimal solution within the iterations. By using this approach, the processing time for a global optimum solution using heuristic algorithms is significantly shorter than using the linear programming approach.

Furthermore, Gibson and Sharp (1992) developed a batching method for a parallel-aisle layout and a large set of orders. Considering the distance approximation measurement as summing up the distances between each item of the seed order and the closest item in the candidate order, Gibson and Sharp (1992) were able to outperform the model proposed by other approaches. However, the limitation of the above two mentioned methods is a simple warehouse layout with a single-aisle and two-dimension consideration. It disregarded the vertical movement of picking. In more advanced warehouse management systems, the horizontal and vertical movements of order picking would be considered simultaneously. This type of system usually is expensive and small-to-medium LSPs are unlikely to be affordable.

2.4 Existing DM and AI techniques Used in Improving Decision-making in Warehouses and Distribution Centres

Data analytics is concerned with the mining of data to reveal hidden knowledge and insights. In the supply chain and logistics field, there is an intensive amount of information, such as customer demand and profiles, order and inventory status, and delivery information, available within the supply chain network that can be used for performing data analytics to generate useful knowledge. In the past decades, the open literature has provided a wide range of applications of artificial intelligence techniques and business intelligence techniques in the area of supply chains and logistics. This section describes state-of-the-art popular artificial intelligence and data mining techniques, which are commonly applied into the supply chain and logistics industry for improving operational efficiency.

2.4.1 Case-based Reasoning

Case-based reasoning (CBR) is a common artificial intelligence technique highlighting knowledge repository information based on past knowledge and experience. A CBR engine organizes past knowledge and experience as “cases”. Through the four typical steps in running the CBR engine, namely, case retrieval, case reuse, case revise and case retain, historical cases with the most similar circumstances to the current problem are retrieved from the case library (Aamodt & Plaza, 1994). Selected past cases are then reused to generate solutions for the new problem. These solutions can be reviewed to meet the circumstances of the existing problem. Lastly, the new solution is retained in the case library of the CBR engine for future retrieval. The output of the CBR engine is a set of recommended solutions that is likely to be feasible and applicable in solving a new problem (Craw et al., 2006).

The case retrieval process in the CBR engine is a crucial step in applying the CBR technique. In general, there are nine steps to achieve case-retrieval by using CBR. Fig. 2.4 shows the procedures of a typical system architecture of a CBR engine. The nine steps are case representation, case indexing, case retrieval, similarity measure analysis, case reuse, case revision and case retention. The nine steps form a closed loop with the case library. There are two commonly used methods in CBR for the creation of the case library: the NNR (nearest neighbour retrieval) method and the inductive indexing method. NNR uses a thorough search by computing the similarity of the problem description between all past cases and the current case to be solved. Although NNR can ensure finding the most similar past case to match with the current one, it requires large storage capacity and long search time (Jahromi et al., 2009). Due to NNR disadvantage, the inductive indexing method should be considering in achieving a shorter search time. Instead of identifying each of the items in the past cases, it tends to categorize items into a series of instances according to their attribute similarities. This method determines which features distinguish cases well and then generates a decision tree to organise the case for retrieval (Shin & Han, 2001). Nevertheless, inductive indexing cannot guarantee matching cases with the highest similarity because it does not require comparison with the entire past cases database. To enhance the performance of inductive indexing, researchers attempted to incorporate NNR into an inductive indexing model to form a k-d tree (Choy et al., 2005). Another technique was proposed by Kang et al. (2007) to reduce the past case retrieval time by using clustering algorithms with the NNR model. By grouping past cases into clusters, and performing case matching based on the cluster can enhance the performance of the retrieving processes as well as its effectiveness (Can et al., 2004).

With the learning ability from real-world decision-making processes, CBR is valuable in environments where decision-making heavily relies on one's knowledge and past practices (Chi et al., 1993). In fact, CBR has been extensively applied in various fields for decision support. Zhang et al. (2015) and Hassanien (2015) applied CBR in tackling environmental issues. Woodbridge et al. (2015) and Sene (2015) adopted CBR in providing decision support in the medical industry. Chow et al. (2006) and Lam et al. (2015) used CBR for managing resources and mitigating risks in the warehouse operating environment. With the decision-making ability and responsiveness being critical elements under the complex e-commerce logistics environment, the application of CBR is useful for enhancing the operating efficiency of LSPs in handling e-commerce orders.

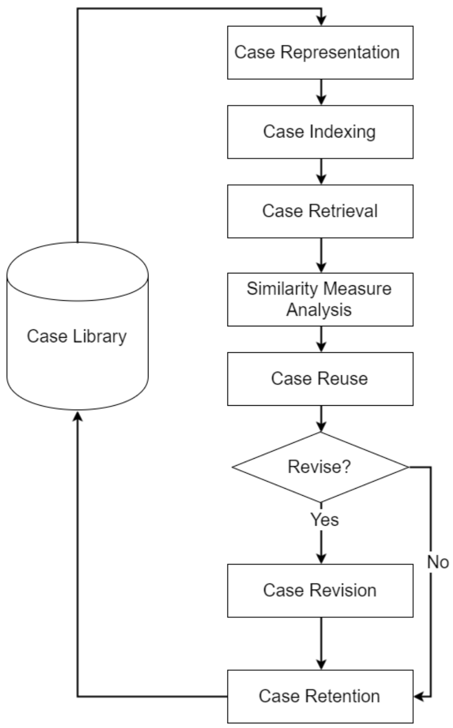


Fig. 2.4 A typical CBR process

2.4.2 Multi-agent technology

Agent technology provides new concepts and abstractions to facilitate the design and implementation of systems that enables automation of operation and decision support (Weiss, 1995 and Wooldridge, 2002). As discussed by Parunak (1999), there are five characteristics for an ideal application of agent technology: (a) Modular - each entity has a well-defined set of state variables that are distinct from those of its environment and that the interface to the environment can be clearly identified, (b) Decentralized - the application can be decomposed into stand-alone software processes capable of performing useful tasks without continuous direction from some other software process, (c) Changeable - the structure of the application may change quickly and frequently, (d) Ill-structured - all information about the application is not available when the system is being designed, and (e) Complex - the system exhibits a large number of different types of behavior which may interact in sophisticated ways. As pointed out by Davidsson et al. (2005), agent technology is particularly useful and applicable in the context of the logistics and transport industry, therefore the development of agent-based applications in the areas of logistics and transport is promising.

Due to the nature of logistics and transportation operations that requires processing a large amount of information and data from multiple sources for making timely decisions and perform sequential tasks, multi-agent technologies have been extensively applied in the field of supply chains, logistics and transport industry. In the context of transportation and traffic management, the mainstream literature applied the multi-agent technology into various aspects. Brézillon et al. (2000) developed a support system for rail traffic control. Findler and Lo (1986) proposed a system for air fleet control through the integration of agent technology, one of the oldest applications of multi-agent systems. The mainstream literature also integrates agent-technology into several areas related to warehouse management and production logistics, such as logistics and production planning optimization (Karageorgos et al., 2003) and solving dynamic logistics process management problems (Chow, Choy & Lee, 2007). Multi-agent systems offer such useful features as parallelism, robustness and scalability. They are highly applicable in particular domains and problems where integration and interaction of multiple sources of knowledge, the resolution of interest and goal conflicts or time bounded processing of data are required (Graudina & Grundspenkis, 2005; Weiss, 1995). As warehousing and transportation operations are dynamic and complex, multi-agent technology is considered to be an essential tool that can yield benefits to logistics practitioners in the goal of maximizing operating efficiency.

2.4.3 Analytical Hierarchy Process

The Multiple Criteria Decision-Making (MCDM) is a frequently applied approach to solve complex real world problems that explicitly evaluate multiple, conflicting, and disproportionate criteria or objectives for the selection of suitable alternative (Gavade, 2014). Various criteria have uniqueness and different degrees of importance in the measurement. For the treatment of uncertainty in MCDM analysis, the weighted sum model (WSM) is the earliest and best known method (Turskis et al., 2016). WSM exposes the simplest way for evaluating a number of alternatives in terms of different units of decision criteria. The weighted product model (WPM), a multiple criteria evaluation model modified from the WSM, was proposed to overcome some of the weaknesses found in WSM (Triantaphyllou, 2000). Each decision alternative is compared with the others by multiplying a number of ratios, one for each decision criterion. Each ratio is elevated to the power corresponding to the relative weight of the equivalent criterion. Some of the first references to this method were by Bridgman (1922) and Miller and Starr (1969). In later development, the Analytic Hierarchy Process (AHP), initially proposed by Saaty (1980), has become popular and considered to be more consistent than the original approach.

AHP is a systematic decision-making tool to solve multi-criteria decision making problems (Saaty, 1980). It decomposes a complex MCDM problem into a system of hierarchies by standardizing the numeric scale for the measurement of both quantitative and qualitative performance. The system of hierarchies in using AHP constructs the objective, criteria, sub-criteria and the decision alternatives at the first level, second level, third level and fourth level respectively. A generic structure of AHP is shown in Fig. 2.5. The measurement of the attributes in the same level involves pair-wise comparisons using the Eigenvalue approach. An n*n matrix is structured in the AHP, as illustrated in Fig. 2.6. The matrix is constructed by listing the relative importance of the choices in terms of each criterion in a particular level, from paired comparison using a nine-point scale (1-9). The scale ranges from 1/9 representing ‘least valued than’, to 1 for ‘equally valued’, and to 9 for ‘completely more important than’, covering the entire spectrum of the comparison, as depicted in Fig. 2.7. The pairwise comparison converts human preferences between different alternatives from the subjective feelings to a more discrete value.

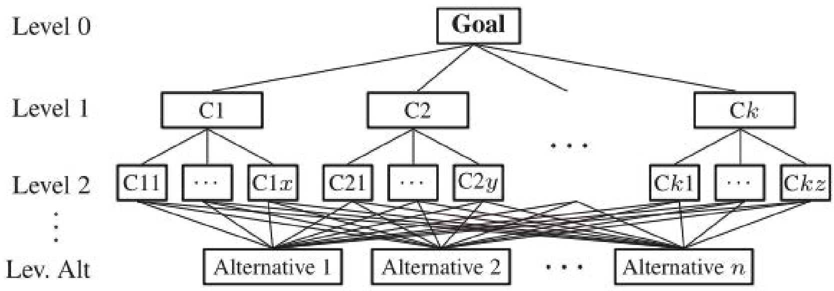


Fig. 2.5. A generic AHP hierarchy structure

$$A_{n\times n} = (a_{ij})_{n\times n} = \begin{array}{c} \\ 1 \\ 2 \\ \vdots \\ n \end{array} \begin{array}{c} \begin{array}{cccc} 1 & 2 & \dots & n \end{array} \\ \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ a_{n1} & a_{n2} & \dots & a_{nn} \end{bmatrix} \end{array}$$

Fig. 2.6. A n*n pairwise comparison matrix

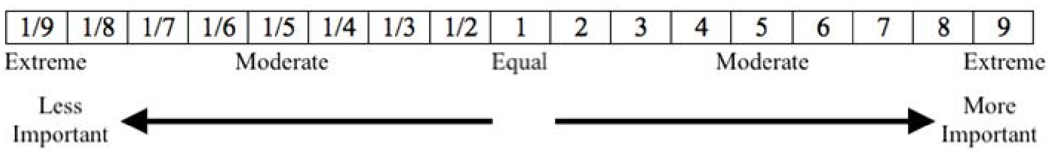


Fig. 2.7. A nine-point scale for pairwise comparison

The hierarchy approach used in AHP delivers various advantages. It helps to integrate a group of different criteria (Zahir, 1999). It solves complicated problems which involve the consideration of multiple criteria and alternatives concurrently. It has the ability to integrate data and human judgement into the model in a logical way. Additionally, it provides a scale for measuring tangible and intangible data and for sorting out the priorities in handling the interdependence of elements, which reduces bias in the system (Macharis et al. 2004). This allows reconsideration of judgements in a short period of time to monitor the consistency in the decision-maker's judgements so as to reduce bias in the decision making process. The ease of usage and the conversion of subjective feelings in prioritizing alternatives makes AHP an important part of the MCDM process.

AHP is a useful technique for decision-makers to solve complex problems. These problems involve human perceptions and judgements on multiple criteria, which impact on the long-term repercussions. It appears unavoidably that an organized method of making decisions is needed. AHP has successfully gained recognition by researchers, due to the effectiveness of the hierarchical problem identification and the application on pairwise comparisons in preference elicitation (Salo & Hämäläinen, 1997). There is a wide range of practical applications of AHP reported, producing extensive results in problems involving making choices, ranking, prioritization, resource allocation, strategic planning and project management (Vargas, 1990). A review of applications of AHP by Subramanian & Ramanathan (2012) indicated that the decisions related to operational strategy, process and product design, planning and scheduling resources, project management, supply chain management, were successfully tackled by AHP. In particular, Lai et al. (2002) introduced a Multi-certeria Authorizing System (MAS) by using the AHP technique for software selection. They evaluated the opinions of six experienced software engineers for selecting three products of MAS. Four hierarchy levels of pair-wise comparison were formed with different criteria: user interface, graphical support, multi-media support, file type support, cost effectiveness, and software maintenances. A selection consensus was then formed by AHP and the best option for production software was selected. In the field of project management, Al Harbi (2001) used the approach to select the best contractor. A hierarchical structure for the pre-qualification criteria was constructed for evaluating five contractors. The highest overall priority value was calculated after comparing the pair-wise criteria and ranking. Furthermore, Korpela & Tuominen (1996) presented an integrated approach to the warehouse location selection process, where both quantitative and qualitative measures were considered. Warehouse site selection was aimed at optimizing inventory management, and facilitating the transportation process, as related to the design of a logistics system.

2.4.4 Genetic Algorithms

The basics of Genetic Algorithm (GA) were first introduced by Holland (1975), and the approach has been used to successfully tackle a wide array of real-world problems without requiring huge computation effort to retrieve an optimized solution. Also, its flexibility allows it to be applied to various types of objective functions and constraints in either discrete, continuous or mixed search spaces (Gen & Cheng, 2000). The fundamental principle of the GA is to mimic the success of natural evolution through random selection and the reproduction of offspring. Two issues must be addressed before applying the genetic evolutionary concept to an optimization problem: (i) encoding the potential solutions into chromosomes, and (ii) defining the objective function, namely the fitness function. A solution (chromosomes) is encoded in a string of variables or “genes”. The initial trial of chromosomes is randomly generated according to certain principles or variables. The algorithm performs evaluation to measure the fitness of the potential solutions. The procedures of the GA mechanism are shown in Fig. 2.8. The optimization process then selects pairs of chromosomes with probabilities proportionate to their fitness and matches them to create new and improved solutions (offspring). In addition to matching (crossover), a small degree of mutation is introduced to the offspring. The replacement of underperformed solutions is based on some fixed strategies. The chromosomes which successfully evolve through the iterations are called generations. The evaluation, optimization and replacement of chromosomes stop when the termination criteria are satisfied (Goldberg, 1989). The solution, which is in form of a chromosome, is then decoded.

The genetic algorithm technique has been proven to excel in solving combinatorial optimization problems (Ho et al., 2008). The GA operation is based on the principles of genetic and natural evolution through random selection and the reproduction of offspring (Renner & Ekárt, 2003; Lee et al., 2016). A nearly optimal solution generated by the GA technique is in a form of chromosome, which involves a string of genes. Two basic operators in GA, the crossover operator and mutation operator, create new offspring from the parent chromosomes by selecting a pair of chromosomes for matching, and performing a random adjustment of some values of the genes in a chromosome, respectively. The generated chromosomes are then evaluated through a defined fitness function. A number of GA applications have been found in the domain of manufacturing, warehousing and distribution, showing the use of GA for solving scheduling-related problems. Lin et al. (2014) developed a genetic algorithm-based optimization model for managing green transportation operations. Mendes et al. (2009) integrated GA with heuristics rules for tackling the joint replenishment problem in warehouses. Lee et al. (2016) provided a comprehensive quality assurance scheme in the garment industry through optimizing the fuzzy rules using a genetic algorithm.

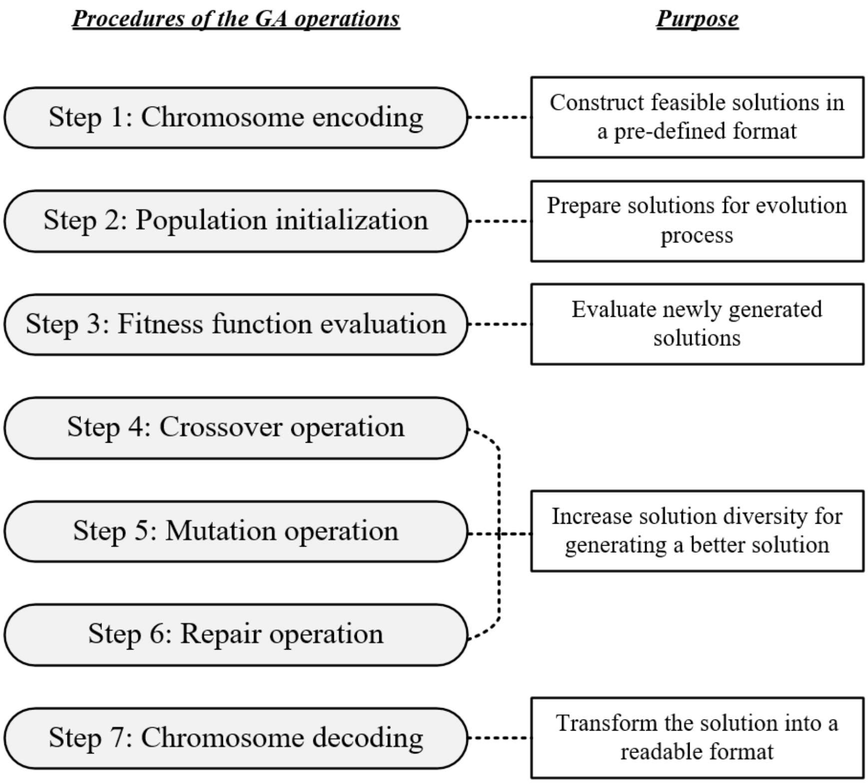


Fig. 2.8. Standard procedures of the GA operations

2.4.5 Fuzzy Logic

In the decision making process, it is often required to identify or describe the current status before making a conclusion or generating some appropriate solutions. These kind of descriptions might not be fully interpreted by "natural languages" (Zimmermann, 2011). Also, the meaning of words in these natural languages is very often vague. The human thinking and feeling forms might not have exact boundaries with each word element. Examples are words such as "fast payment", "high sales value" and "creditworthy customers". It is difficult to distinguish which sets they belong to. Thus, these sets become vague or fuzzy because they are dependent on other contexts. Zadeh (1965) and Goguen (1969) were the first generation of scholars who generalized the classical perception of a set and accommodate fuzziness in human judgement. Zadeh (1965) proved that fuzzy set theory has wider scope of applicability, especially in the fields of data processing and pattern classification. Fuzzy set theory provides a mathematical framework for transforming a vague concept into a precise and rigorous numerical set which makes the decision making process more supportive. Zadeh (1978) initiated the Fuzzy Logic technique as an artificial intelligence methodology for simulating human reasoning (Jain et al., 2015). The ability to transform sophisticated sentences from natural language into mathematical expressions allows fuzzy logic technique to provide the flexibility for modeling using linguistic expressions (Jain et al., 2015).

Fuzzy Logic is a many-valued logical method that assigns a grade of membership between true value zero to one to each item. It is fundamentally different from Boolean Logic as the true value of the variables of Boolean Logic can only be integer values, i.e. zero or one, which means completely true or completely false. Instead, the true value of variables in Fuzzy Logic can be in the range of zero to one ([0,1]), such as a value of 0.7 (Novák et al., 2012). In early use, the most successful application of Fuzzy Logic was in the high-speed trains in Sendai, Japan, for improving the ease and accuracy of the ride (Kosko, 1994). Fuzzy Logic has been used in many different aspects, such as electrical, chemical, environmental and biomedical engineering (Singh et al, 2013).

The computing method based on fuzzy logic can be used in the development of intelligent systems for optimization, identification, pattern recognition, control and decision making. There are three major stages in applying the Fuzzy Logic technique: Fuzzification, Inference engine, and Defuzzification (Siddique, 2013). The Fuzzy Logic process starts with fuzzification. Fuzzy membership functions are defined to address the degree of fuzziness for each parameter. To perform this fuzzification process, the universe of discourse and membership function must be specified in order to determine the function of the fuzzy sets. An example is illustrated in Fig. 2.9. The universe of discourse is divided into several areas, which belong to different predicates, such as short, medium, and tall.

The inference process is performed followed by the fuzzification stage where the universe of discourse and membership functions of each input and output parameter are defined. IF-THEN rules are created and stored in the fuzzy inference engine to convert the input fuzzy set into an output fuzzy sets (Galindo, 2006). The inference process includes rule block formation, rule composition, rule firing, implication and aggregation in order to easily identify the rules and situations between membership functions. Rule composition and rule block information are used to display membership functions into a table for ease of searching. In rule firing, IF-THEN rules are used to state the rules of the membership functions. Implication and aggregation are used to merge the input date into the rule firing in order to demonstrate which data belongs to which rule set(s).

The final step of Fuzzy Logic is defuzzification. It is used to determine the crisp value. Decision support systems needs Fuzzy Logic because decision making plays an important role in business for evaluation and cost reduction (Kumar, 2013). Fuzzy Logic can handle various attributes associated with particular problems. For example, Omero et al. (2005) solved the problem of measuring the performance of a set of production items by applying fuzzy logic to the decision support systems.

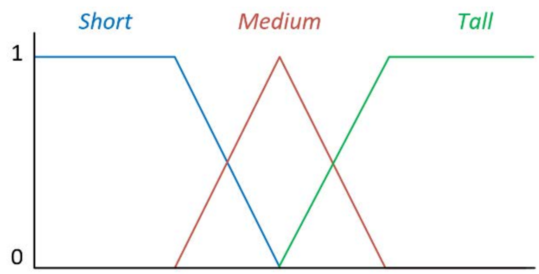


Fig. 2.9. The merged membership functions in fuzzy logic technique

2.4.6 Association Rule Mining

An association rule is a rule-based method for showing characteristic value conditions that occur normally together in each dataset (Rajak, 2008). It provides information in the form of "IF-THEN" statements. The rules are calculated from the data, unlike the "IF-THEN" rules of Fuzzy Logic. Association rule mining is probabilistic in nature, and there are two parts, the antecedent ("if") and the consequent ("then") (Agrawal, 1993). An antecedent is finding an item in the data, while a consequent is finding an item in combination with the antecedent. In association analysis, the antecedent and consequent are called "itemsets". There are three useful concepts for the association rule, i.e. support, confidence and lift (Petry, 2013).

Association rule analysis has been broadly applied in various areas, such as market analysis, medical science, and web usage mining (Rajak, 2008). It is used to uncover specific patterns in the dataset. Also, the pattern exposes groupings of events that occur at the same time. The most typical example of association rule mining is in market analysis. The reason why association mining is useful for market analysis is that it can go through numerous transaction records (e.g. 1,000,000 point-of-sale transactions) which lists all items the customers bought in every single purchase. Managers would like to know if certain groups of items are consistently purchased together in order to adjust the store layout, promotions and identify customer segments to increase the sales by attracting and bringing convenience to customers. It is a complicated and time-consuming step if mangers do not use data mining techniques (Mueller, 2005). In medical science, applying the association rule is an important step in medical diagnosis and protein sequencing (Serban, 2006). The reason why it is important in medical science is that the medical science process is complex, and the association rule helps physicians diagnose and determine the DNA sequence by guaranteeing the correctness of the induced hypotheses in order to improve the prediction accuracy in complex medical applications (Gupta, 2006). Further, in the business field, discovering association rules is an effective way that helps in decision making and marketing (Moreno, 2005). Hence, association rule mining is useful for analyzing customer behavior and background.

2.4.7 Adaptive Network-Based Fuzzy Inference System

ANFIS is a fuzzy inference system implemented in the framework of adaptive networks, indicating that the fuzzy inference system is based on neural networks (Jang, 1993). Similar to ANN, ANFIS has a capability of modeling linear and nonlinear functions (Jang et al., 1997).

ANFIS is comprised of fuzzy inference system and adaptive neural network as the major elements. For the fuzzy inference system (FIS), it is based on the fuzzy “If-Then” rules for human knowledge and inference procedures to perform qualitative description and analysis, except for the lack of accurate quantitative analysis and correction of values (Su & Cheng, 2016). ANFIS is used to link the input characteristics to input membership function (MFs), input MFs to a set of If-Then rules, the set of rules to output characteristics, output characteristics to output MFs and finally to the single-valued output or the decision associated with the output. For the adaptive network of ANFIS, it is a network structure consisting of a number of nodes connected through directional links. The outputs of these adaptive nodes depend on modifiable parameters pertaining to these nodes. The learning rule specifies how these parameters should be updated to minimize error (Güneri et al., 2011). Details for fundamental principles of ANFIS are published elsewhere (Jang, 1993, Jang et al., 1997,), so detailed descriptions of these methods are not given here. The theoretical rationale of the ANFIS models proposed in this study is discussed in Section 3.6.2 – ANFIS Model Construction.

ANFIS has been widely used in solving different sorts of problems. In the literature, researchers apply the hybrid learning structure of ANFIS for performance comparison with other neural network oriented studies (Lee, 2008; Shiri et al., 2011; Areerachakul, 2012; Alrashed wt al., 2018). Polat and Güneş (2007) used principal component analysis and ANFIS to improve the diagnostic accuracy in diabetes disease. The dimension of the diabetes disease dataset that has 8 features is reduced to 4 features using principal component analysis, followed by a diagnosis of diabetes disease through using an adaptive neuro-fuzzy inference system classifier, which is able to give a 89% of classification accuracy. In the context of supply chain management, researchers applied ANFIS models for tackling common problems addressed in the literature, such as supplier selection and evaluation of supply chain performance. Güneri et al. (2011) proposed an ANFIS-based approach to deal with supplier selection problem by applying the ANFIS model for selecting supplier selection criteria. The results revealed a better performance by the developed ANFIS model over the multiple regression method in selecting the criteria for supplier selection. Didehkhani et al. (2009) developed a supply chain flexibility assessment model using ANFIS through taking flexibility attributes, such as operation, new product and responsiveness, into the modelling of the ANFIS model.

In general, ANFIS models have a diverse area of applications in the literature, with a number of studies adopting ANFIS for tackling a forecasting problem. These studies suggest that the integration of the fuzzy inference system and adaptive neural network in ANFIS is capable of modeling linear and non-linear functons and predicting a subject well. For the studies using ANFIS for solving forecasting problems, a review and discussion is given in section 2.5.2.2 – ANFIS-based Forecasting Model.

2.5 Existing Approaches for Time-series Data Prediction

2.5.1 Stochastic Modelling for Time Series Data Prediction

Stochastic time series models for time series demand forecasting, such as moving average (MA), autoregressive moving average (ARMA), and autoregressive integrated moving average (ARIMA), have been widely applied in various areas in the past few decades. These methods assume that the time series is linear and follows a particular known statistical distribution. The high dependency on historical data of these time series models limits their applicability, as real data can be incomplete, imprecise, and given in linguistic values. However, stochastic time series models are still perceived to be essential tools for forecasting time series data. This section discusses some popular stochastic time series forecasting tools, including: linear regression, moving average, exponential smoothing, auto regressive and autoregressive integrated moving average model.

2.5.1.1 Linear Regression Model

Linear regression is a prediction technique that involves the extent to which the independent variables can predict the dependent variable (Hair et al., 2010). It is a statistical method that can summarize and study the relationship between two continuous variables x and y. Variable x is a predictor or independent variable while y is a response or dependent variable. It is assumed that the relationships between variables are linear, of two basic type: simple linear regression (SLR) and multiple linear regression (MLB).

- *Simple linear regression (SLR)*

  Simple linear regression (SLR) is a linear regression model with a single explanatory variable (Seltman, 2008). SLR forecasting models are expressed as Eq. 1:

$$Y_t = b_0 + b_1 x_t + \varepsilon_t \tag{1}$$

  where Y_t is the dependent variable and predicted value of Y at time t, b_0 is the estimation of regression intercept, b_1 is the estimation of the regression slope and x_t is the independent variable and value of x at time t. ε is the individual error term which has a mean of zero.

- *Multiple linear regression (MLR)*

  Multiple linear regression (MLR) is used to examine the linear relationship between a single dependent variable and two of more independent variables. MLR forecasting models are expressed as Eq. 2:

$$Y_t = x_t \beta + \varepsilon_t \tag{2}$$

  where Y_t is the dependent variable and predicted value of Y at time t, x_t is the vector of k explanatory variables at time t, i.e. x_t = 1, $x_{i1}, x_{2t}, \ldots, x_{kt}$. β represents the vector of coefficient, i.e. $\beta = (\beta_0, \beta_1, \ldots, \beta_k)^T$ and ε_t is the individual error term at time t, i.e. $t = 1, 2, \ldots, N$.

Linear regression is a technique that fits a trend equation or a curve to a series of historical data points and projects the curve into the future for medium and long term forecasts. It has been widely used to measure the strength of the relationship between independent and dependent variables. Bartosz (2014) proposed the use of Simple Linear Regression and Multivariate Adaptive Regression Splines to estimate the share returns on the Warsaw Stock Exchange. Lin & Tsai (2015) used a simple linear regression approach for forecasting mortality rates. Bas et al. (2017) proposed a multiple linear regression model and a SARIMA model for air concentration forecasting. Latt & Hartmut (2014) used stepwise multiple linear regression (SMLR) and artificial neural network (ANN) models as tools for multi-step forecasting of the Chindwin River floods in northern Myanmar.

2.5.1.2 Moving Average (MA) Model

The moving average method is one of the time series analysis techniques used for smoothing short period fluctuations, showing the trend by generating the weighted average of the past period observation (Lauren & Harlili, 2014). There are two types of moving average: simple moving average (SMA) and weighted moving average (WMA).

- *Simple moving average*

  Simple Moving Average is the average demand of a number of periods that is used for forecasting the next period. It is used for stable demand with no pronounced behavioral pattern, and is calculated by Eq. (3).

$$SMA_n = \frac{\sum_{i=1}^{n} D_i}{n} \tag{3}$$

where SMA_n is the forecasted rate for period *n, Di* represents the demand for the period and *n* denotes to the number of periods considered in the moving average calculation.

- *Weighted Moving Average*

  Weighted Moving Average is the adjusted moving average method that more closely reflects data fluctuations. It can modify the technique to give greater weight to a more recent observation. It is calculated by Eq (4).

$$WMA_n = \sum_{i=1}^{n} W_i D_i \tag{4}$$

where WMA_n is the forecasted rate for *n* period, *Di* represents the demand for the period, *Wi* represents the weighting of period *i* which between 0% and 100% and *n* responses to the number of periods in the moving average.

The moving average predicts the trend of the data. It is simple and more effective than other comparably more complex techniques (Lauren & Harlili, 2014). MA can avoid noise and therefore smoothing of the trend environment. There are short-term moving average and long-term moving average. If the value of short-term moving average is greater than the long-term simple moving average, an up-going trend is indicated. On contrary, the reverse occurs.

There are many factors affecting the prediction of the time series data. Due to the simplicity of MA, it is rarely used independently. It is combined with other factors or algorithms in particular aspects. For stock trend prediction, Lauren & Harlili (2014) proposed the combination of the simple moving average and news classification by artificial neural network (ANN). Sulandari & Yudhanto (2015) proposed a hybrid approach of moving average and weighted fuzzy time series to enhance the forecasting accuracy in the trend data. For environmental forecasting, Fhira et al. (2015) suggested using MA to smooth the rainfall time series data and observe the input vector for the prediction process by using an Evolving Neural Network. It shows that although MA is rarely used independently, it can be integrated with other prediction methods for conducting the prediction.

2.5.1.3 Exponential Smoothing Model

The exponential smoothing model is a powerful tool for forecasting future demand and is one of the moving average methods. (Liljana et al., 2016; Su et al., 2018). Exponential smoothing generates forecasting by weighting the averages of past observation and giving the recent values a relatively more weight than the older observation in forecasting (Makridakis et al., 1998; Su et ai, 2018). Past data is rejected gradually rather than suddenly. Holt (1975) and Brown (1959 &1963) introduced the single exponential smoothing of time series data and extended by Holt to linear exponential smoothing to enable forecasting of the data with trends. Exponential smoothing assumes that time series are built from unobserved components such as trend and seasonal effects. Those components have been adapted over time to follow the demand pattern (Billah et al., 2006). The formula of exponential smoothing is:

$$F_{t+1} = \alpha D_t + (1 - \alpha) F_t \tag{5}$$

where F_{t+1} is the forecast for next period, D_t represents the actual demand for the current period, F_t refers to the previously determined forecast for current period and α is the weighing factor, a smoothing constant between 0 and 1. If great variation in a short period is observed, a small value of the smoothing constant should be selected.

On the contrary, the high value of the smoothing constant should be selected. The greater the variation observed, the smaller value of the smoothing constant to be selected.

Exponential Smoothing can predict the data with the trend. It is suitable for forecasting the short-term and medium-term time periods with good accuracy compared with other algorithms. Due to its simplicity, the forecasting method is comparable to forecasts of more complex statistical time series data (Makridakis and Hibon, 2000). Exponential smoothing is widely used in forecasting the data with the trend. In an environmental application, Su et al. (2018) proposed exponential smoothing for forecasting the water ecological footprint (WEF) as well as defining the future trends of WEF. In the field of logistics, Liljana et al. (2016) developed a smoothing method for forecasting the time series data with several zero entries and substantial noise, with the Holt-Winters smoothing methods introduced. Taylor (2011) proposed an exponential smoothing based model for forecasting the density of intraday call center arrivals. It shows that exponential smoothing can be widely used in different applications and is appropriate for forecasting the data with the trend.

2.5.1.4 Auto Regressive (AR) Model

An autoregressive model is a linear regression of the current value of the series against one or more prior values of the series (Wei et al., 2014). The AR model includes one or more past values of the dependent variable among its explanatory variables. The autoregressive moving average model (ARMA) is a conventional method which is applicable to forecast regular periodic data, such as seasonal or cyclical time series data. It is a statistical approach that enables modelling the time series and predicting time series data behavior (Flores et al., 2012). Box and Jenkins (1976) developed a general linear stochastics model by assuming random shocks.

An AR model is used when a value from a time series is regressed on a previous value from that same time-series data, i.e. y_t on y_{t-1}. The order of the AR is the number of immediately preceding value in the series that are used to predict the value at the present time. For first-order autoregression, the model can be expressed as Eq. 6.

AR (1):

$$y_t = \emptyset_1 y_{t-1} + \mu + \upsilon_t \tag{6}$$

where υ_t is the white noise viewed as a random error, μ represents the constant term and $\emptyset_1$ is the first-order autoregression coefficient. It can be thought of as that for a given value *y* in time period *t* that has a relationship with time period *t+1*. For *p* order autoregression, the autoregressive model can be expressed as Eq. 7.

AR (p):

$$y_t = \mu + \emptyset_1 y_{t-1} + \emptyset_2 y_{t-2} + \cdots + \emptyset_p y_{t-p} + \upsilon_t \tag{7}$$

The AR model is used to describe certain time-varying processes. It specifies that the output variable linearly depends on its own previous values and on an imperfectly predictable term. AR is not always stationary as it may contain a unit root. AR can be combined with other time series forecasting models such as the moving average. Kristiansen (2012) proposed an autoregressive model with exogenous variables to predict the price. Othman et al. (2015) suggested an HAR model which combined the Hammerstein model to an Auto-Regressive approach to forecast recursive wind speed, and it was found that the HAR model had a better performance compared with ARIMA and ANN in terms of the prediction accuracy. Yu et al. (2014) developed a hybrid model combining the seasonal auto-regressive integrated moving average (ARIMA) model and the nonlinear auto-regressive neural network to forecast the expected incidence cases of hand-foot-mouth disease in Shenzhen, China.

2.5.1.5 Autoregressive Integrated Moving Average (ARIMA) Model

The ARIMA model is a statistical technique for time series prediction that was proposed by Box–Jenkins in 1970 (Box et al., 2008). The ARIMA is one of the most popular time series forecasting analysis approaches that originated from the autoregressive model (AR), the moving average model (MA) and the combination of the ARMA models (Ho et al., 2002). It can be used when the time series data is stationary and there are no missing data within the time series. ARIMA generates an identified underlying process based on observations to a time series for generating a good model that shows the process-generating mechanism precisely (Box and Jenkins, 1976). The ARIMA technique includes identification, estimation and diagnostic checking (Abdel-Aal &Al Garni, 1997). A non-seasonal ARIMA model is classified as an ARIMA *(p, d, q)* model and expressed as shown in Eq. 8, where *p* represents the number of autoregressive term, *d* represents the number of non-seasonal differences needed for stationary and q is the number of lagged forecast errors in the predicted equation.

$$Y_t = \mu + \emptyset_1 y_{t-1} + \cdots + \emptyset_p y_{t-p} - \theta_1 e_{t-1} - \cdots - \theta_q e_{t-q} \tag{8}$$

where *y* is the d^{th} difference of *Y*. For d =1, $y_t = Y_t + Y_{t-1}$. For d =2, $y_t = (Y_t + Y_{t-1})$ - $(Y_{t-1} + Y_{t-2})$. The second difference of *Y* indicates the first difference of the first difference, which is discrete analog of the second derivative. θ represents the moving average parameter. Hence, ARIMA (0,1,1) with a constant value means simple exponential smoothing. The seasonal components which are determined where the autocorrelation functions cut the confidence limits, can be included in the ARIMA model and is called SARIMA.

ARIMA is a sophisticated forecasting method as it combines the features of all other methods. It is not required to choose the initial values of any variable and the values of various parameters a priori. ARIMA can reduce a non-stationary series to a stationary series using a sequence of differencing steps and can determine the best-fit model for the respective time series (Sen et al. 2016). Its flexibility and orderly searching at each stage takes advantage by comparing with other forecasting methods. When the time series is stationary and data is complete, the ARIMA model can be used in the time series.

ARIMA has a wide range of applications in forecasting time series data. Edigera and Akar (2007) proposed the usage of the Integrated Moving Average (ARIMA) and seasonal ARIMA (SARIMA) methods to estimate the future primary energy demand of Turkey. Arunraj & Ahrens (2015) suggested the usage of hybrid seasonal autoregressive integrated moving average and quantile regression for daily food sales forecasting. Jiang et al (2018) used ARIMA for forecasting China's coal consumption, price and investment by 2030. Mohamed and Bodger (2005) considered the ARIMA model to forecast the electricity consumption in the eastern part of Saudi Arabia and Lebanon.

ARIMA models are flexible as they are able to represent several different types of time series, such as pure autoregressive (AR), pure moving average (MA) and combined AR and MA (ARMA) series. However, Zhang (2003) suggested that the pre-assumed linearity of ARIMA models is a major bottleneck in using ARIMA models to forecast real-life problems. The approximation of linear models to complex real-world problem is not always satisfactory. Therefore, formally specifying and assuming the linearity characteristics and a probability distribution for time series data makes the development and deployment of this type of linear time series model difficult (Hansen et al., 1999).

2.5.2 Machine Learning Techniques for Time Series Data Prediction

For more than half a century, ARIMA models dominated many areas of time series forecasting. In recent times, machine learning techniques, particularly Artificial Neural Network-based and ANFIS-based models, have become widely adopted for time series data forecasting. The application of these techniques suggest that there may be more accurate time series forecasting models other than the conventional stochastic linear time series models, such as MLR, ARMA and ARIMA models, as introduced in the previous section. Therefore, the applicability of Artificial Neural Network-based and ANFIS-based models in forecasting time-series models are discussed in the following sections.

2.5.2.1 Artificial Neural Network-based Forecasting Model

ANN can be defined as an information processing system whose structure and functioning are inspired by biological neural networks. They have three fundamental features: parallel processing, distributed memory and adaptability. Such features enable ANN to outperform other processing systems in terms of robustness and a tolerance to error and noise (Palmer et al., 2006). ANNs are universal function approximators capable of mapping any linear or non-linear function (Cybenko, 1989; Funahashi, 1989). They are able to approximate a large class of functions with a high degree of accuracy, attributed to the ability of parallel information processing from the data (Zhang, 2003). For this reason, the study of artificial neural networks (ANN) has aroused great interest in fields as diverse as biology, economics, mathematics, statistics and computers (Palmer et al., 2006).

In general, an ANN is a network model made up of a large number of simple processing elements, which are known as nodes or neurons. In the network, these neurons, which are organized in several layers, are inter-connected to other neurons by communication links, with each link associated with a numerical value known as "weight". The network structure of an ANN is largely determined by the characteristics of the data, and no pre-assumption of the form of the model is required in the model building process. Due to the capability of solving a wide variety of problems, single hidden layer feedforward network is the most widely applied model form of ANN for time series modeling and forecasting (Kaastra & Boyd, 1996; Zhang, Patuwo & Hu, 1998). The model, as discussed by Zhang (2003), is characterized by a network of three layers of simple processing units. The relationship between the output (y_t) and the inputs ($y_{t-1}, y_{t-2}, \ldots, y_{t-p}$) can be expressed by the following equations:

$$y_t = \alpha_0 + \sum_{j=1}^{q} \alpha_j g(\beta_{0j} + \sum_{i=1}^{p} \beta_{ij} y_{t-i}) + \varepsilon_t \tag{9}$$

where α_j, for $j = 0, 1, 2, ..., q$ and β_{ij}, for $i = 0, 1, 2, ..., p$, and $j = 0, 1, 2, ..., q$, are the model parameters known as "weight", containing the knowledge that ANN possess about a specific problem; p and q respectively denotes the number of input nodes and hidden nodes. A logistic function is often used as the hidden layer transfer function, that is,

$$g(x) = \frac{1}{1+\exp(-x)} \tag{10}$$

With the ANN model mathematically expressed in (x), the model is equivalent to a nonlinear autoregressive model that maps the past observations, i.e. y_{t-1}, y_{t-2}, …, y_{t-p}

to the predicted value y_t. As ANN has been found to be a viable contender to various traditional time series models (Giordano et al., 2007, Jain & Kumar, 2007), the application of ANN can be found across a variety of fields, such as marketing and segmentation analysis (Dolnicar & Fluker, 2003; Cho, 2003; Bloom, 2005), demand forecasting in environmental aspects (Neto & Fiorelli, 2008; Kaytez et al., 2015; Ahmad et al., 2017; Lee et al., 1992), forecasting problems in supply chain management (Kochak & Sharma, 2015; Jaipuria & Mahapatra, 2014).

2.5.2.2 ANFIS-based Forecasting Model

Fuzzy forecasting approaches are capable of dealing with vague and incomplete time series data under uncertain circumstances (Egrioglu et al., 2011; Lu et al., 2014; Dombi et al., 2018). The adaptive neuro-fuzzy inference system (ANFIS), a fuzzy Sugeno model integrated into the framework of adaptive systems to facilitate machine learning and adaption using testing data sets (Jang, 1993), is one of the popular fuzzy approaches for forecast modelling. It combines the advantages of the neural network and fuzzy systems, thereby being more flexible, adaptive and effective on highly non-linear complex problems among other fuzzy inference systems (Kar et al., 2014). The ANFIS creates its own structure and can serve as a basis for constructing fuzzy if–then rules with appropriate membership functions so as to generate the stipulated input–output pairs (Admuthe & Apte, 2010). The self-learning ability of ANFIS makes it less reliant on human knowledge and experience for making wise decisions (Übeyli & Güler, 2006). ANFIS has been established as one of the most popular approaches for making accurate forecasting. Researchers have successfully applied ANFIS to a variety of areas in the past decades. ANFIS can improve the uncertainty of the model and the imprecision of the system. Its self-learning ability to learn through data sets and the organizational capacity is able to adjust the parameters of the model (Su &

Cheng, 2016). In comparing with other forecasting models, ANFIS has a high speed of training, and the most effective learning algorithm (Jang et al., 1997). Moreover, ANFIS is the best function approximator among the several neuro-fuzzy models and is faster in convergence in comparion with others neuro-fuzzy models (Akcayol, 2004). It provides the best result when applied without any pretraining (Altug et al., 1999). Therefore, ANFIS is appropriate for forecasting time series data when compared with other models.

In recent years, the ANFIS system has been widely used for forecasting nonlinear models of processes to determine the input-output relationships in many areas. In the stock market, Wei et al. (2014) and Su & Cheng (2016) proposed the forecasting of stock using a hybrid ANFIS model. Due to the complex factors and nonlinear relationship between those factors existing in different periods, forecasting in the stock market is difficult. The ANFIS forecasting method was proposed to forecast stock prices in order to eliminate the drawback of other forecasting methods. In the environmental aspects, Sinvaldo et al. (2018) proposed a hybrid SSA-ANFIS-FCM approach for wind speed forecasting. The hybrid model can learn the trend and the wind time series structure. The prediction errors were significantly decreased by applying the proposed technique. Prasad et al. (2016) suggested an ANFIS model in forecasting the air pollution concentration of five air pollutants (sulphur dioxide, nitrogen dioxide, carbon monoxide, ozone and particulate matter). In the logistics aspect, Wang and Chen (2008) suggested rush order control application by applying the neuro-fuzzy based forecasting approach. The proposed model solves the problem of predicting rush orders for regulating the capacity reservation mechanism in advance.

Popular areas of ANFIS forecasting applications include the stock market (Guresen et al., 2011; Esfahanipour & Aghamiri, 2010; Svalina et al., 2013), environmental-related aspects and energy consumption prediction (Khoshnevisan et al., 2014; Zahedi et al., 2013), weather forecast (El-Shafie et al., 2011; Osório et al., 2015), and demand forecast in various industries (Wang et al., 2011; Xiao et al., 2014; Nilashi et al., 2011). However, the application of ANFIS in the field of order management in the retail and logistics sector is rarely found. Wang and Chen (2008) applied ANFIS to forecast product items, quantities and the occurance of contingent rush orders in a manufacturing firm. Aengchuan and Phruksaphanrat (2018) compared the fuzzy inference system (FIS), FIS with artificial neural networks (FIS+ANN) and FIS with adaptive neuro-fuzzy inference system (FIS+ANFIS) for inventory control. This research extends the application area of ANFIS in the literature by proposing an ANFIS with the integration of the autoregressive (AR) model for the prediction of e-commerce logistics order arrival in distribution centres. Through the prediction of the arrival pattern of e-orders, logistics practitioners are able to wisely allocate resources in advance, and consolidate discrete, fragmented e-commerce orders prior to actual batch processing of consolidated orders in distribution centres, so as to improve the order handling capability and supply chain efficiency especially in the complex and dynamic e-commerce operating environment.

2.6 Summary

Logistics practitioners have been facing enormous challenges in the order fulfillment process under the emerging e-commerce operating environment. The reason behind the difficulty in handing e-commerce orders lies in the fact that most practitioners are still sticking with the conventional order processing flow to handle e-commerce orders, i.e. perform order handling operations in warehouses immediately upon receiving an order delivery instruction by the customers, such as retailers and wholesalers. However, in today’s e-commerce business environment, orders are placed by the end consumers at anytime. Immediate order handling of one single e-commerce order is illogical and irrational. In the literature, studies that focus on improving the operating efficiency in e-fulfillment distribution centres have been lacking. Most studies in the past decade attempt to tackle specific cases, settings or scenarios in the warehouse, without a focus of the e-commerce order handling bottlenecks that lead to a serious order handling inefficiency.

To this end, this study proposes the need to re-engineer the e-order fulfilment process by grouping e-orders for batch processing. To effectively deal with e-orders for bulk order handling, two essential factors must be carefully considered, i.e. how they are grouped and when they should be released ("When to release") for batch processing in distribution centres. To provide decision support for these issues, this research integrates GA and ANFIS to respectively group e-orders and determine the timing for a batch release of e-orders. As the "When to release" decision is concerned with forecasting the arrival of e-orders, conventional stochastics times series models and machine learning models for time series data forecasting are also thoroughly reviewed in this chapter. It is suggested that improving time series forecasting accuracy is an important yet often difficult task facing forecasters. Moreover, assuming the e-order arrival data to have linear characteristics and follow a probability distribution is not justifiable. Therefore, a hybrid methodology that integrates the elements of ARIMA into the construction process of ANFIS models, is proposed to take advantage of the unique strength of ARIMA and ANN models in linear and nonlinear modeling. Past observations of the same variable are collected and analyzed to develop a model for describing the underlying relationship.

Chapter 3 – An E-commerce Fulfillment Decision Support System (EF-DSS)

3.1 Introduction

In this chapter, the design of the E-commerce Fulfilment Decision System (EF-DSS) is presented. The EF-DSS is designed with an aim of re-engineering of the e-commerce order processing flow in distribution centres. This objective is achieved by applying the “Warehouse Postponement Strategy” (WPS) to group fragmented, discrete and small lot-sized e-commerce orders before releasing the consolidated e-orders in a batch for processing these orders at the same time. To better illustrate the need to implement WPS, this chapter begins with an introduction of the WPS proposed in this research study in Section 3.2, followed by a comprehensive discussion of the architecture and the elements involved in the EF-DSS in Section 3.3. The E-order consolidation module (ECM) of the EF-DSS, which serves as the consolidation pool of e-commerce orders, is presented in Section 3.4. The E-order grouping module (EGM) of the EF-DSS, which integrates a GA-based algorithm for grouping e-commerce orders with similar attributes, is introduced in Section 3.5. Lastly, the E-order batch releasing module (EBRM) that determines the timing for releasing the grouped e-orders through the prediction of the arrival rate of e-commerce orders in the coming time periods using multiple novel Autoregressive-momentum-moving average-based adaptive neuro-fuzzy inference system (AR-MO-MA-ANFIS) models, is discussed in Section 3.6.

3.2 The Concept of Warehouse Postponement Strategy

- *Why WPS is needed?*

The rapid growth of the e-commerce market around the globe over the last decade has drastically revamped the retail industry. End-consumers are not only able to purchase goods at local physical stores, but also from online shops from any corner of the world. According to market research conducted by Statista Inc. (2015), over 40 percent of global internet users purchased products online in 2013. In 2018, this figure is expected to edge close to 50 percent of internet users worldwide (Statista Inc., 2015), showing the growing trend of delivering online-to-offline (O2O) shopping experience to consumers. Due to the changing consumer purchasing behavior, as well as the environment in the retail industry, logistics practitioners are capturing e-commerce logistics markets while improving their capability and capacity of handling such e-commerce business. On the technical side, for example, logistics service providers provide real-time order tracking capability for realizing supply chain information transparency.

The boundary spanning of logistics service providers (LSPs), however, is never easy to accomplish. The transformation of their core businesses into integrated e-commerce logistics solution provision is formidable, owing to the fact that operational capability could very probably be the major obstacle to face. While cross-border e-commerce and O2O business is a huge market opportunity for logistics practitioners around the world such as third-party logistics service providers and freight forwarders, they have been facing fundamental challenges in complying with the ever increasing and challenging needs of providing proper logistics and supply chain solutions for e-commerce businesses.

Conventionally, in the absence of O2O and e-commerce business models, consumers purchase items solely at physical retail stores. In this sense, LSPs handle goods in bulk for delivery to wholesalers or retailers, usually on a weekly or bi-weekly basis, primarily for stock replenishment. However, with the presence of online shopping platforms which enable customers to purchase online, LSPs are required to handle a large number of stock-keeping units (SKUs), pick and pack small volume orders and deliver them in small parcel shipments to end consumers with tighter schedules. Therefore, the traditional order fulfillment process in warehouses and distribution centers (DC) that encompasses receiving, put-away, picking and transport of goods in bulk, is unable to fulfill the order handling requirements of e-commerce shipments. The fundamental differences between traditional order handling and e-commerce order handling could well explain why e-commerce businesses have had serious challenges to the efficiency of the last-mile of e-commerce fulfillment, and have been reshaping the position and degree of importance of LSPs along the supply chains.

In view of the increasing concern over the order fulfillment performance of LSPs in the e-commerce business environment, Warehouse Postponement Strategy (WPS), a process-oriented tactic addressing logistics process postponement in warehouses and DCs, is conceptualized and proposed. Such a strategy enables logistics practitioners to cope with e-commerce order handling requirements through streamlining order handling procedures. Ultimately, it enables operations to align with the strategic directions in integrating e-commerce logistics businesses.

- *The Definition of WPS*

Postponement, also called delayed differentiation, is a widely accepted tactic for dealing with uncertainties and fluctuations in demand, delays the customization and final assembling of products (Yang et al., 2004). It has been recognized as an effective strategy to manage uncertainties and variability in demand. Zinn and Bowersox (1988) identified five deferral strategies, four of which related to changes in the product, including labeling, packaging, assembling, and manufacturing. The remaining postponement strategy focuses on logistics postponement, that is, (i) place postponement – the storage of finished products in centralized logistics systems, and (ii) time postponement – a time delay for slowing the movement of the product until the last possible moment, rather than responding rapidly to customer demand.

With the intensified challenges of managing a global supply chain that is responsive to customer demand in today's long-tail market, the concept of postponement strategy has been noted as a viable solution in the face of increasing product variety, shorter product lifecycle, and faster response to customer needs (Twede et al., 2000; Boone et al., 2007; Yang et al., 2004; Yang and Yang, 2010; Choi et al., 2012). It has been researched as an essential topic in the production and inventory management literature (Lee and Tang, 1997; Pagh and Cooper, 1998; Yang et al., 2004). While postponement strategy in supply chains is widely recognized as an indispensable means of dealing with the risk pooling effect through properly managing the inventory for meeting unavoidable demand uncertainties, the focus of conventional postponement strategy is on how the configuration and assembling of a product can be delayed until the last possible moment.

When the concept of conventional postponement strategy is introduced at the warehouse operational level, it would be beneficial for logistics practitioners to manage discrete, fragmented and small lot-sized e-commerce orders under today's dynamic and complex e-commerce and O2O logistics operating environment. The proposed Warehouse Postponement Strategy (WPS) is transformed from the concept of conventional product-oriented supply chain postponement strategy. It is defined as "an operation strategy to delay the execution of a logistics process until the last possible moment". Considering the receiving, storage, picking and shipping operaitons as the four typical categories of warehousing activities (Berg & Zijm, 1999), the implementation of WPS in warehouses allows the postponement of performing the next category of warehouse operation. Fig. 3.1 illustrates a before and after comparison of WPS in warehouses and distribution centers. Without the introduction of WPS, orders received from customers directly initiate the order processing procedures in a warehouse. The warehouse order throughput rate fluctuates throughout the working hours and is dependent on the actual number of orders received throughout the day. In this sense, taking order pick-and-pack operation as an example, warehouses operators are required to repeatedly visit the storage locations to pick the goods for fulfilling the orders throughout the whole day. The efficiency is therefore heavily affected by the absence of postponing or grouping outstanding orders for batch or wave processing.

With the introduction of WPS, operators no longer perform warehouse operations solely based on the immediate order they have just received. Instead, a pre-process order pool, as illustrated in Fig. 3.1, allows logistics practitioners to configure the cut-off time and amount in order to postpone the order processing operations until the "last possible moment". Upon reaching the pre-defined cut-off criteria, grouped outstanding orders are released to the warehouse for batch process execution. Therefore, the throughput rate in a warehouse would follow a wave pattern instead of a fluctuating one. The rearranged throughput rate then derives several benefits in aspects such as order handling efficiency, resource management and workforce level adjustment.

However, the cut-off criterion is not a straightforward decision to make, in the absence of IT or artificial intelligence techniques, aiding decision support. Without these decision support tools, logistics practitioners rely on their previous experience and practice to determine the "optimal" cut-off point, which is very often unable to meet the fast changing warehouses and distribution center environment particularly in today's e-commerce logistics business environment.

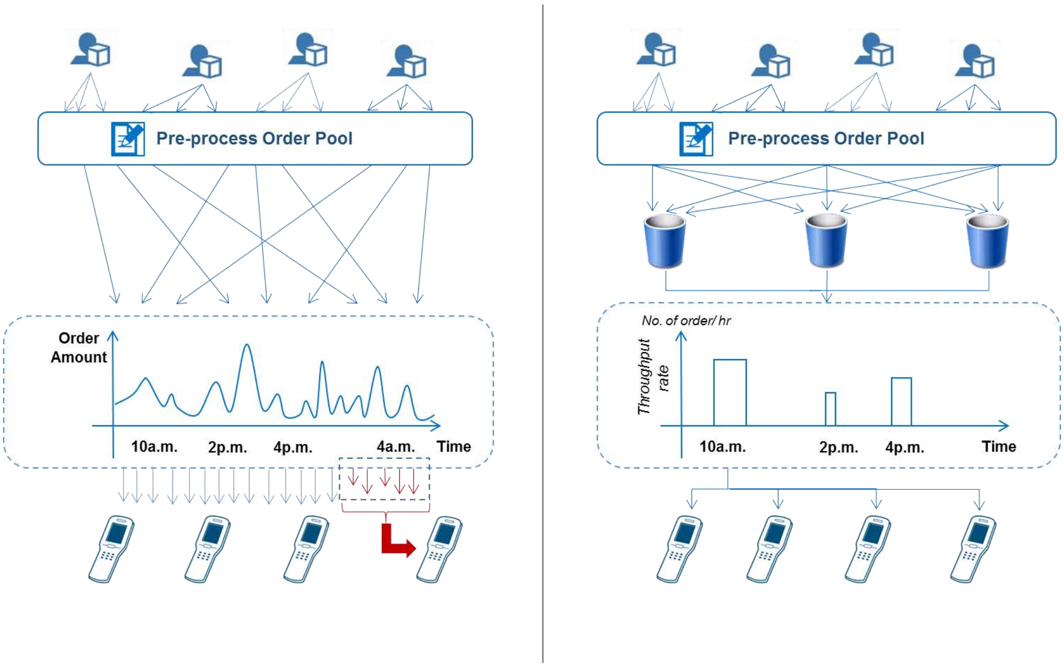


Fig. 3.1. Order throughput difference with and without the application of WPS

3.3 Architecture of the EF-DSS

Effective deployment of Warehouse Postponement Strategy requires making accurate decisions regarding: (i) How to group the e-commerce orders, and (ii) when to release the grouped e-commerce orders. Therefore, the EF-DSS is designed to provide decision support as to how the e-orders are grouped and when they should be released in batch, so as to realize the concept of Warehouse Postponement Strategy for facilitating LSPs in managing today's e-commerce logistics orders. The architecture of EF-DSS, as shown in Fig. 3.2, consists of three modules: E-order consolidation module (ECM), E-order grouping module (EGM), and E-order batch releasing module (EBRM).

In the ECM, there is a centralized database to gather and store data, such as e-commerce order information, customer profiles, and resource status in distribution centres. To deploy the proposed warehouse postponement strategy, e-commerce orders received by the logistics service providers have to be grouped before batch releasing to the distribution centres for processing in batch. The grouping and consolidation of pending e-commerce orders is achieved by an e-order consolidation pool built in the ECM of the EF-DSS. Other relevant information collected and stored in the database of ECM is then used for generating and extracting useful decision support in the next module of the EF-DSS.

In the EGM, data stored in the centralized database in the ECM are processed and serve as the inputs of this module to determine "How to group" the pending e-commerce orders. Ordered items, which are pending in the e-order consolidation pool of the ECM, are grouped based on the proximity of storage locations using a genetic algorithm approach. In other words, items with similar storage locations in the distribution centres or warehouses are grouped together for batch order picking. By grouping the pending ordered items in several batches using the GA, the order pickers in the distribution centres are able to perform batch order picking operations for the discrete, fragmented e-commerce orders.

Though the EGM provides decision support for the logistics service providers to effectively group the e-orders for batch order picking operations, the logistics service providers still have to decide the cut-off time or quantity to stop consolidation of the e-commerce orders. In this respect, the EF-DSS further suggests the cut-off time based on a prediction of the e-order arrival frequency in the upcoming period using a novel autoregressive-based Adaptive Network-Based Fuzzy Inference System (AR-ANFIS) approach. Hence, the logistics service providers are able to identify how much time can they still consolidate the incoming e-commerce orders. Once the cut-off time

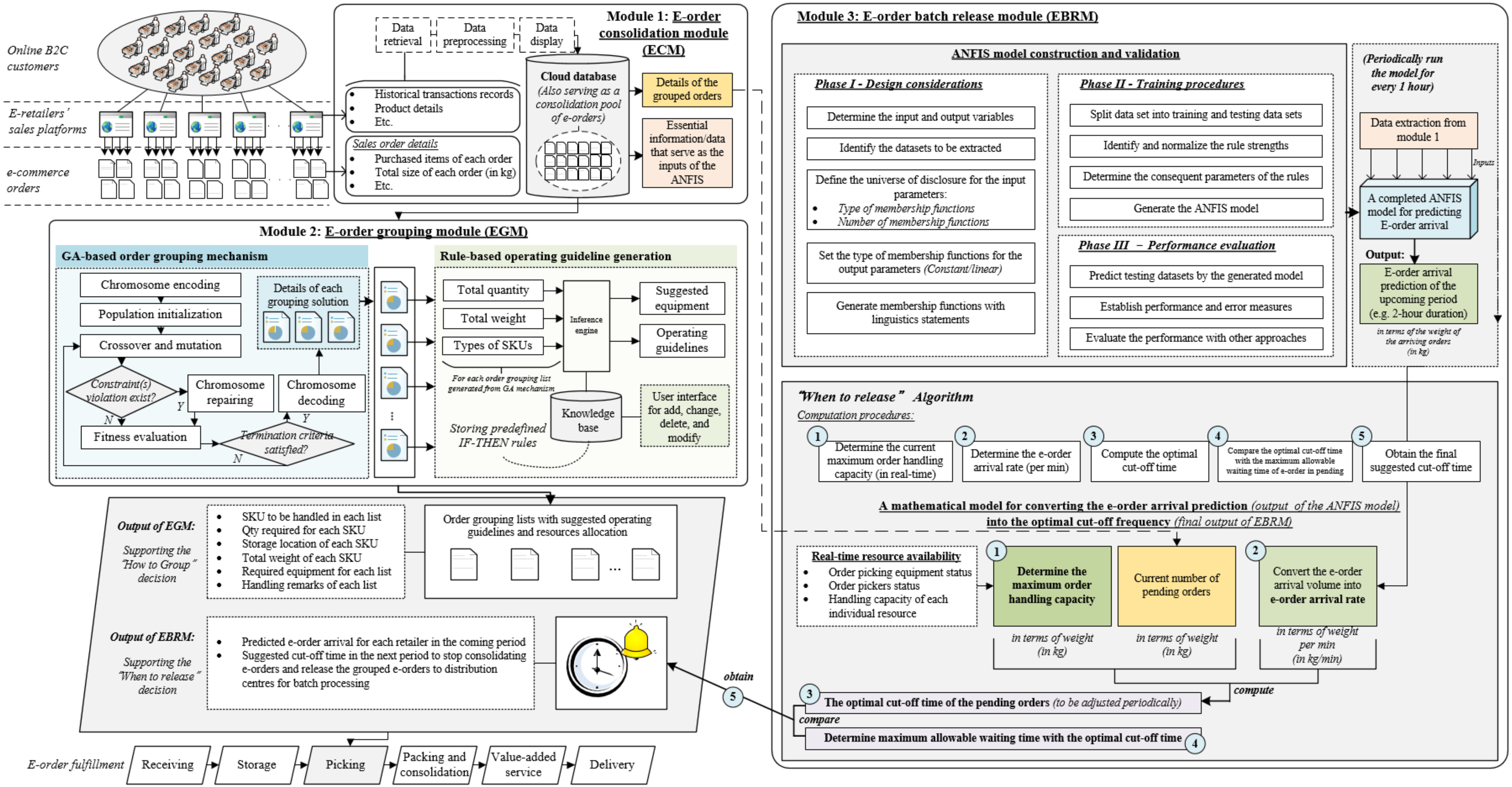


Fig. 3.2. Architecture of the EF-DSS

has been reached, the pending e-orders are grouped in several batches based on their storage location proximity. Therefore, the proposed warehouse postponement strategy can effectively be deployed with essential decision support provided by the EF-DSS. Details of each module are presented in the following sections.

3.4 E-order consolidation module (ECM)

In the era of the e-commerce business, delivery orders placed by end consumers are retrieved from the Internet. Efficient retrieval and consolidation of an order therefore requires a cloud database integrated into a web app for real time data retrieval and processing. The front-end of this module involves a user interface (UI) in the EF-DSS's web app. It allows users, typically the customer service (CS) staff in a logistics company, to retrieve the details of e-orders pending for further processing and confirmation and to manually update them if necessary. The web app, which consists of a series of web pages, is constructed by Hypertext Mark-up Language (HTML). Any action made by the users on the web pages would trigger an update on the cloud database of EF-DSS. The database of EF-DSS is the information repository for collecting, storing and sorting two types of data: (i) delivery order details which are received in real time via the Internet either from e-retailers or directly from end consumers, and (ii) the basic settings of e-fulfilment center, static information preliminarily stored in the cloud database for retrieval. The details of these two major types of data stored in the cloud database are displayed in Table 3.1.

The major data processing operations in this module includes database query processing, data sorting and display. For database query processing, insert, view, edit, delete and update can be performed in the UI of the EF-DSS through a set of structure query language (SQL) statements designed and stored in the SQL database. For data sorting and display, the operation is done automatically in the back-end of the database so that all retrieved e-orders are aggregated and sorted by stock-keeping units (SKUs), disregarding which particular SKUs are fulfilling which customer order. An illustration is shown in Fig. 3.3. With the rearranged order information, a list of items to be processed in the e-fulfilment center is displayed in the UI of the EF-DSS, which serves as the input of the subsequent module for e-order grouping and resource allocation decision support.

Table 3.1. Generic details of the information stored in database of the EF-DSS

Types of data:		
(i) **Customer order details**		
Details	*Data type*	*Data source*
Ordered item (presented as SKU no.)	*Numeric*	Real time retrieval from retailers of end consumers
Item quantity	*Numeric*	
Item weight	*Numeric*	
Order time	*Date*	
Estimated time of delivery (ETD)	*Date*	
Delivery location	*String*	
Order number	*Numeric*	
Order priority	*String*	
Customer ID	*Numeric*	
(ii) **Initial setting of e-fulfilment centers**		
Storage location setting (Zone and bin level)	*String*	Initial input as part of the construction of the cloud database
Travel distance between each bin location	*Numeric*	
Storage location of each SKU	*String*	
Equipment master	*String*	

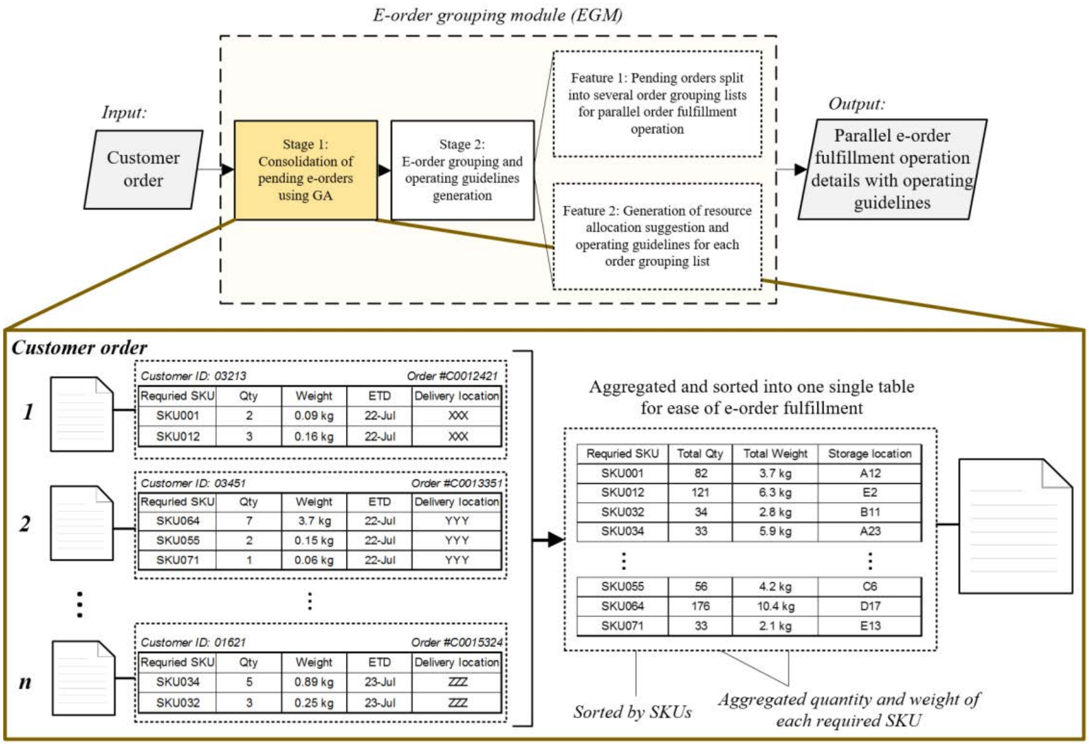


Fig. 3.3. Consolidation and sorting of customer e-order in EF-DSS

3.5 E-order grouping module (EGM)

This module groups SKUs into several batches so that logistics practitioners can perform batch order picking accordingly. Information stored and processed in the previous module, including the sorted order details and storage location of SKUs pending to be picked, serves as the inputs of this module. The grouping of e-orders is done by a GA mechanism, which starts with encoding the proposed order grouping model into a chromosome. An initial population of the e-orders grouping solution is then formed, followed by the fitness of each chromosome being evaluated with the adoption of a quantitative model that includes constraints as the representation of the order grouping criteria. Prior to reaching the termination criteria, crossover and mutation operations are repeatedly performed to generate different sets of solutions. Upon fulfilling the termination criteria, the chromosome with smallest fitness value is selected as the near-optimal solution, which is then decoded and transformed into a complete e-order grouping plan with resource and operating guidelines generated for each order grouping list. An overview of the procedures in the EGM of EF-DSS is shown in Fig. 3.4.

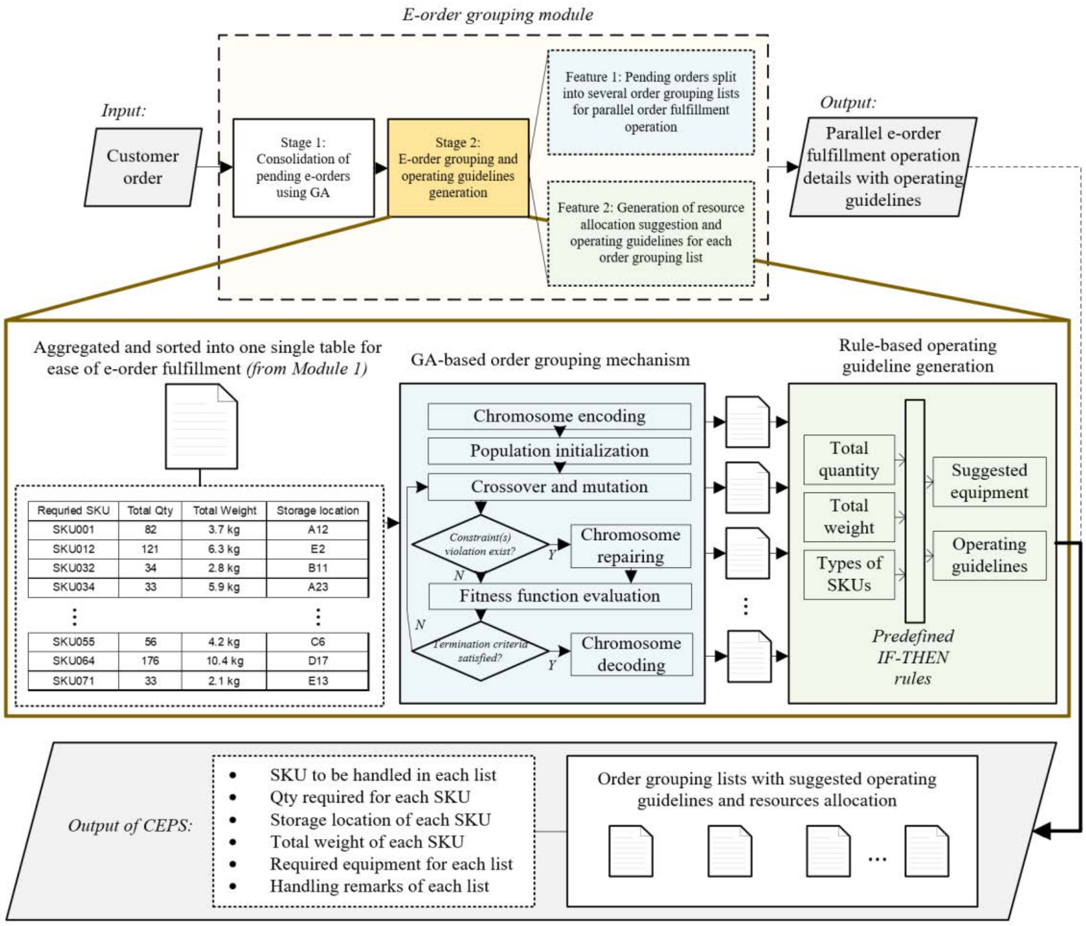


Fig. 3.4. E-order grouping and operating guidelines generation in EF-DSS

3.5.1 Chromosome Encoding

The chromosome in the EF-DSS is a solution for identifying the nearly optimal combinations of SKUs to be picked under the same order grouping list. Several order grouping lists will be formed and presented in the chromosome. As shown in Fig. 3.5, the generic format of a chromosome is divided into two areas: (i) order grouping region, and (ii) parameter region.

(i) Order grouping region

The basic idea of the chromosome encoding scheme of this region comes from Lin et al. (2014). The value of each gene is a real number, where “0” represents the depot, and other values indicate the storage bin location. Take the chromosome in Fig. 6 as an example, a chromosome “112 114 145 0 243 231 212 321 0 410 412 413 415 0” can be interpreted as 0-112-114-145-0, 0-243-231-212-321-0, and 0-410-412-413-415-0, which implies that a total of three order grouping lists are generated, with the storage location under each order grouping list specified in the chromosome. For example, the order grouping list with chromosome “0-112-114-145-0” denotes that three storage bin locations, i.e. 112, 114 and 145, are to be travelled to when the operator in the e-fulfilment center follows this order grouping list to execute e-order fulfilment operations.

(ii) Parameter region

The parameter region shows the chromosome genes which can further be classified into three different areas: total weight, total quantity and required equipment. Based on the order grouping solutions generated in the chromosome genes in the order grouping region, the corresponding total weight (W), total quantity (Q) and types of SKUs involved (S) of each order grouping list are displayed. The value of total weight (W), total quantity (Q) and the type of SKUs involved in the order grouping list, are used to generate pre-set operating guidelines and suggest the required equipment based on the pre-defined rules in the rule-based inference system. As shown in Fig. 6, the corresponding total weight, total quantity and required equipment of order grouping list 1, i.e. chromosome gene B_{1j}, where j = 1, 2, …, N, is denoted as W_1, Q_1, S_1 respectively. The length of the chromosome in the parameter region depends on the number of order picking lists generated for the current problem.

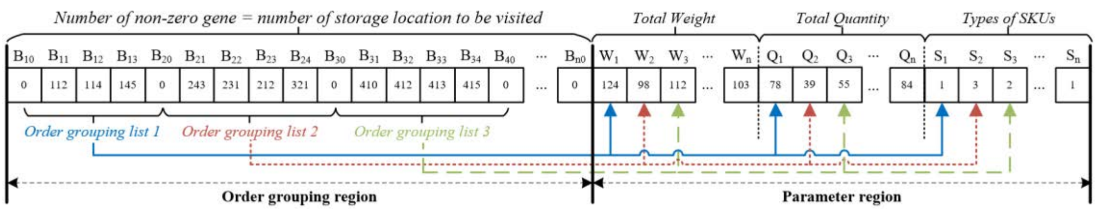


Fig. 3.5. The generic format of a chromosome

3.5.2 Population Initialization

An initial population of the feasible solution represented as a chromosome is formed. Assuming that the initial population size is s and the parameter index p is set as 1. For p < s, then p = p + 1, so as to continue generating chromosomes, else stop. Due to a large number of storage locations required to be visited in an e-fulfilment center for order picking of various items ordered by different online customers, the long length of a chromosome suggests that a large population size is required for generating a considerable number of possible combinations in crossover and mutation operations in the GA mechanism.

3.5.3 Fitness Evaluation

A fitness function that minimizes the one-dimensional travel distance between two adjacent nodes, i.e. storage bin location, is used to evaluate the fitness of each chromosome. Considering the placement and alignment of a series of pallet racks in parallel as a common facility layout in the storage area of e-fulfilment centers, warehouses and distribution centers, a distance matrix that calculates and indicates the inter-bin distances among each storage bin is proposed, instead of a conventional computation of the distance between two adjacent nodes i and i+1 with coordinates (x_i, y_i) and (x_j, y_j) using $D_{i,j} = \sqrt{(x_j - x_i)^2 + (y_j - y_i)^2}$. The preparation of an inter-bin distance matrix is considered to be a more rational and appropriate one, in comparison to a simple calculation of the distance between two adjacent nodes using their *x* and *y* coordinates, due to the fact an operator who is about to visit two storage bin locations, say bin A1 and bin B1 in Fig. 3.6, must be either picking route 1 or route 2, as illustrated in Fig. 3.6. A distance matrix that illustrates the shortest possible travel distance between each bin therefore achieves a better accuracy for fitness function evaluation. The shortest inter-bin travel distance ($D_{i,j}$) for bin i and j is calculated by Eq. 11:

$$D_{i,j} = min\ [X_i + X_j, (L - X_i) + (L - X_j)] + N_s \times S + N_A \times A \quad (11)$$

where X_i is distance between x-coordinate of storage bin *i* and the starting position of the aisle (the origin), L is the total length of an aisle, N_A and N_s are respectively the number of aisles and storage bins vertically travelled across, and A and S are respectively the widths of an aisle and storage bin.

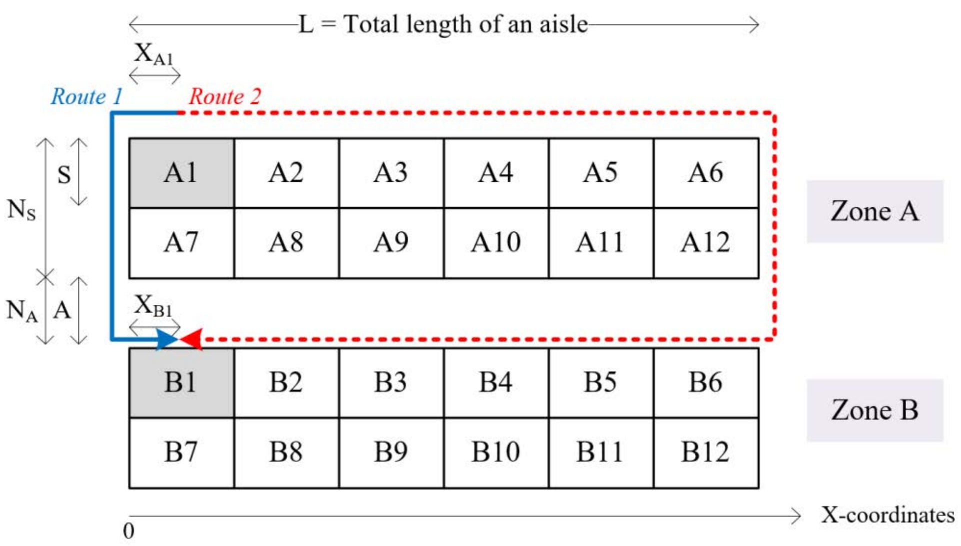


Fig. 3.6. An example of the shortest inter-bin travel distance calculation between two storage bins

For each order grouping problem, n out of N storage bins are required to be visited to pick up the items ordered by online customers, where N is the total number of storage bins, and $n \leq N$. With the N×N distance matrix that contains all inter-bin shortest travel distances in the e-fulfilment center, the inter-bin distances among n out of N storage bins are required to be extracted from the parent distance matrix, by filtering out the inter-bin distances of all storage bins which will not be visited in this order fulfilment wave. This allows the GA mechanism to evaluate the fitness of each chromosome by only coping with the inter-bin distances of the n storage bins concerned in the current problem using the n×n distance matrix extracted from the original N×N distance matrix. The quantitative format of EF-DSS for e-order grouping is presented below. The notations are depicted in Table 3.2. Eq. (12) determines the shortest travel distance of all generated chromosomes. Constraint (3) ensures that the order grouping list includes visiting storage bin location j immediately after storage bin location i. Constraints (14) and (15) ensure that each travel path only has one order grouping list and each storage bin location is included in only one single order grouping list. Constraints (16) and (17) respectively specify the volume and weight limit of an order grouping list. Constraint (18) ensures the continuity of path.

$$Minimize \sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{g=1}^{G} D_{ij}x_{ijg} \tag{12}$$

$$x_{ijg} = \begin{cases} 1, & \text{if order grouping list g includes visiting bin location j just after i} \\ 0, & \text{otherwise} \end{cases}$$

$$\forall g \in G \tag{13}$$

$$\sum_{i \in N}\sum_{g \in G} x_{ijg} = 1, \qquad \forall\ j \in N \tag{14}$$

$$\sum_{j \in N}\sum_{g \in G} x_{ijg} = 1, \qquad \forall\ i \in N \tag{15}$$

$$\sum_{i \in N} \sum_{j \in N} v_i x_{ijg} \leq \; V_g, \qquad \forall \; g \in G \tag{16}$$

$$\sum_{i \in N} \sum_{j \in N} w_i x_{ijg} \leq \; W_g, \qquad \forall \; g \in G \tag{17}$$

$$\sum_{\substack{j \in N \\ j \neq i}} x_{ijg} = \sum_{\substack{j \in N \\ j \neq i}} x_{jig}\,, \qquad \forall \; i \in N\,, \forall \; g \in G \tag{18}$$

Table 3.2. Notation table for quantitative model of EF-DSS

Notation	Definition
G	Index set of all order grouping lists, G={1,2,…,g}
N	Index set of all storage bin location, N={1,2,…,n}
g	Index for order grouping list
i, j	Index for storage bin location
$\boldsymbol{v_i}$	Volume of items to be picked at storage bin location i
$\boldsymbol{w_i}$	Weight of items to be picked at storage bin location i
$\boldsymbol{V_g}$	Volume limit of order grouping list g
$\boldsymbol{W_g}$	Weight limit of order grouping list g
$\boldsymbol{D_{ij}}$	Shortest inter-bin distance between storage bin location i and j
$\boldsymbol{x_{ijg}}$	Binary variable indicating whether order grouping list g∈G travels storage bin location i and j

3.5.4 Genetic Operations

The genetic operations in GA for generating new offspring involve chromosome crossover and mutation operations. Appropriate chromosomes are selected prior to performing the genetic operations. Among the common selection operators of chromosomes, the tournament selection operator is proposed over the roulette-wheel-based proportionate selection operator, as the latter approach is unable to handle minimization problems directly. The former approach can handle both maximization and minimization problems and the complete selection process can be performed quickly. Upon selection of the chromosomes, they are transferred from the parent pool to the mating pool for creating new offspring through combining the selected chromosomes in crossover operations and changing the genes in the chromosomes in mutation operations, with a crossover rate and mutation rate pre-defined. In crossover operations, a crossover probability index between 0 and 1 is randomly generated for each chromosome in the mating pool, so that chromosomes with a crossover probability index less than the pre-defined rate of crossover are chosen for performing crossover operations. In mutation operations, a random number between 0 and 1 is generated for each gene in the chromosome. Genes with a random number less than the rate of mutation undergo mutation operations. After crossover and mutation of chromosomes, chromosome repairing is performed to fix the chromosomes to ensure every chromosome obeys the encoding scheme. Violations of the encoding scheme include the inconsistencies between two regions of the chromosome and violations of the volume or weight constraints of an order grouping list. The repairing operation, which can be classified into three stages (Ho et al., 2008), i.e. forward repairing, backward repairing and limit repairing, is performed.

3.5.5 Termination criteria and chromosome decoding

The fitness of each chromosome is again evaluated for identifying the best order grouping solution, namely a chromosome with the smallest fitness value. The maximum number of iterations is chosen as the pre-defined termination criteria of the GA mechanism in EF-DSS. When the number of iterations has reached this threshold value, the GA iteration process is stopped. The best chromosome is then selected as the near-optimal solution and decoded into a readable format of order grouping solutions, allowing users to obtain the suggested number of order grouping lists required and the details of each order grouping list, including the storage bin locations sequence to be visited in each order grouping list and the corresponding items with quantity information to be handled at each storage bin location.

3.5.6 Rule-based guidelines decision support

Rule-based operating guidelines decision support is generated in addition to the order grouping solutions. As the operating procedures and equipment selections vary depending on the nature of an order, the total weight and quantity of each order grouping list as indicated in the parameter region of the chromosome, along with the product categories handled in each order grouping list, serve as the antecedents, i.e. the "IF" part of the "IF-THEN" rules pre-defined in EF-DSS. The required equipment and a set of suggested operating procedures are the consequent, the "THEN" part of a rule. Among the two broad kinds of inference engines used in rule-based systems, forward chaining and backward chaining systems, the former one, that is, a data-driving reasoning strategy, is adopted in EF-DSS so as to process the known parameters given in the parameter region of the chromosome to keep using the "IF-THEN" rules to suggest an appropriate set of operating procedures and handling equipment.

With the order grouping decision support and knowledge support through suggesting an appropriate set of operating procedures and equipment, the e-commerce order processing flow in the e-fulfilment center is reengineered, as the top management of the e-fulfilment center can flexibly consolidate pending a large number of discrete, small lot-sized online customer orders and then release the jobs in waves with clear instructions of how these jobs are to be handled.

3.6 E-order batch releasing module (EBRM)

To deploy the warehouse postponement strategy in e-fulfilment distribution centres, not only do the logistics service providers need to consolidate the incoming e-orders and group them into different batches for the subsequent bulk order processing, but determining an appropriate timing to stop the e-order consolidation process is also essential. In EF-DSS, the ECM is developed to consolidate the incoming e-orders so that the e-orders will not be processed in the distribution centres immediately upon their arrival. The EGM of the EF-DSS is responsible to group the pending e-orders according to the location proximity of the SKUs. In this module, a proper timing for terminating the e-order consolidation process is generated. Such information allows the logistics service provider to realize the remaining time to continue receiving and grouping the e-orders to the current lot. Once the cut-off time has been reached, the pending e-orders stored in the e-order consolidation pool of the ECM are be grouped into several batches as suggested by the EGM.

In this module, to identify the right timing to release the pending e-orders, the arrival pattern of e-orders in distribution centres is an essential criterion for consideration. Therefore, the first critical task of this module is to forecast the arrival of e-orders using a novel ANFIS-based approach for forecasting the e-order arrival figures in the coming period (say two to three hours). Then, an algorithm is developed to convert "the predicted e-order arrival figure of the next period" into "the remaining time for order consolidation". An overview of the procedures in the EBGM of EF-DSS is shown in Fig. 3.7. Details of this module is presented in the following sections.

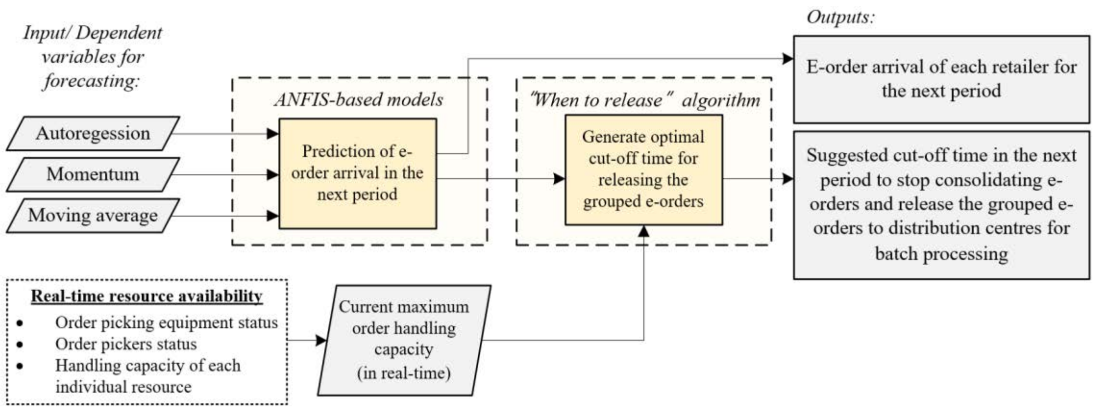


Fig. 3.7. E-order arrival prediction and cut-off time decision support generated by the EBRM

3.6.1 Model selection for forecasting

To generate decision support regarding the timing to release the pending e-orders, forecasting the arrival of an e-order in the upcoming period is the pre-requisite. A prediction model is constructed in EBRM. It is noted that the effect of variables on demand forecasting is not always definite (Thomassey et al., 2005). Thus, assuming the input variables of the e-order arrival prediction as either linear or non-linear is not justifiable. Compared to other hybrid neuro-fuzzy models, ANFIS is found to be best function approximator with fast convergence (Akcayol, 2004). Therefore, to provide a mapping relation between the input and output parameters, the EF-DSS integrates an adaptive neuro-fuzzy inference system (ANFIS), which includes both an artificial neural network (ANN) and a fuzzy logic approach in the architecture (Avci et al., 2007; Jang, 1993; Avci, 2008). To obtain better results and model the performance, Takagi-Sugeno type fuzzy inference is used in this study. It has been widely used for model-based applications and has proven to give better performance in terms of accuracy and ease of interpretation as compared to Mamdani type fuzzy inference (Thiesing & Vornberger, 1997; Sugeno & Yasukawa, 1993; Wang & Chen, 2008).

3.6.2 ANFIS Model Construction

The architecture of ANFIS consists of five fixed layers, as shown in Fig. 3.8. Each layer contains several nodes described by the node function. To simplify the explanation, it is assumed two inputs (x and y) and an output (f) are used in this system. For a first order two-rule Takagi-Sugeno type fuzzy inference system, the two fuzzy if-then rules can be expressed as (Takagi-Sugeno, 1983):

If x is A_1, and y is B_1, then $f_1 = p_1 x + q_1 y + r_1$

If x is A_2, and y is B_2, then $f_2 = p_2 x + q_2 y + r_2$

where A_i and B_i are the fuzzy sets, f_i is the output set within the fuzzy region specified by the fuzzy rule, and p, q and r are linear output parameters determined during the training process. Fig. 3.9 illustrates the fuzzy reasoning mechanism adopted in this application. The notation definitions of a first order two-rule Takagi-Sugeno type fuzzy inference system are summarized in Table 3.3. The defined tasks for the fuzzy inference system under the five-layer architecture are described as follows.

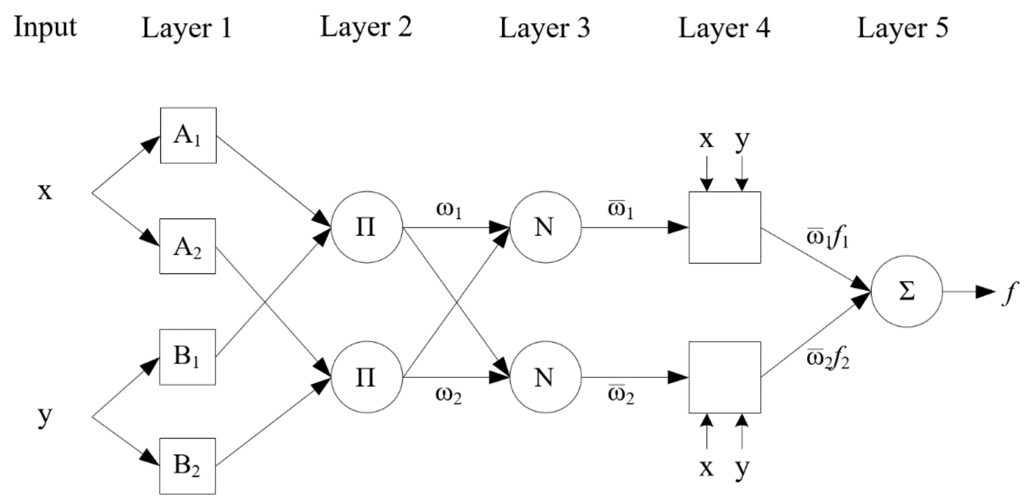


Fig. 3.8. Architecture of ANFIS network

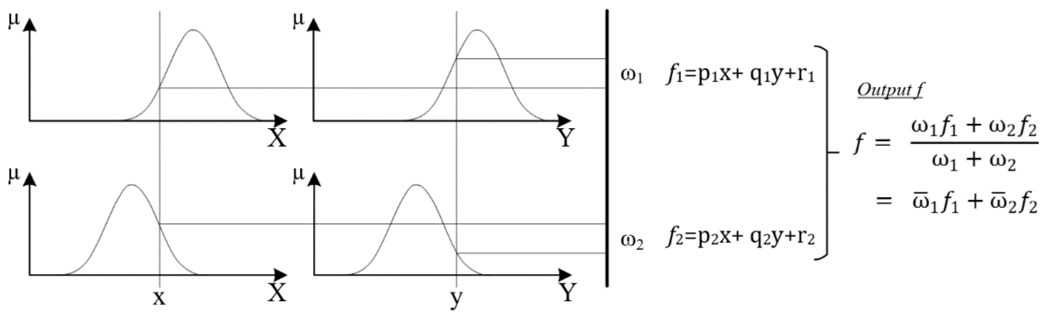


Fig. 3.9. Fuzzy reasoning mechanism in ANFIS

Table 3.3. Notation definitions for ANFIS network architecture

Network architecture of a typical first order two-rule Takagi-Sugeno type fuzzy inference system (refer to Figs. 3.8 and 3.9):	
Notation	**Definition**
x , y	Inputs
f	Overall output
A_i, B_i	Fuzzy sets
f_i	Output set within the fuzzy region specified by the fuzzy rule
p, q, r	Linear output parameters (determined during the training process)
$O_{j,i}$	Output of the *i*th node in layer *j*
$\mu_{Ai}(x)$	Bell shape membership function with a parameter set of {ai, bi, ci}
ω_i	Firing strength of each rule (i.e. the output of layer 2, symbolized by a Π notation)
$\bar{\omega}_i$	Ratio of the *i*th node firing strength to the sum of the firing strength of all rules (i.e. the output of layer 3, symbolized by a N notation)

Layer 1. Each node i in this layer is a square node with a node function represented as:

$$O_{1,i} = \mu_{Ai}(x) = \frac{1}{1+(\frac{x-c_i}{a_i})^{2bi}} \quad \text{for } i = 1, 2 \tag{19}$$

where $O_{1,i}$ represents the output of the *i*th node in this layer, x is an input to node i, A_i is the linguistic label for the input, such as short and long, and $\mu_{Ai}(x)$ is the membership function which is commonly of bell shape with a minimum and maximum value of 0 and 1 respectively. The bell shape membership function has a parameter set of {a_i, b_i, c_i} that is referred to as the premise parameters. These parameters change the bell shape of the membership function automatically.

Layer 2. Each fixed node in this layer is a circle node symbolized by a Π notation. The output of this layer, ω_i, denotes the firing strength of each rule, which is calculated by the multiplication of the input signals:

$$O_{2,i} = \omega_i = \mu_{Ai}(x)\ \mu_{Bi}(y) \qquad \text{for } i = 1, 2 \tag{20}$$

Layer 3. Each fixed node in this layer is a circle node symbolized by a N notation. The output of this layer, $\overline{\omega}_i$, denotes the ratio of the *i*th node firing strength to the sum of the firing strength of all rules, which is expressed as:

$$O_{3,i} = \overline{\omega}_i = \frac{\omega_i}{\sum \omega_i} = \frac{\omega_i}{\omega_1 + \omega_2} \qquad \text{for } i = 1, 2 \tag{21}$$

Layer 4. Each adaptive node in this layer is a square node for calculating the contribution of the *i*th node towards the overall output, which is expressed as:

$$O_{4,i} = \overline{\omega}_i f_i = \overline{\omega}_i (p_i x + q_i y + r_i) \qquad \text{for } i = 1, 2 \tag{22}$$

since f_i represents the fuzzy if-then rules with $\{p_i, q_i, r_i\}$ being the parameter set, where these parameters are referred to as the consequent parameters.

Layer 5. The single fixed node in this layer is a circle node symbolized by a Σ notation. It computes the overall output of the network by calculating the summation of the contribution of all rules:

$$O_{5,i} = \sum \overline{\omega}_i f_i = \frac{\sum \omega_i f_i}{\sum \omega_i} = f = \text{overall output} \qquad \text{for } i = 1, 2 \tag{23}$$

With the values of the premise parameters being constant, the overall output can be expressed as the linear combination of the consequent parameters:

$$
\begin{aligned}
f &= \frac{\omega_1}{\omega_1+\omega_2} f_1 + \frac{\omega_2}{\omega_1+\omega_2} f_2 \\
&= \bar{\omega}_1 f_1 + \bar{\omega}_2 f_2 \\
&= \bar{\omega}_1 (p_1 x + q_1 y + r_1) + \bar{\omega}_2 (p_2 x + q_2 y + r_2) \\
&= (\bar{\omega}_1 x) p_1 + (\bar{\omega}_1 y) q_1 + (\bar{\omega}_1) r_1 + (\bar{\omega}_2 x) p_2 + (\bar{\omega}_2 y) q_2 + (\bar{\omega}_2) r_2 \qquad (24)
\end{aligned}
$$

In order to allow the fuzzy inference system to learn through the training data sets, the hybrid learning algorithm for ANFIS is used. The algorithm combines the back-propagation gradient descent and least square methods to create a fuzzy inference system with the membership functions being adjusted iteratively through updating the parameters. To update the parameters, for instance, the algorithm is composed of a forward pass and a backward pass. The forward pass makes use of least square methods to optimize the consequent parameters, i.e. p_i, q_i, r_i. with the premise parameters, i.e. a_i, b_i, c_i, fixed as constant. Immediately after obtaining the optimal values of the consequent parameters, the backward pass starts by making use of the gradient descent method to update the optimal values of the premise parameters. Chapter 5 illustrates the application of ANFIS in the perspective of e-commerce order management in two distribution centres.

The output of the ANFIS model is the predicted e-order arrival within a specified period of time. Such e-order arrival prediction allows logistics practitioners to determine the cut-off time of the pending e-orders so that an appropriate size of e-orders in terms of the weight of the orders (measured in kg), can be grouped and subsequently released in a batch for bulk order picking in the distribution centres or order fulfilment centres. The real-time availability of resources, such as order picking equipment and order pickers, is also taken into consideration, so as to ensure that there are sufficient resources to handle the size of the grouped e-orders. Details of the decision support for determining the cut-off time are further discussed in section 3.6.3.

In the structural design of the ANFIS model for forecasting the e-order arrival in distribution centres, the model construction process includes three sequential stages, as depicted in Fig. 3.2, they are: Stage I – Design Considerations Fitness Evaluation, Stage II – Model Training and Testing, and Stage III – Performance Evaluations. Details steps for model construction under each stage are discussed in the following sections.

3.6.2.1 Stage I – Design Considerations

In Stage I – Design Considerations, the initial model settings are determined and configured based on the operating size and nature of business of the logistics service providers. There are in total 5 steps involved in this stage:

- **Step 1** – *Determine the cycle time for reviewing the e-order consolidation cut-off policy*,
- **Step 2** – *Identify the input and output variables in the ANFIS models*,
- **Step 3** – *Select and extract dataset for model training and testing*,
- **Step 4** – *Define the universe of disclosure for each input parameter*, and
- **Step 5** – *Define the type of output functions for each output parameter*.

Step 1 – *Determine the cycle time for reviewing the e-order consolidation cut-off policy*

The e-order consolidation cut-off time is the final output of the EBRM. It denotes how much time is left for the logistics service providers to continue consolidating the e-orders before releasing them in batch. To generate such decision support, users are required to use the EBRM of the EF-DSS periodically to forecast the number of e-orders that will be arriving at the distribution centres in the coming “period”. However, it is up to the decision makers to decide how long should the “period” be. Therefore, prior to the construction of the ANFIS-based forecasting models, the “period”, that is, the cycle time for reviewing the e-order consolidation cut-off time is required to be determined. By identifying the cycle time, the ANFIS-based forecasting model in the ERBM is suggested to be used at the end of each cycle. For example, if the cycle time is 2 hours, then the operators can use the ERBM of the EF-DSS to obtain the predicted number of e-orders in the coming two hours using the ANFIS forecasting model. Consequently, by using the proposed algorithm presented in section 3.6.3, the current available order handling capacity is compared with the predicted number of e-orders in the coming two hours, so as to determine how much time is left for batch release of the pending e-orders.

There are two factors for determining the cycle time for reviewing the e-order consolidation cut-off time: the maximum order handling capacity in the e-fulfilment distribution centres and the average number of orders (in kg) received per hour. The maximum order handling capacity is an estimation of the maximum weight of orders (in kg) that can be handled by the available resources, assuming all resources including the order picking equipment and order pickers are completely idle and can be fully allocated for handling the e-orders once they are released in batch for bulk processing in the distribution centres. For the average number of orders received per hour, the figure is collected based on the historical order receiving amount. To better illustrate how the cycle time is identified, an example is given in Table 3.4. If the maximum order handling capacity of a distribution centre is 200 kg, and the statistics reveals that the average number of e-orders received per hour is only 60 kg. In this regard, the approximate cut-off time for consolidating the e-commerce orders is 3.33 hours (by dividing the order handling capacity by the number of e-orders received per hour).

Therefore, the cycle time for making a periodic review of the cut-off time must be less than 3.33 hours, say 2 or 3 hours, to avoid any overloading of resources due to consolidating too many e-orders at a single time. With the cycle time ("period") identified, the output of the ANFIS forecasting models to be built in the EBRM of the EF-DSS would be the e-order arrival figure in the coming period.

Table 3.4. Example of cycle time determination

Considerations in determining the cycle time for reviewing the e-order consolidation cut-off time	Example
Maximum order handling capacity in distribution centres	200 kg
Historical average number of orders received per hour	60 kg
Approximate cut-off time for e-order consolidation:	Every 3.33 hours (= 200/60)
Cycle time for periodic review:	Every 2 or 3 hours

Step 2 – *Identify the input and output variables in the ANFIS models*

After determining the cycle time ("period") for reviewing the cut-off policy, the output variable of the ANFIS models is identified, that is, $Q_d(t+1)$, the predicted arrival of the e-orders (in kg) in the upcoming period $t+1$ in the current day d. For the input variables, it is noted that the prediction subject, $Q_d(t+1)$, is time-series data. In this regard, three types of variables are considered as the determinants of the time-series-type e-order arrival figure: actual e-order arrival of the previous n_1 periods, volatility of e-order arrival among the previous n_2 periods, and the n_3-period simple moving average. The justification of selecting these input variables is presented in Table 3.5.

Table 3.5. Justifications of the input variables of the ANFIS forecasting models

Input variable	Justifications
Actual e-order arrival of the previous n_1 periods	In time-series data prediction study, lag variables, i.e. previous figures, are the essential indicators for predicting the next figure. Thus, the actual e-order arrival in the previous n_1 periods, i.e. period t, t-1, t-2, …, t-n_1, are considered as essential prediction indicators for predicting the e-order arrival figure at the upcoming period t+1.
Volatility of e-order arrival among the previous n_2 periods	The volatility of previous e-order arrival (momentum) is an essential indicator of the trend of the time-series-based e-order arrival. This indicator has been used to predict the stock prices. Tanaka-Yamawaki & Tokuoka (2007) introduced one and two-order momentum as a technical indicator of intra-day stock price prediction. Chang et al. (2011) also introduced one and two-order momentum for forecasting the stock prices. Thus, this study considers both one and two-order momentum of e-order arrival as the input variables.
n_3-period simple moving average	Simple moving average is another obvious figure that has been commonly introduced as a prediction indicator. Therefore, a two-period and three-period simple moving average are introduced as the input variables for ANFIS forecasting modelling.

Step 3 – *Select and extract dataset for model training and testing*

The training and testing process is a critical model construction procedure to build an ANFIS model with satisfactory prediction capability. To effectively train and then test the models, a real production data set needs to be gathered and extracted from the distribution centre where e-order fulfilment operations take place. With the cut-off review cycle identified during *Step 1 – Determine the cycle time for reviewing the e-order consolidation cut-off policy*, the data sets are pre-processed and converted into useful input values for the proposed ANFIS models. For example, if the cut-off review cycle is 2 hours, the data set is then pre-processed to demonstrate the e-order arrival figures of every 2 hours. An example of data set in 2-hour time interval is shown in Table 3.6.

Table 3.6. An example of data set in 2-hour time interval

	Time											
Date	**0-2**	**2-4**	**4-6**	**6-8**	**8-10**	**10-12**	**12-14**	**14-16**	**16-18**	**18-20**	**20-22**	**22-24**
Mon	14	21	12	14	25	46	49	55	68	53	79	94
Tue	41	32	25	10	27	47	56	78	84	63	89	84
Wed	45	34	21	22	35	42	39	52	73	81	71	78
Thu	43	32	30	19	21	41	46	52	62	73	75	68
Fri	56	42	21	21	37	47	52	62	57	69	73	68
Sat	78	52	31	23	36	68	58	63	67	73	83	84
Sun	94	77	47	23	49	64	72	62	89	52	96	67

Step 4 – *Define the universe of disclosure for each input parameter*

To achieve the best result generated from the ANFIS model, system parameter modifications are critical. In the MATLAB's ANFIS editor, different types of membership functions (MFs), such as triangular (Tri), trapezoidal (Trap), generalized bell (Gbell), Gaussian curve (Guass), Gaussian combination, Π-shaped, difference between two sigmoid functions, and product of two sigmoid functions, are available for selection. In addition, the number of MFs for each input and the types of output MFs (either constant or linear) can also be modified. Due to a large number of possible combinations of the parameter settings of the ANFIS model, the best combination of the ANFIS model needs to be identified. A summary of the configurable model settings that need to be tested is presented in Table 3.7.

Table 3.7. A summary of the configurable model settings that need to be tested

Types of model configuration	Configurations to be tested
Initial FIS generation	Grid partitioning
Types of input MFs*	Tri/Trap/Gbell/Guass
Number of MFs for each input*	2/3/4
Types of output function*	Constant /linear
Learning algorithm	Least square method and Back-propagation gradient descent method

**Further experiments were made to identify the best MFs characteristics*

Step 5 – *Define the type of output functions for each output parameter*

Apart from a number of configurable settings available that are required for proper selection through performing model testing, the output function of the ANFIS model can either be "Constant" or "Linear". Therefore, during *Stage II – Model Training and Testing*, different combinations of configurable settings need to be tested so as to identify the best combination of setting for an ANFIS model.

3.6.2.2 Stage II – Model Training and Testing

The dataset, which is selected in *Step 3 - Select and extract dataset for model training and testing* under *Stage I*, needs to be split into two different data sets, i.e. training dataset and testing dataset. Usually, the training data set contains 70% or 90% of all data and the remaining data serves as the testing data set (Sánchez et al., 2007). The training data set is used to train and build the adaptive network. The testing data set is used to determine if any over fitting of model occurs during training. Therefore, in order to check the generalization capability of the developed neural system and to avoid the model from overfitting the training data set, the trained fuzzy inference system under different combinations of settings is then applied using the testing data set. The optimal model setting for an ANFS model can then be identified.

3.6.2.3 Stage III – Performance Evaluations

With the best setting obtained for the developed ANFIS models, they are then compared with an autoregressive integrated moving average (ARIMA) model for further performance validation. The root-mean square error (RMSE), mean absolute deviation (MAD) and mean absolute percentage error (MAPE), which are respectively given by Eq. (25), (26), and (27), are adopted for model performance comparisons.

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{t=1}^{n}(A_t - Q_t)^2}{n}} \tag{25}$$

$$\mathrm{MAD} = \frac{1}{n}\sum_{t=1}^{n}|A_t - Q_t| \tag{26}$$

$$\mathrm{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - Q_t}{A_t} * 100\right| \tag{27}$$

where A_t and Q_t are respectively the actual arrival of e-order and predict arrival of e-order (in terms of weight in kg) at period t, and n is the number of data patterns in the independent data set.

3.6.3 Algorithm for Determining "When to release" decision

This sub-module makes use of the output of the ANFIS model in EBRM of the EF-DSS, i.e. the predicted arrival of e-commerce orders in the upcoming period measured by the weight in kg, to generate decision support for logistics practitioners so as to adjust the cut-off frequency of releasing the grouped orders for actual order picking operations in a batch. To compute the cut-off time of the e-order grouping, the proposed approach in the EF-DSS suggests taking the maximum order handling capacity in the distribution centre into consideration. The maximum order handling capacity, Q_{max}, can be obtained by identifying the total weight that can be handled by the resources for order handling, such as equipment and order pickers, which are currently idle and available for performing picking operations of e-orders. With the known constant value of Q_{max}, EF-DSS is able to automatically generate the cut-off time, denoted as T_{final}, with the notation definitions shown in Table 3.8 and the underlying calculations as described below.

In order to avoid any potential over-utilization of the order handling resources, especially human resources, the maximum allowable order handling capacity (Q_{max}) is multiplied by a constant factor k (in %), to give an adjusted order handling capacity ($Q_{adjusted}$). It is recommended that the value of k should be within the range of 0.6 to 0.8, based on the suggestion given by domain experts. To obtain the current remaining order handling capacity ($Q_{remaining}$), the adjusted order handling capacity is subtracted by the total weight of pending orders in the e-order consolidate pool ($Q_{current}$), which is expressed as:

$$Q_{adjusted} = Q_{max} \times k \tag{28}$$

$$Q_{remaining} = Q_{adjusted} - Q_{current} \tag{29}$$

The predicted e-order arrival rate per minute (Q_t) is computed by dividing the predicted weight of the incoming e-orders in the upcoming period *t+1* ($Q_d(t+1)$, the output of the ANFIS model), by the total duration in the specified period (in minutes) (n). It is expressed as:

$$Q_t = \frac{Q_d(t+1)}{n} \tag{30}$$

The optimal cut-off time for batch order release can then be computed by dividing Eq. (8) by Eq. (9), that is:

$$T_{optimal} = \frac{Q_{remaining}}{Q_t} \tag{31}$$

In order to avoid any e-order pending in the e-order consolidation pool for too long a duration, an additional variable, T_{max}, is introduced. It is defined as the maximum allowable waiting time of an e-order pending in the e-order consolidation pool. The purpose of introducing this variable is to govern the final suggested output of the EAPS, i.e. the cut-off time of e-orders (T_{final}), so that T_{final} would not exceed the maximum allowable waiting time of the e-order pending in the e-order consolidation pool. The logic is mathematically expressed as:

$$T_{final} = \begin{cases} \mathrm{T}_{optimal} & \text{for} \quad \mathrm{T}_{optimal} \leq T_{max} \\ \mathrm{T}_{max} & \text{for} \quad \mathrm{T}_{optimal} > T_{max} \end{cases} \tag{32}$$

Table 3.8. Notation definitions for the cut-off frequency decision support in EBRM

Cut-off frequency decision support model:		
Notation	**Definition**	**Unit of measurement**
$\mathbf{Q_{max}}$	Maximum allowable order handling capacity	kg
$\mathbf{Q_{current}}$	Total weight of pending orders in the e-order consolidation pool	kg
$\mathbf{Q_d(t+1)}$	Predicted weight of incoming orders of the upcoming period *t+1 (Output of the ANFIS model)*	kg per period
$\mathbf{Q_t}$	Predicted e-order arrival rate per minute	kg per minute
n	Total minutes in the specified period	-
k	Constant factor for creating buffer for order handling	%
$\mathbf{T_{optimal}}$	Optimal cut-off time for batch order release	minutes
$\mathbf{T_{max}}$	Maximum allowable waiting time of an e-order pending in the e-order consolidation pool	minutes
$\mathbf{T_{final}}$	Suggested cut-off time remaining for batch order release *(Final output of the EAPS)*	minutes

The final output of the EBRM enables decision makers to realize how long the e-order consolidation pool can still be collecting e-orders before they are released in batch in the distribution centres for performing the subsequent batch order picking operations. The output of this module, in conjunction with the use of EGM to group the pending e-orders into several batches for batch order picking in the distribution centres, allows logistics practitioners to effectively apply the concept of warehouse postponement. The order fulfilment process is re-engineered from conventionally handling orders on an individual basis to handling orders in a batch, as the incoming e-orders can be consolidated in a pool and the subsequent warehouse operations can be delayed until the last possible moment.

The sequence of generating decision support for e-order handling is to first use the EBRM to obtain the suggested cut-off time for order batching, followed by the use of EGM for systematically grouping the consolidated orders, which are pending in the consolidation pool of the ECM, into several orer batches presented as order picking lists. Warehouse operators can make use of the generated order picking lists in each period to assign order pickers to handle the subsequent order fulfilment operations in distribution centres or warehouses.

3.7 Summary

This chapter introduces the proposed warehouse postponement strategy for efficient handling e-commerce orders in e-fulfilment distribution centres and describes the system architecture of the EF-DSS, which contains three modules: ECM – for consolidation of incoming e-orders for later batch processing in the distribution centres, EGM – for generating e-order grouping solution for logistics service providers to split the consolidated e-orders into several batches based on the SKUs' location proximity, and EBRM – for assisting the logistics service providers to determine the cut-off time that terminates the e-order consolidation process and release of the pending e-orders in batch. The ultimate goal of the EF-DSS is to assist logistics practitioners in effectively deploying the warehouse postponement strategy by providing them with decision support regarding "How e-orders are grouped for batch processing" and "When the e-order consolidation process should be terminated for batch releasing".

To demonstrate the feasibility and applicability of the EF-DSS in e-fulfilment distribution centres, system implementation procedures have to be followed. The roadmap and details of the system implementation is presented in Chapter 4.

Chapter 4 – Implementation Procedures of the System

4.1 Introduction

This chapter provides a roadmap for the design and implementation of the EF-DSS in real practice. A systematic approach on how to develop the intelligent system for executing the proposed warehouse postponement strategy in a e-fulfillment distribution centre is given. The development and implementation of the EF-DSS involves six phases, as depicted in Fig. 4.1: (i) Understanding of the e-commerce order fulfillment operating categories, (ii) Structural Formulation of an Action Plan for System Implementation, (iii) Structural Formulation of ECM, (iv) Structural Formulation of EGM, (v) Structural Formulation of EBRM, and (vi) System performance review and evaluation.

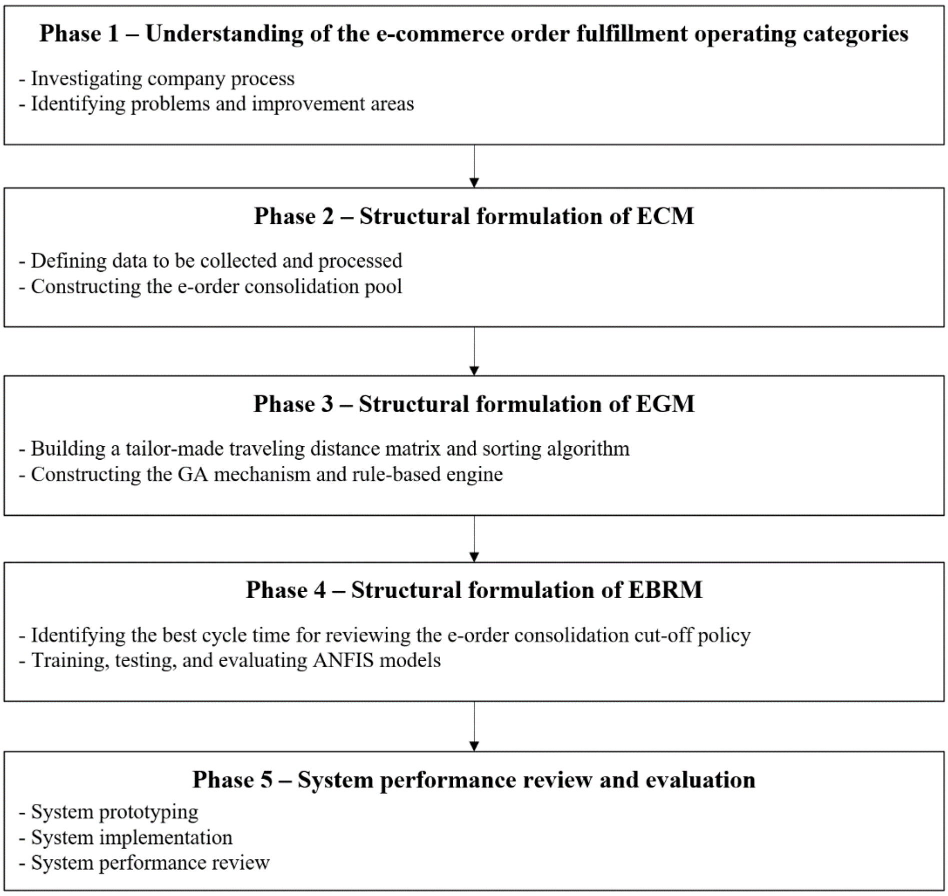


Fig. 4.1. The implementation procedures of the EF-DSS

4.2 Phase 1 – Understanding of the E-commerce Order Fulfillment Operating Categories

In Phase 1, the operation size and characteristics of the e-fulfillment centre are investigated. It is an essential stage prior to any structural development of the EF-DSS, as identifying the major bottlenecks currently encountered by the LSP is essential for the EF-DSS to be able to tackle the problems directly. To ensure the EF-DSS can be fitted into the LSP's distribution centre for production use, there are three steps in this phase: (i) Company process investigation, (ii) Problems and improvement areas identification, and (iii) Preparation of a pilot run of the system.

4.2.1 Investigating Company Process

Information and knowledge sharing across departments can be achieved through the integration of IT tools. With E-commerce and IT being the interrelated components of the structural change in distribution, integration of IT tools can be regarded as the enabler for LSPs to be efficient in processing orders at the distribution centres and delivering them at high frequencies. To facilitate the effective information sharing process, the order handling procedures are studied to understand the operational flow of e-commerce orders. An example is shown in Figs. 4.2 to 4.5, demonstrating the operational flow from inbound receiving, internal processing in distribution centres, to outbound delivery, which requires a comprehensive process investigation to identify the improvements needed for enhancing the operating efficiency.

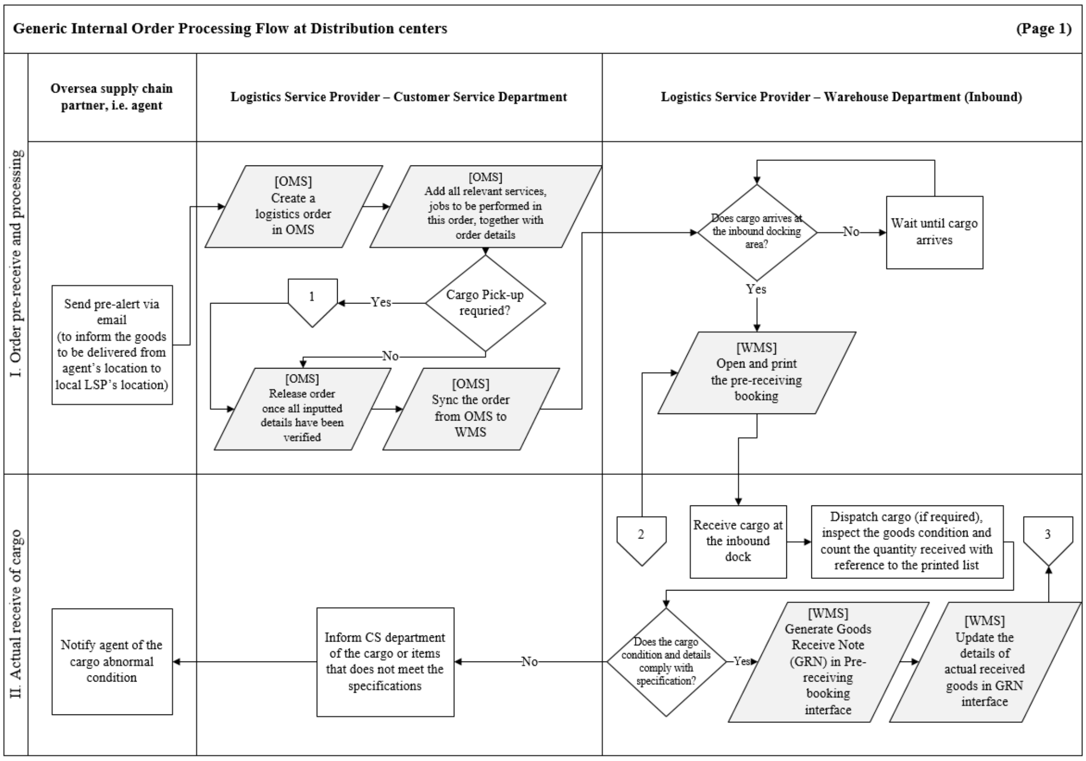


Fig. 4.2. An example of internal process investigation for logistics order handling (1)

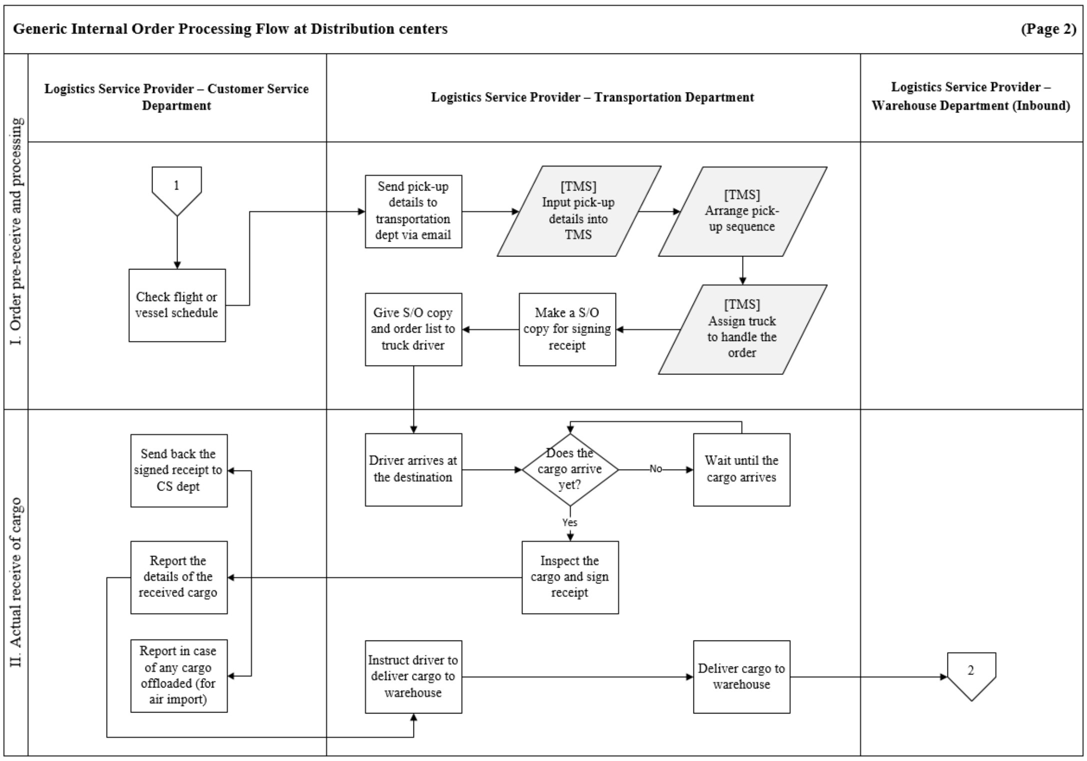


Fig. 4.3. An example of internal process investigation for logistics order handling (2)

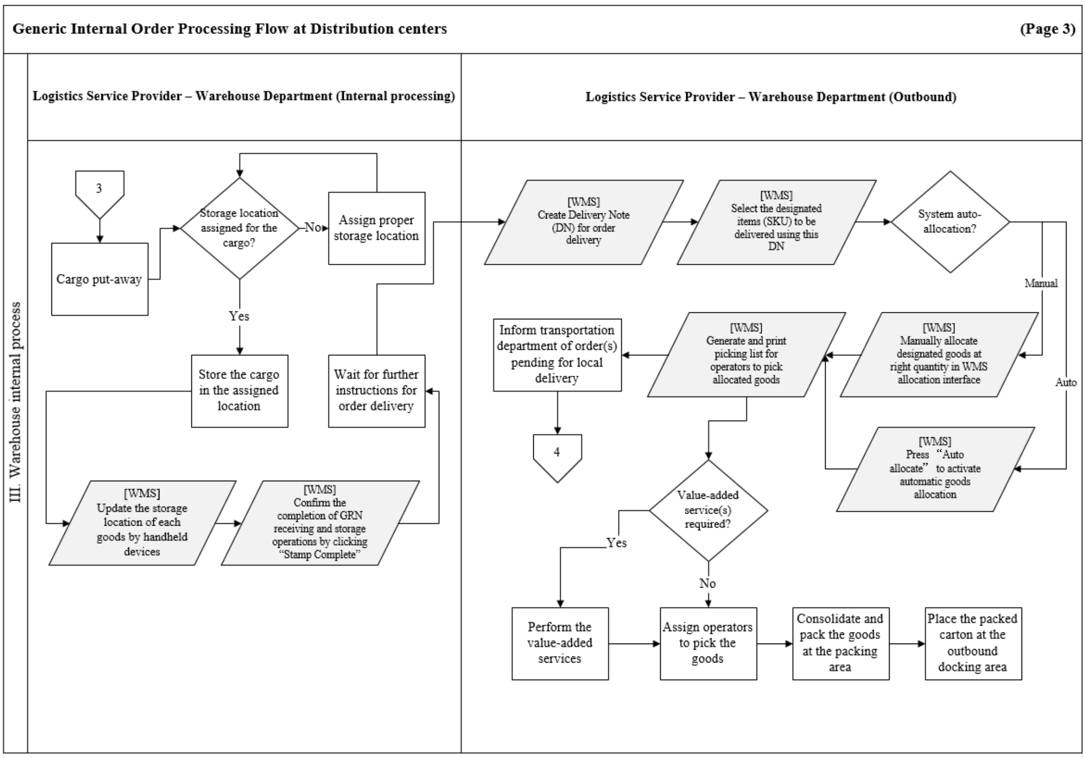


Fig. 4.4. An example of internal process investigation for logistics order handling (3)

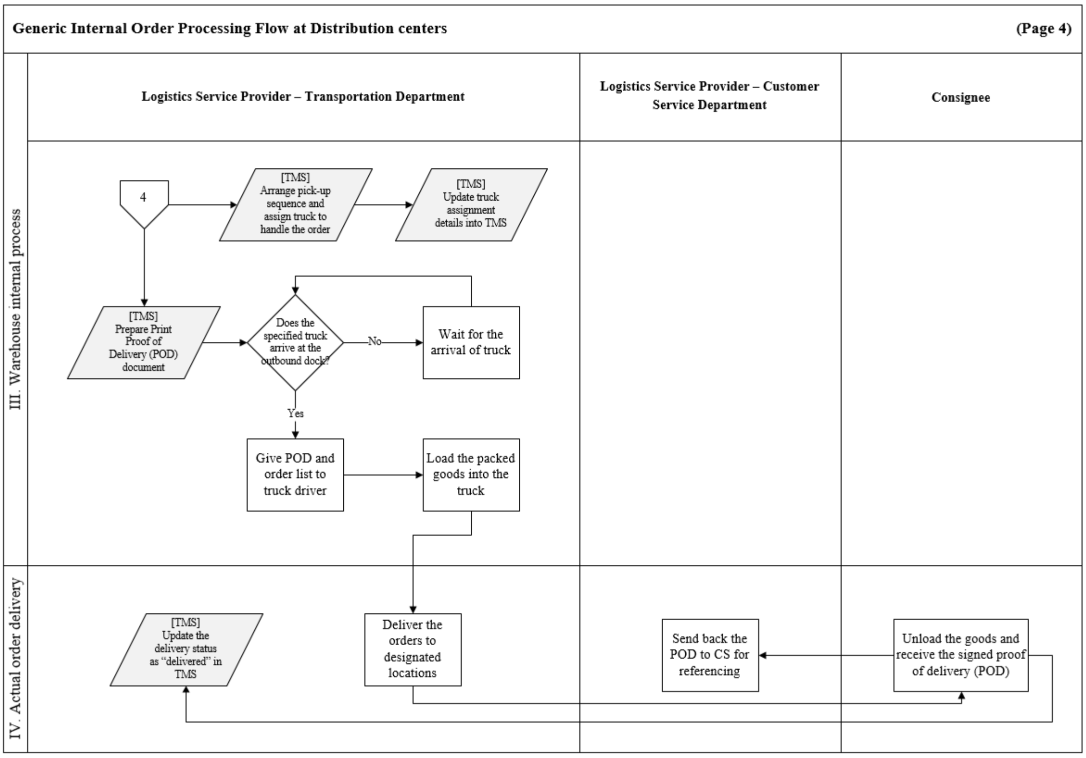


Fig. 4.5. An example of internal process investigation for logistics order handling (4)

4.2.2 Identifying Problems and Improvement Areas

Any IT system implementation requires a comprehensive study of the user requirements in advance. The user requirement study is a typical process an IT solution provider performs by visiting the client, i.e. the system users, or in this case, the logistics practitioners, to listen to the voice of the customers and their requirements for system deployment. By investigating the company operating policies and procedures, a system feature and function list can be compiled to address the user's specific system requirements. An example of a system function and feature list is shown in Fig. 4.6. Before proceeding to system design and development, interviews and meetings with the logistics service provider are also regularly held to identify and prioritize the logistics service provider's concerns on the operational bottlenecks. An official agreement between the IT developer and user is made to specify the system specifications and other relevant issues. With the comprehensive study of the existing order processing flow and the underlying bottlenecks or improvement areas, an action plan for system implementation can be formulated accordingly.

Though each system user, i.e. logistics service providers, has specific requirements and needs towards a system solution, the EF-DSS proposed in this study is a generic system that tackles the major operational bottlenecks faced by logistics practitioners, that is, the operating inefficiency of handling e-commerce orders due to ineffective and manual order consolidation processes. In the following section, the structural formulation of each module in the EF-DSS, namely ECM, EGM and the EBRM, is presented for the structure and theoretical rationale of the EF-DSS. For any technical issue or difficulty in system implementation in the real production environment of distribution centres, it is suggested to consult the IT solution provider for further advice.

Function List for EF-DSS
Configurable order consolidation threshold value - *Configurable order consolidation threshold value provided by EF-DSS enables users to define the number of discrete orders from various sources to be consolidated and displayed at the interface. Users are able to receive alert upon reaching threshold value such as the maximum allowable number of orders to be grouped, and the amount of time aggregated.*
Virtual order filling - *The "Fill Order" button enables users to verify whether there is enough quantity for picking. This function minimizes potential occurrence of being unable to fill up the exact quantity of the orders as required. Consequently, the productivity of actual order-picking is enhanced resulting from guaranteed order-picking fill rate.*
Order-picking progress tracking - *Search function in order-picking interface enables users to retrieve all historical order-picking history. The details of each order picking waves generated and executed are fully traceable. Managers can make use of this tracking feature for productivity measurement and improvement.*
Real-time content sharing to social media across supply chain - *For the consideration of supply chain efficiency, upon having an order status update after successful pick and pack of orders, the order status can be seamlessly synchronized to social media.*
Customizable formats and templates of shipment delivery notice - *Instead of hardcore content and format of shipment delivery notice, the console stores customizable and re-usable shipment delivery notice format template, allowing LSPs to provide tailor-made shipment delivery notice to their supply chain partners according to the specific requirements. This enables LSPs in dealing with different types of customers and supply chain partners for seamless order fulfillment efficiency effortlessly along the supply chain. The agility and resilience is provided in case of having new customers to customize format of shipment delivery notice, due to the easily changeable and traceable format for standardization.*

Fig. 4.6. An example of a system function and feature list

4.3 Phase 2 – Structural Formulation of ECM

The aim of this phase is to formulate the E-order consolidation module (ECM) of the EF-DSS. Recall that the development of ECM contributes two essential purposes for the entire EF-DSS. First, the ECM consists of an E-order consolidation pool for consolidating the e-commerce orders, so that they will be stored in the pool instead of undertaking the order processing procedures immediately upon their arrival. Second, the ECM collects and pre-process the data, such as order information, storage location of each SKU and resource status in the distribution centres. To build these two features, the structural formulation of ECM involves two steps: (i) Defining the data to be collected and processed, and (ii) Constructing the e-order consolidation pool.

4.3.1 Defining the Data to be Collected and Processed

The introduction of the E-order consolidation pool in EF-DSS has brought a number of structural changes in the order processing sequence in warehouses and distribution centres. One noticeable change in the order processing procedure is the requirement of collecting and storing new order attributes for each of the incoming logistics orders. In order to facilitate the smooth transition of orders for processing under the ECM using the EF-DSS, a framework of data collection and storage in a standardized format is presented. Depending on the nature of the logistics business and the operation size of the logistics service provider, the data to be collected varies. Normally, there are in total six types of data to be gathered and stored in the EF-DSS: general order information, detailed order specifications, inbound order SOP setup, outbound order SOP setup, party master and party SKU master. Details of each category of information are shown in Tables 4.1 to 4.3.

Table 4.1. Example of the data to be collected under “general order information” and “detailed order specifications” data category

General order information	**Detailed order specifications**
SOP ID	*SOP ID*
Sub. A/C	*GN#*
Master A/C	*Waybill No.*
Consignee ID	*SKU #*
Goods Receive Note No. (GN#)	*Pallet ID*
Receiving Date	*Quantity (Qty)*
Estimated Time of Delivery (ETD)	*No. of Packages (Pkgs)*
Waybill No.	*Net Gross Weight*
Warehouse No. (WH#)	*Total Gross Weight*
	Unit CBM
	Total CBM
	Lot/Serial Number

Table 4.2. Example of the data to be collected under “inbound order SOP setup” and “outbound order SOP setup” data category

Inbound SOP setup information	**Outbound SOP setup information**
SOP ID	*SOP ID*
Sub. A/C	*Sub. A/C*
Master A/C	*Master A/C*
Outbound SOP Related	*Inbound SOP Related*
Storage Specification	*Allocation Model*
Temp. Control (Y/N)	
Humidity Control (Y/N)	
Security Control (Y/N)	

Table 4.3. Example of the data to be collected under “party master” and “party SKU master” data category

Party master	**Party SKU master**
Party Code	*SKU #*
Name	*Item Category*
Address	*Item Description*
Country	*Unit Price*
Currency	*Total order Value*
Contact number	*Package Measurement (Length, Width, Height)*
Fax number	*ABC Code*
Email address	*Serial Control (Yes/No)*

4.3.2 Constructing the E-order Consolidation Pool

E-order consolidation and sorting in the cloud database is one of the most crucial functions of the EF-DSS for the purpose of logistics process re-engineering in the e-commerce business. Table 4.4 summarizes the essential functions of the centralized cloud database for data storage across various e-order fulfilment activities. The cloud database collects e-orders and displays the collected e-orders, pending processing. The logistics order processing flow is re-engineered by allowing users to control when pending orders are ready for batch release to the warehouse department so as to perform the order fulfilment operations. The centralized relational database also sorts the received orders by SKUs, so that the SKUs to be handled in the e-fulfilment centers are grouped for ease of actual processing.

Table 4.4. Database construction for various e-logistics activities

Related department	Logistics activities	Functions of the cloud database
Customer service department	**Customer order inquiry**	Create log for track and trace of order inquiry history
	E-order collection	Retrieve new orders and stores information in the database
	Documents for order processing	Prepare required documents and import and export, update the documentation completion status of each order
	Shipment notification to customers	Generate shipment notification templates for notifying customers of their orders ready for delivery
Warehouse department	**Order fulfilment in e-fulfilment centers**	Follow the tables for order receiving, put-away, pick-and-pack, and delivery operations
	Order status update	Update the status of e-order for order visibility and transparency
	Inventory update	Cross-checking and updating of inventory in database and in storage areas of e-fulfilment centers

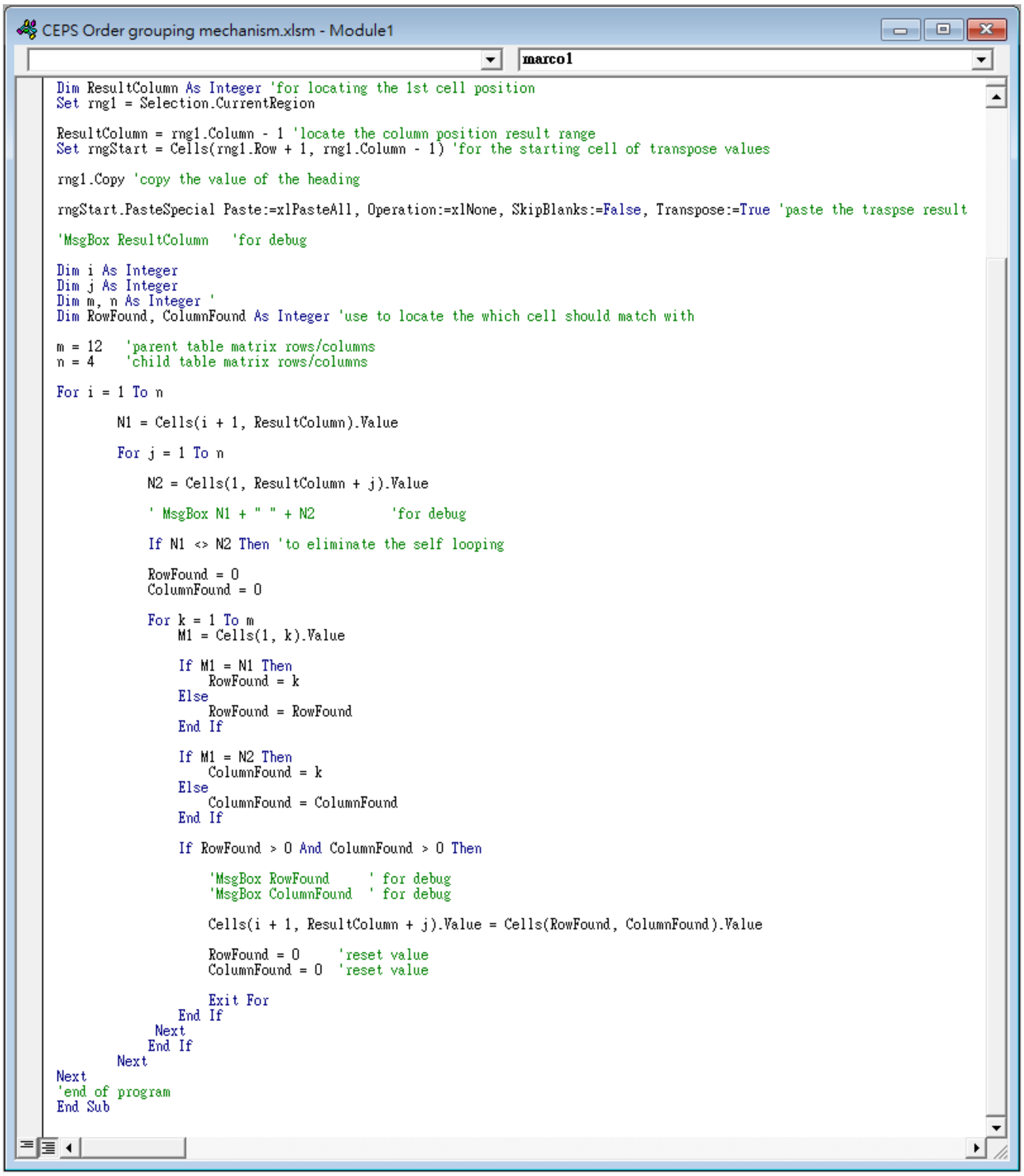
4.4 Phase 3 – Structural Formulation of EGM

In this phase, the E-order grouping module (EGM) is constructed to split the grouped orders into several batches for batch order picking, and the order grouping decision support is generated through the use of a GA mechanism. Therefore, this phase consists of two steps: (i) Building a tailor-made traveling distance matrix, and (ii) Constructing the GA mechanism and rule-based engine.

4.4.1 Building a Tailor-made Traveling Distance Matrix and Sorting Algorithm

To govern the e-fulfilment operational flow, decision support for grouping SKUs with similar storage locations in e-fulfilment centers, and an appropriate set of handling specifications and handling equipment, is generated through the construction of the proposed GA mechanism and the rule-based inference engine. Storage bin locations of the e-fulfilment centers are decoded into real numbers for formulating a valid chromosome encoding scheme. A Microsoft Excel spreadsheet is used for the back-end algorithm development, and Evolver, a software developed by the Palisade Corporation, is adopted to minimize the fitness function in the GA mechanism in order to search for the best global solution of order grouping.

Based on the layout design of the storage bin locations in the distribution centre, an inter-storage bin distance matrix that calculates all the inter-bin distances among each storage bin is constructed and stored in a MS Excel spreadsheet. For each order grouping problem, the pending e-orders only involve part of the total number of SKUs stored in the storage areas. In other words, the GA mechanism evaluates the fitness of each chromosome by only coping with the inter-bin distances of the n storage bins concerned in the current problem using the $n \times n$ distance matrix extracted from the original $N \times N$ distance matrix. Therefore, using the parent distance matrix, including all inter-bin distances, is unnecessary. In this regard, a sorting algorithm, developed using Visual Basic for Applications (VBA), a programming language that automate tasks in MS Excel, is built for extracting the required inter-bin distances from the parent distance matrix to form a child distance matrix. An example of the programming code for the sorting algorithm is depicted in Fig. 4.7.



CEPS Order grouping mechanism.xlsm - Module1

marco1

```
Dim ResultColumn As Integer 'for locating the 1st cell position
Set rng1 = Selection.CurrentRegion

ResultColumn = rng1.Column - 1 'locate the column position result range
Set rngStart = Cells(rng1.Row + 1, rng1.Column - 1) 'for the starting cell of transpose values

rng1.Copy 'copy the value of the heading

rngStart.PasteSpecial Paste:=xlPasteAll, Operation:=xlNone, SkipBlanks:=False, Transpose:=True 'paste the traspse result

'MsgBox ResultColumn   'for debug

Dim i As Integer
Dim j As Integer
Dim m, n As Integer '
Dim RowFound, ColumnFound As Integer 'use to locate the which cell should match with

m = 12   'parent table matrix rows/columns
n = 4    'child table matrix rows/columns

For i = 1 To n

        N1 = Cells(i + 1, ResultColumn).Value

        For j = 1 To n

            N2 = Cells(1, ResultColumn + j).Value

            ' MsgBox N1 + " " + N2          'for debug

            If N1 <> N2 Then 'to eliminate the self looping

            RowFound = 0
            ColumnFound = 0

            For k = 1 To m
                M1 = Cells(1, k).Value

                If M1 = N1 Then
                    RowFound = k
                Else
                    RowFound = RowFound
                End If

                If M1 = N2 Then
                    ColumnFound = k
                Else
                    ColumnFound = ColumnFound
                End If

                If RowFound > 0 And ColumnFound > 0 Then

                    'MsgBox RowFound     ' for debug
                    'MsgBox ColumnFound  ' for debug

                    Cells(i + 1, ResultColumn + j).Value = Cells(RowFound, ColumnFound).Value

                    RowFound = 0     'reset value
                    ColumnFound = 0  'reset value

                    Exit For
                End If
             Next
            End If
        Next
Next
'end of program
End Sub
```

Fig. 4.7. An example of the sorting algorithm for extracting the required inter-bin distances from the parent distance matrix

4.4.2 Constructing the GA Mechanism and Rule-based Engine

A GA-based algorithm is built using the same MS Excel spreadsheet used in storing the inter-bin distance matrix. A set of constraints governing the order grouping logic in the GA mechanism is constructed based on the order processing environment of the logistics service provider who is going to implement the EF-DSS. For instance, the quantitative format of EF-DSS for e-order grouping is constructed accordingly, which includes constraints to ensure:

- the order grouping list includes the visiting storage bin location j immediately after storage bin location i;
- each travel path only has one order grouping list and each storage bin location is included in only one single order grouping list;
- the volume and weight limit of an order grouping list;
- the continuity of path;
- other restrictions (depending on the specific operating procedures of the logistics service provider).

Apart from the GA mechanism to be built under the EGM, a rule-based inference engine is constructed for providing guidance to the management in allocating the appropriate resources to handle the batch picking operations for the grouped e-commerce orders. The rule-based inference engine is developed for ease of storing and manipulating human knowledge so as to interpret the order grouping information in a useful way. The engine is customized for the case company based on the current throughput volume and resource availability for e-order fulfilment operations.

4.5 Phase 4 – Structural Formulation of EBRM

In this phase, the E-order batch realeasing module (EBRM) is constructed to generate decision support regarding the proper timing for terminating the order grouping and releasing the pending e-orders. This batch release timing decision support is generated through the use of ANFIS forecasting models and a "When to release" algorithm. To develop the features of EBRM according to the operations of the company, this phase consists of two steps: (i) Identifying the best cycle time for reviewing the e-order consolidation cut-off policy, and (ii) the ANFIS model construction.

4.5.1 Identifying the Best Cycle Time for Reviewing the E-order Consolidation Cut-off Policy

The e-order consolidation cut-off time is the final output of the EBRM. It denotes how much time is left for the logistics service providers to continue consolidating the e-orders before releasing them in batches. To generate such decision support, as discussed earlier in Chapter 3, users are required to use the EBRM of the EF-DSS periodically to forecast the number of e-orders that will arrive at the distribution centres in the coming “period”. However, it is necessary for the decision makers to decide how long the “period” should be. Therefore, prior to the construction of the ANFIS-based forecasting models, the “period”, that is, the cycle time for reviewing the e-order consolidation cut-off time needs to be determined. By identifying the cycle time, it is suggested that the ANFIS-based forecasting model in the ERBM is used at the end of each cycle.

As suggested in Chapter 3, the two factors for determining the cycle time for reviewing the e-order consolidation cut-off time are the maximum order handling capacity in the e-fulfilment distribution centres and the average number of orders (in kg) received per hour. Therefore, in identifying the best cycle time for reviewing the e-order consolidation cut-off policy, the management of the logistics service providers, typically the warehouse managers, are involved in deciding the most appropriate cycle time. In section 3.6.2.1, a detailed explanation regarding the need and approach to determine a proper cycle time is provided.

4.5.2 Training, Testing, and Evaluating ANFIS models

ANFIS-based forecasting models are developed in the EBRM for forecasting the e-order arrival in the coming period. It is noted that ANFIS models require historical data to train and test the neural network. As each company has its own order arrival dataset to import to the ANFIS for training and testing, the parameter settings of the ANFIS models constructed using a different set of data will not be identical. In other words, the best combination of model parameters for company A may not be the same as for company B. In this research, though three input variables, namely, actual e-order arrival of the previous n_1 periods, volatility of e-order arrival among the previous n_2 periods, and the n_3-period simple moving average, are identified and verified as the major determinants for predicting the e-order arrival in the coming period, a comprehensive process of model training and testing is still necessary for a company to identify the best model parameter setting combination in terms of: the types of input MFs, the number of MFs for each input, the types of output function. After determining the best combination of the model parameters, the model prediction performance has to be compared with the ARIMA models for verifying the predicting ability of the developed ANFIS model. In Case study 2 and 3 in Chapter 5, details are discussed on how the best combination of the model parameters of ANFIS models and how developed ANFIS models are evaluated and compared with ARIMA models,

4.6 Phase 5 – System performance review and evaluation

The system implementation, performance review and evaluation is the last phase of the EF-DSS. This phase consists of three steps: prototyping, implementation and performance review. In the first step, a pilot prototype, which adopts Visual Studio.Net as the major programming language, is designed and developed in accordance with the infrastructural details and design methodologies suggested in the previous phases.

For database development, Microsoft SQL server is adopted for database structure construction in the ECM of the EF-DSS. The inter-bin distance matrix and the GA mechanism for order grouping in the EGM are preliminarily built using Microsoft Excel with Visual Basic for Applications (VBA). The ANFIS forecasting models are trained and tested under the environment provided by MATLAB Fuzzy Logic Toolbox. In the second step, i.e. system implementation, pilot runs of the prototype are performed in the distribution centres to examine the feasibility of the system in handling consolidating e-orders and generating the decision support for assisting the operators to handle the entre e-order fulfilment process in the distribution centres. Any system bugs or performance instabilities will be detected and rectified, so as to ensure the final system can successfully go online for use in a production environment. In the last step, i.e. performance evaluation and review, the quality of the decision support examined. The grouping solution generated by the GA mechanism in the EGM and the batch release timing decision generated by the ANFIS models and the "When to release" algorithm in the EBRM, are closely monitored in no less than a three-month horizon. In particular, the predicting ability of the ANFIS models are regularly checked. If the ANFIS model prediction accuracy drops below 80%, a more recent dataset is imported to the ANFIS models to re-train and re-test in order to obtain a new combination of model parameters. This allows the adaptive neural network in the ANFIS models to be able to learn new order arrival patterns for better forecasting of e-order arrival in the future.

4.7 Summary

In this chapter, a roadmap of implementation of the EF-DSS is presented. The implementation of EF-DSS involves five phases:

- Phase 1 – Understanding of the e-commerce order fulfillment operating categories,
- Phase 2 – Structural Formulation of ECM,
- Phase 3 – Structural Formulation of EGM,
- Phase 4 – Structural Formulation of EBRM, and
- Phase 5 – System performance review and evaluation.

Key steps in developing the EF-DSS and deploying it in a distribution centre are discussed under each phase. Logistics practitioners may follow the guidelines for developing and implementing the EF-DSS for executing the warehouse postponement strategy as proposed in this study, thereby increasing the efficiency in handling fragmented, discrete, frequently-arrived e-commerce logistics orders in their distribution centres. To validate the EF-DSS, three case studies are presented in the next chapter.

Chapter 5 – Case Studies

5.1 Introduction

This chapter presents three case studies for demonstrating the viability of the EF-DSS in managing e-commerce orders in distribution centres. As introduced in Chapter 3, the E-order fulfillment decision support system (EF-DSS) consists of three modules, namely the E-order consolidation module (ECM), the E-order grouping module (EGM), and the E-order batch release module (EBRM). Each of these modules serve various purposes to reach the ultimate goal of the development of the entire system, that is, to provide all necessary decision support for logistics practitioners to deploy the Warehouse Postponement Strategy (WPS), the logistics operational strategy proposed in this research for efficient handling of e-commerce orders in e-fulfillment distribution centres by "delaying the order handling process of an order until the last possible moment". As depicted in Fig. 5.1, the ECM and EGM are applied in a case company as presented in Case study 1, so as to provide the logistics service provider with order grouping decision support to consolidate and group incoming e-commerce orders into batches for later batch order fulfillment. For Case studies 2 and 3, the ECM and EBRM are applied in the two different logistics service providers based in Hong Kong, with the goal of providing the case companies with order batch release timing decision support. With such decision support, the case companies are able to predict the e-order arrival rate in the coming period, thereby realizing the time remaining for them to continue consolidating e-commerce orders until terminating the order consolidation process and subsequently releasing the pending orders for immediate processing. The differences between Case studies 2 and 3, lie in the fact that the ECM and EBRM are deployed in two different logistics companies. In this regard, the datasets for ANFIS model construction, training, and testing in the EBRM are different.

Furthermore, Case studies 2 and 3 have different methodologies and sets of input variables for their own ANFIS-based forecasting models. Evaluations and performance comparisons of the ANFIS models built in Case studies 2 and 3 are made, and presented in Chapter 6 – Results and Discussion. Details of each Case study are discussed in the remaining sections of this chapter.

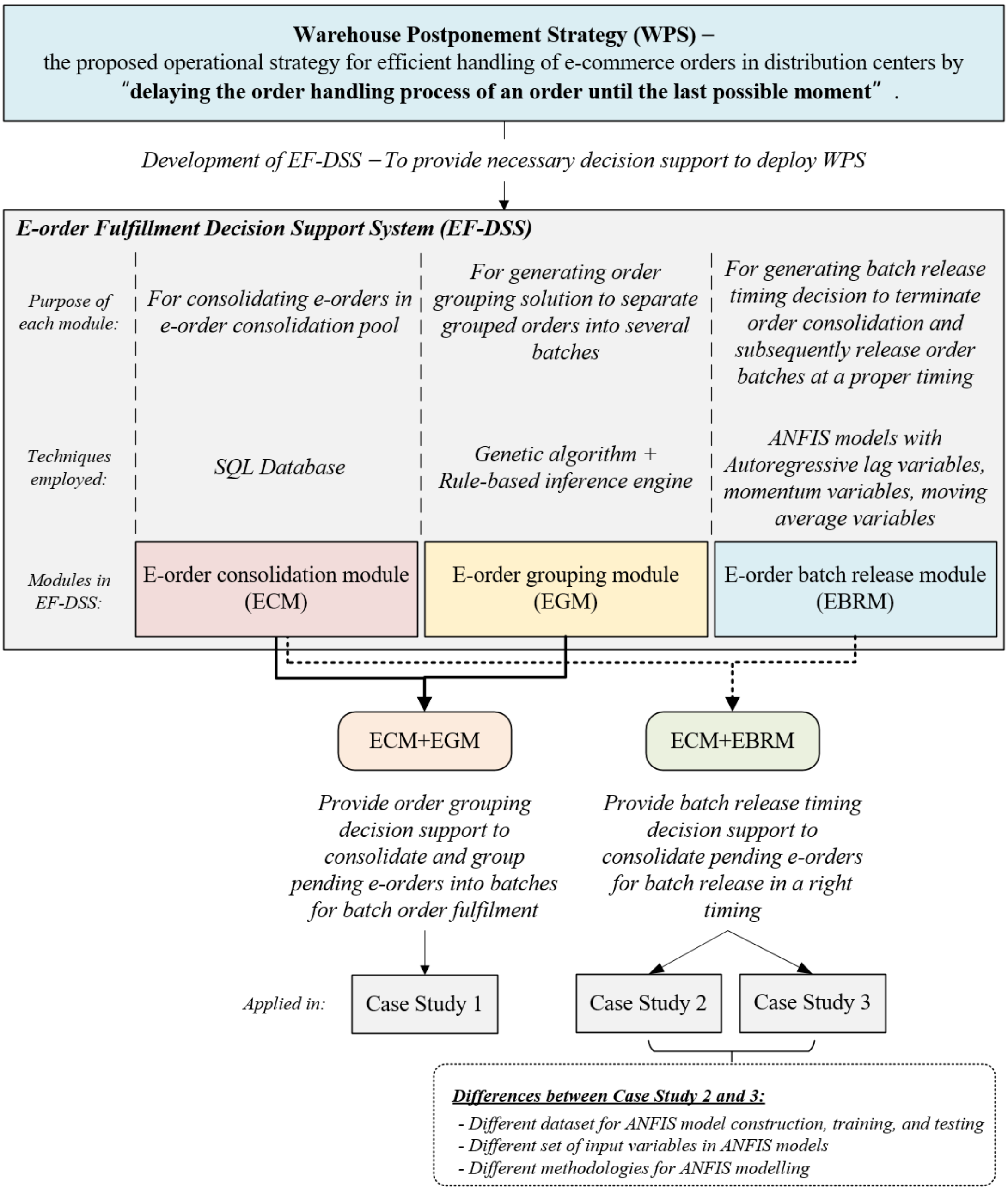


Fig. 5.1 An overview of the research and case study setting

5.2 Case Study 1 – The Use of Hybrid GA-rule-based Approach for Generating "How to Group" Decision Support

In Case study 1, the ECM and the EGM of the EF-DSS are deployed for assisting the logistics service provider in consolidating and grouping the e-commerce orders according to the proximity of the location of each SKU requested in the consolidated orders. There are two essential features of the ECM and EGM provided for facilitating the LSP in handling e-orders:

- Facilitating the e-order consolidation process through the use of the e-order consolidation pool in the ECM, and
- Generating order grouping decision support for ease of fulfillment of consolidated orders in the distribution centre.

In this section, the company background and problems encountered by the company are described, followed by a discussion of the deployment of ECM and the EGM.

5.2.1 Company Background and Existing Problems Encountered

The case company is a medium-sized Hong Kong-based logistics service provider that has specialized in B2C e-commerce logistics and distribution services in recent years. As China continues to drive cross-border growth, and its share of the online cross-border market is expected to grow from 27% in 2015 to 40% in 2021 (Forrester Research, 2016b), the developing trend of e-commerce in China has created a golden opportunity in recent years for logistics practitioners in Hong Kong and within the Pearl River Delta region to grasp a large part of the e-commerce pie by transforming their traditional B2B logistics businesses into e-commerce logistics businesses. This can be achieved by providing total e-logistics solutions so that e-retailers can concentrate on their core business by outsourcing the entire e-order fulfilment, including e-commerce last-mile delivery operations, to logistics service providers.

In view of the emerging trend of the e-commerce business, the company started opening the e-commerce logistics business line in 2012. However, the company faces enormous challenges in the e-commerce logistics business not only due to the tight handling requirements of e-commerce orders, in which it is becoming popular for e-retailers to guarantee 24-to-48-hour delivery to customers, but is also affected by the internal inefficiency of e-order handling and processing. The challenges are generic across the industry and are thus faced by the case company, and include:

(i) *Heavy workload of warehouse operators in fulfilling the orders in a timely manner*

(ii) *An increasing frequency of picking and packing wrong items*

Both of these problems result from the irregular arrival of e-orders as online customers can place orders at any time via the Internet. Another reason is due to the fact that each B2C customer order involve a relatively large number of various types of SKUs. This results in a higher chance of inaccurate order fulfilment considering the large number of fragmented e-orders that are required to be fulfilled within a limited time.

In view of the operating inefficiency in managing their e-commerce business, the ECM and EGM of the EF-DSS are implemented in the case company with an implementation roadmap as illustrated below, which highlights the essential stages of development for the proposed system to function in a production environment.

5.2.2 Deployment of the ECM and EGM

The implementation procedures can be divided into four phases: (i) Cloud database development, (ii) Customization of GA mechanism and rule-based inference engine, and (iii) Front-end user interface development.

(i) Development of database and E-order consolidation pool

A database and an e-order consolidation pool are built in accordance with the operating parameters and logistics orders that the company handle. As discussed in Chapter 4 – Implementation procedures of the system, any system implementation can be done only after a comprehensive user requirement study. Therefore, based on the user requirement study, the database of the EF-DSS built for the company has the types of data shown in Table 5.1.

As logistics orders of the company are received from the e-commerce online retail sites, the retrieval and consolidation of an order therefore requires a cloud database integrated into a web app for real time data retrieval and processing. A web app, which consists of a series of web pages, is constructed in Hypertext Mark-up Language (HTML) and is designed for the customer service staff of the company to retrieve e-orders and allocate the e-orders to the e-order consolidation pool. Any action made by the users on the web pages triggers an update on the cloud database of EF-DSS. The database of EF-DSS is the information repository for collecting, storing and sorting two types of data: (i) delivery order details, which are received in real time directly from end consumers, and (ii) the basic settings of the e-fulfilment center, which are static information preliminarily stored in the cloud database for retrieval. The details of these two major types of data stored in the cloud database are displayed in Table 5.1.

The major data processing operations in this module includes database query processing, data sorting and display. For database query processing, essential data as shown in Table 5.1 for insert, view, edit, delete and update can be performed in the UI of the EF-DSS through a set of structure query language (SQL) statements designed and stored in the SQL database. For data sorting and display, the operation is done automatically in the back-end of the database so that all retrieved e-orders are aggregated and sorted by stock-keeping units (SKUs), disregarding which particular SKUs are fulfilling which customer order. With the rearranged order information, as depicted in Fig. 5.2, a list of items to be processed in the e-fulfilment center is displayed in the UI of the EF-DSS, which serves as the input of the subsequent module for e-order grouping and resource allocation decision support.

Table 5.1. Types of data stored and collected in the database for the case company

Types of data for collection and storage in database:	
(iii) Customer order details	
Details	*Data type*
Order number	*Numeric*
SKU number	*Numeric*
Total quantity of each SKU	*Numeric*
Total weight of each SKU	*Numeric*
Delivery location	*String*
(iv) **Initial setting of e-fulfilment centers**	
Storage location setting (Zone and bin level)	*String*
Travel distance between each bin location	*Numeric*
Storage location of each SKU	*String*
Equipment master	*String*

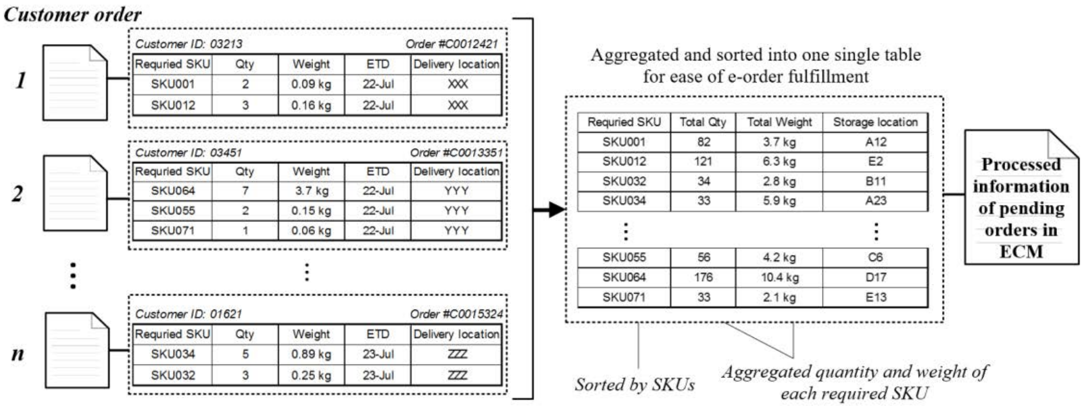


Fig. 5.2. The underlying e-order information processing logic in ECM

With the database and e-order consolidation pool built for collecting, processing e-order information and displaying the collected e-orders pending processing, the logistics order processing flow is re-engineered by allowing users to control when pending orders are ready for batch release to the warehouse department so as to perform the order fulfilment operations. The centralized relational database sorts the received orders by SKUs so that the SKUs to be handled in the e-fulfilment centers are grouped for ease of actual processing. Figs. 5.3 and 5.4 show respectively the storage area of the e-fulfilment centers of the case company where order picking operations take place, and the computer terminal for the display and consolidation of e-orders.

Fig. 5.3. Order picking operations in storage bin locations of e-fulfilment centers

Fig. 5.4. Computer terminal for e-order consolidation and generating order grouping list

(ii) Customization of GA mechanism and rule-based inference engine

- *Customization of GA mechanism*

To govern the e-fulfilment operational flow, decision support for grouping SKUs with similar storage locations in e-fulfilment centers, and suggesting an appropriate set of handling remarks and handling equipment, is developed through the construction of the proposed GA mechanism. Storage bin locations of the e-fulfilment centers are decoded into real numbers for formulating a valid chromosome encoding scheme. A Microsoft Excel spreadsheet is used for the back-end algorithm development, and Evolver, a software developed by the Palisade Corporation, is adopted to minimize the fitness function using Eq. (12), in Chapter 3, section 3.5.3, in order to search for the best global solution of order grouping. Fig. 5.5 shows the order grouping decision support development using an MS Excel spreadsheet. A distance matrix that calculates all the inter-bin distances among each storage bin is proposed. A distance matrix is prepared for the case company based on the layout design of the storage bin locations in the e-fulfilment center, as shown in Fig. 5.3. For each order grouping problem, the pending e-orders only involve part of the total number of SKUs stored in the storage areas. Therefore, using the parent distance matrix, that includes all inter-bin distances, is unnecessary. In this regard, a sorting algorithm, which is developed using Visual Basic for Applications (VBA), a programming language that automate tasks in MS Excel, is built for extracting the required inter-bin distances from the parent distance matrix to form a child distance matrix. The programming code for the sorting algorithm is shown in Fig. 5.6.

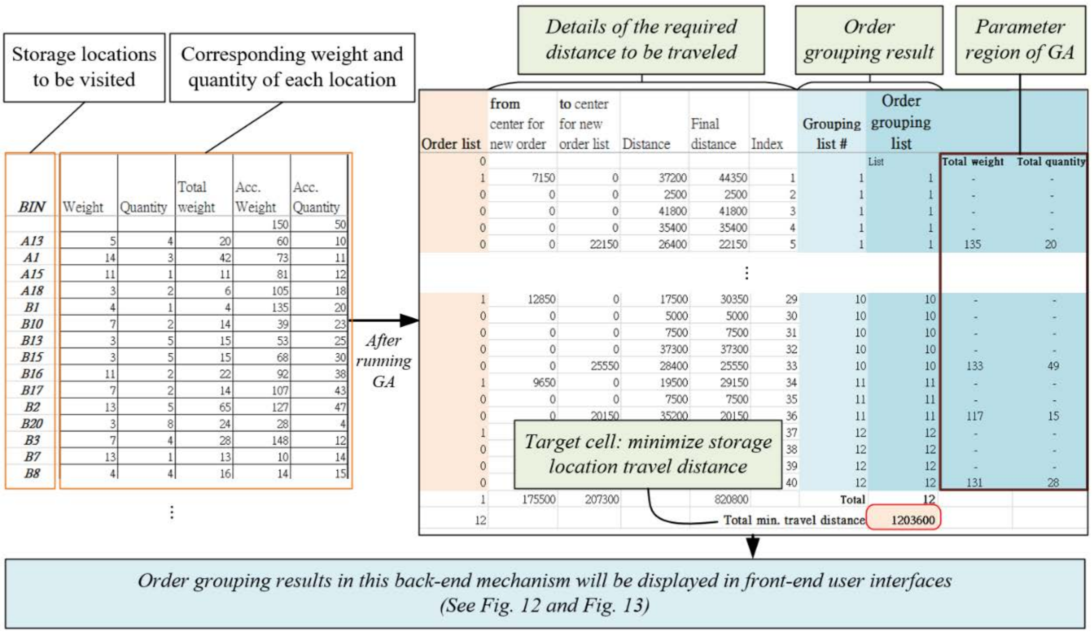
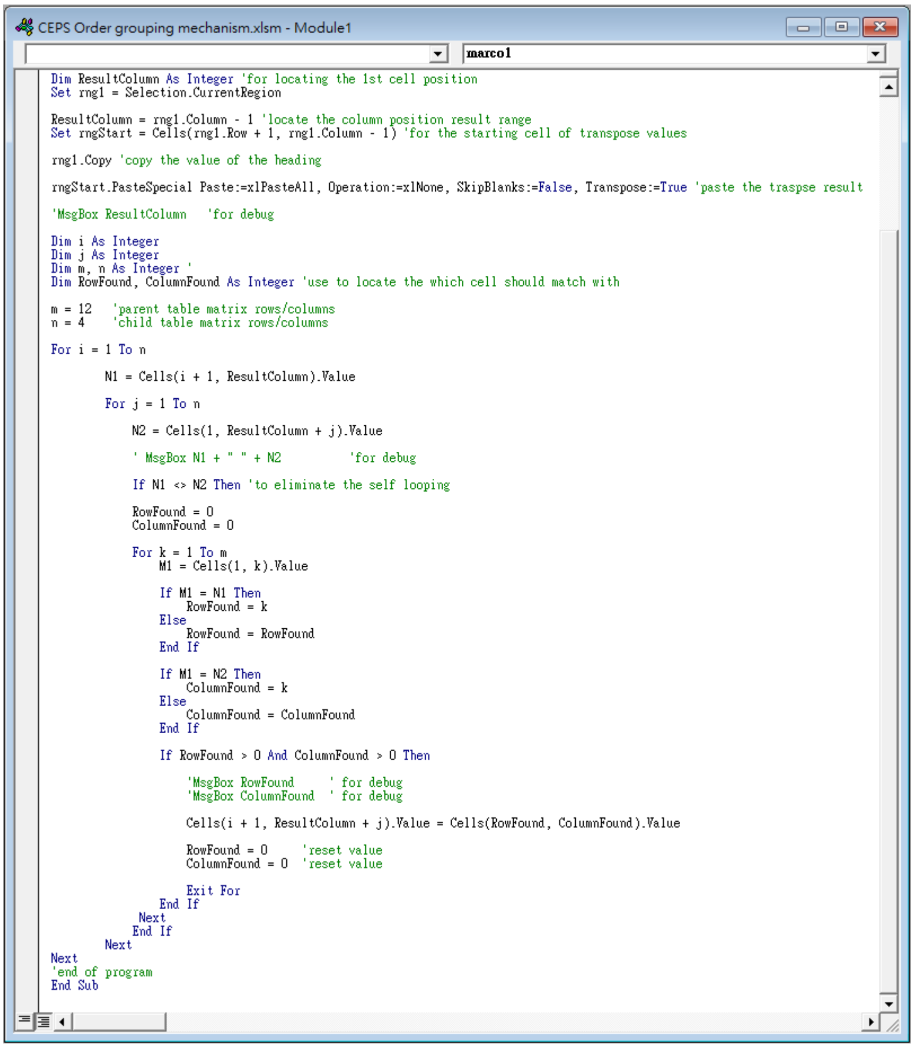


Fig. 5.5. Order grouping decision support development using GA

- *Customization of the rule-based inference engine*

An appropriate set of operating guidelines and order handling equipment are suggested through a rule-based inference engine for each of the e-order grouping solutions generated from the GA mechanism. A rule-based inference engine is adopted for ease of storing and manipulating human knowledge so as to interpret order grouping information in a useful way. The engine is customized for the case company based on the current throughput volume and resource availability for e-order fulfilment operations in the e-fulfilment center. Three parameters are identified as the factors that influence the operating procedures and equipment selection: total quantity, total volume of the order grouping list, and the types of SKUs involved in the order grouping list. An example of the "IF-THEN" rules are presented in decision table format in Table 5.2. In the EF-DSS, the warehouse manager has the access right to preview all active rules, and add, change, delete a rule whenever necessary. Any change in the database which stores the "IF-THEN" rules is subject to internal checking by the system itself for ensuring there is no violation or contradiction among the rules.




```
Dim ResultColumn As Integer 'for locating the 1st cell position
Set rng1 = Selection.CurrentRegion

ResultColumn = rng1.Column - 1 'locate the column position result range
Set rngStart = Cells(rng1.Row + 1, rng1.Column - 1) 'for the starting cell of transpose values

rng1.Copy 'copy the value of the heading

rngStart.PasteSpecial Paste:=xlPasteAll, Operation:=xlNone, SkipBlanks:=False, Transpose:=True 'paste the traspse result

'MsgBox ResultColumn   'for debug

Dim i As Integer
Dim j As Integer
Dim m, n As Integer '
Dim RowFound, ColumnFound As Integer 'use to locate the which cell should match with

m = 12   'parent table matrix rows/columns
n = 4    'child table matrix rows/columns

For i = 1 To n

        N1 = Cells(i + 1, ResultColumn).Value

        For j = 1 To n

            N2 = Cells(1, ResultColumn + j).Value

            ' MsgBox N1 + " " + N2          'for debug

            If N1 <> N2 Then 'to eliminate the self looping

            RowFound = 0
            ColumnFound = 0

            For k = 1 To m
                M1 = Cells(1, k).Value

                If M1 = N1 Then
                    RowFound = k
                Else
                    RowFound = RowFound
                End If

                If M1 = N2 Then
                    ColumnFound = k
                Else
                    ColumnFound = ColumnFound
                End If

                If RowFound > 0 And ColumnFound > 0 Then

                    'MsgBox RowFound     ' for debug
                    'MsgBox ColumnFound  ' for debug

                    Cells(i + 1, ResultColumn + j).Value = Cells(RowFound, ColumnFound).Value

                    RowFound = 0     'reset value
                    ColumnFound = 0  'reset value

                    Exit For
                End If
             Next
            End If
        Next
Next
'end of program
End Sub
```

Fig. 5.6. Codes for distance matrix sorting

Table 5.2. Example rules applied in the case company

"IF" condition	**"THEN" Action**
Example rules for operating guidelines	
Quantity is more than 50	Double check if the quantity picked for each SKU is correct at the end of operation
Volume is more than 20 kg	Reserve lower space for heavier item
Types of SKUs is more than 5	Pick up item separation tool for separating different SKUs;
Example rules for equipment selection	
Volume is 26-50 kg	Use Multi-Storey Trolley for separation of different SKUs
Volume is more than 50 kg	Use Lifter

(iii) Front-end user interface development

A front-end user interface (UI) serving as the presentation and interaction tier for users is designed, as shown in Figs. 5.7 and 5.8. It integrates the cloud database, back-end GA mechanism and rule-based inference engine, so that users are able to conveniently view the newly received e-orders which are retrieved from the Intranet and stored in the cloud database; obtain decision support from the GA mechanism regarding how the required SKUs from the pending e-orders are to be grouped for batch processing in e-fulfilment centers; and receive suggestions from the rule-based inference engine regarding the equipment and handling procedures of each order grouping list generated in the GA mechanism. The EF-DSS is a web-based application so that users can login to the system via the Internet. The Customer Service department can decide when to stop the consolidation of e-orders and start initiating the EF-DSS so as to generate order grouping suggestions, as shown in Fig. 5.8. The suggested outputs can then be exported to other formats for modification or printed for the warehouse department to execute accordingly. The warehouse department can modify or add particular information to the EF-DSS, including the available material handling equipment, operating guidelines for different types of e-orders and the storage location of SKUs, so that the database is up-to-date and the decision support provided by EF-DSS is feasible.

Fig. 5.7. User interfaces of EF-DSS – Order consolidation and grouping

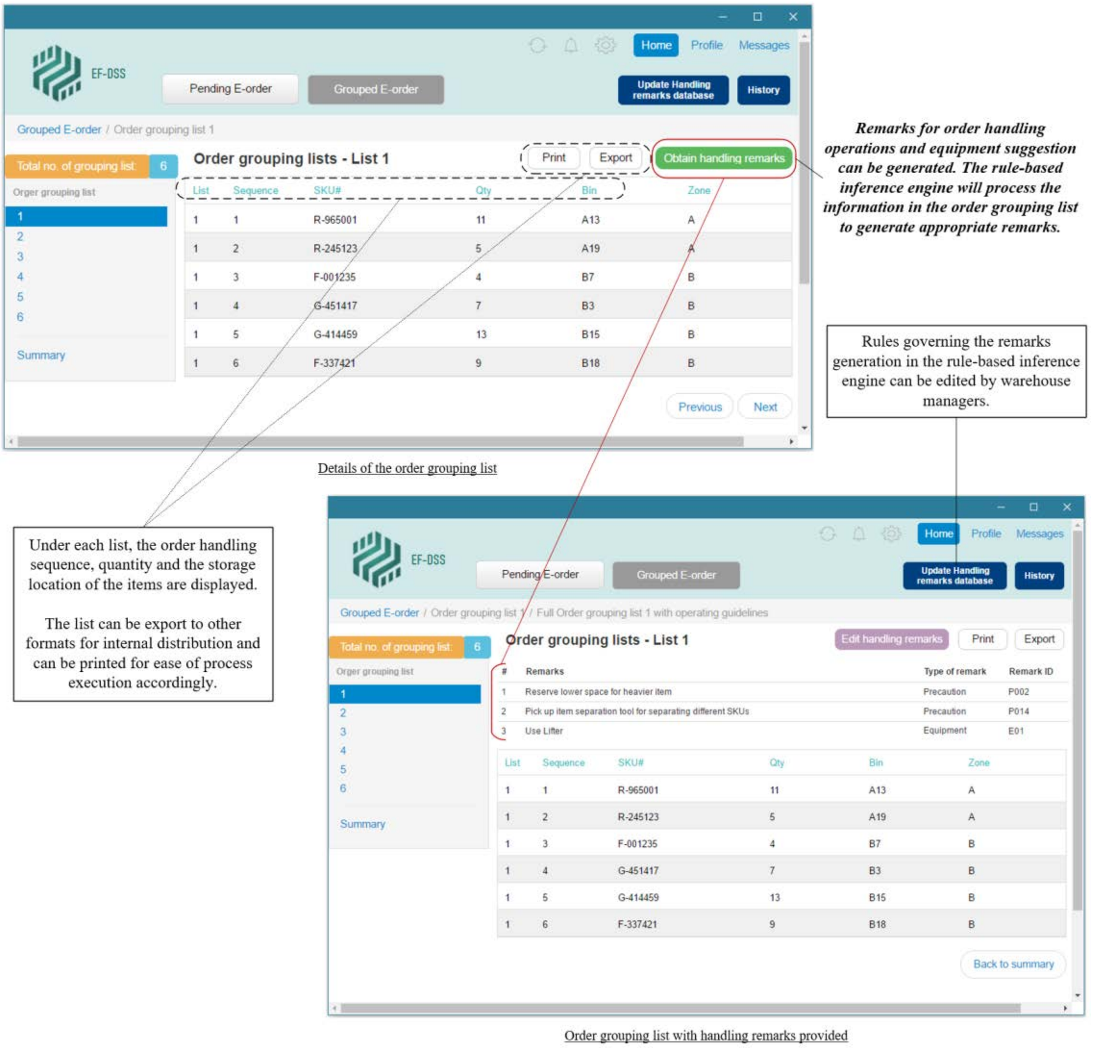


Fig. 5.8. User interfaces of EF-DSS – Details of order grouping list and generating operating guidelines

5.3 Case Study 2 – The Use of AR-MO-ANFIS model for Generating "When to Release" Decision Support

In Case study 2, the ECM and the EBRM of the EF-DSS is deployed for assisting the logistics service provider in consolidating e-commerce orders and determining the best timing for batch release of the grouped e-orders. The ECM and EBRM have two essential features for facilitating the LSPs in handling e-orders:

- Facilitating the e-order consolidation process through the use of the e-order consolidation pool in the ECM, and
- Generating batch release decision support for predicting the e-order arrival rate in the coming period, thereby realizing the remaining time for them to continue consolidating e-commerce orders until terminating the order consolidation process and subsequently releasing the pending orders for immediate processing.

In this section, the company background and problems encountered by the company are described, followed by a discussion of the deployment of ECM and the EBRM.

5.3.1 Company Background and Existing Problems Encountered

The case company in this case study is a Hong Kong based logistics service provider specialized in providing a wide range of logistics and transportation services for cross-border shipments. With the emerging trend of e-commerce business, the company started handling e-commerce shipments in 2014. However, due to the great difference in the operating procedures and requirements in handling e-commerce shipments as compared to traditional cross-border shipments, where e-commerce orders were received at a much higher frequency and in smaller lot sizes, the company has been struggling to sustain the e-commerce business, and is desperate to expand the e-commerce logistics business by 2020. However, the following problems have been faced by the company for a long time, which heavily affect the order handling efficiency:

(i) *Difficulty in resource allocation for order picking* – Due to the high frequency in receiving delivery orders from e-commerce customers, the company found it difficult to assign human resources to pick the orders. The utilization rate of the warehouse worker is therefore increasing, which gradually becomes a bottleneck in the entire warehouse operations.

(ii) *Increase in travelling distance of warehouse workers which is deemed unnecessary* – Instead of picking orders in a large batch and shipping large volume orders as single shipment, e-commerce orders are picked, packed and delivered in a smaller volume but at a higher frequency. Therefore, warehouse workers are required to visit the same or nearby storage locations of the warehouse repeatedly over the whole day in order to pick the orders.

In an attempt to rectify these problems, the ECM and the EBRM of EF-DSS are deployed in the distribution centre of the company to assist them in handling e-commerce shipments more efficiently by means of developing a warehouse postponement strategy that groups the orders for batch picking and processing at the most appropriate timing.

5.3.2 Deployment of the ECM and EBRM

The implementation procedures are divided into four phases: (i) Database development, (ii) Identification of cut-off review cycle time and ANFIS model construction, training and testing, (iii) “When to release” algorithm development and implementation, and (iv) Front-end user interface development. In particular, in the second phase, the ANFIS model construction methodology for Case studies 2 and 3 are different, for the sake of undertaking comprehensive testing to justify which methodology is more suitable in predicting the e-order arrival. Details of each phase of system implementation are discussed below.

(i) Database development

Data collection is conducted to build the cloud database and server. The details of over 500 historical e-commerce order receiving pre-bookings are collected and analyzed for the construction of a relational database, a core component of the ECM in EF-DSS. With the database and e-order consolidation pool, the ECM collects historical online sales data and receives e-commerce orders from the cloud. Other relevant data, such as the real time availability of order pickers and order handling equipment, etc., are also retrieved from the e-commerce sales platform and transmitted to the cloud database of the EF-DSS. Any update of the information, such as receiving a new order from an online customer, will be synchronized with the cloud database of the EF-DSS. The cloud database also serves an e-order consolidation pool to consolidate the incoming e-orders for subsequently releasing them in a batch.

The major data processing operations in this module include database query processing, data sorting and data display, which is similar to the database development discussed in Case study 1. Similarly, with a set of structure query language (SQL) statements designed and stored in the SQL database, the EF-DSS enables users to view and edit the information in the system user interfaces. Back-end data sorting and order detail aggregation are performed, so that the grouped e-orders are aggregated and sorted according to the stock-keeping units (SKUs), rather than the order number. This e-order information processing logic in the ECM is the same as depicted in Fig. 5.2 in Case study 1. The processed data in this module then serves as the inputs values of the ANFIS model in EBRM of the EF-DSS.

(ii) Identification of cut-off review cycle time and ANFIS model construction, training and testing

The conceptual framework for ANFIS model construction for this case study is presented in Fig. 5.9. Typically, to gain brand exposure and expand the target customer segments, e-retailers list their product lineup on various e-commerce sales channels, such as Tmall, Amazon, JD.com, etc., so that online customers can place orders in these sales channels. As the case company had agreements with several e-retailers to handle the outsourced order fulfillment activities, such as stocking of goods, order pick and pack, and order delivery operations, the details of online e-commerce orders placed by the end consumers are transmitted to the case company by the e-retailers.

Before the deployment of the EF-DSS, these e-orders are processed immediately upon arrival at the company. With the deployment of EF-DSS, the ECM consolidates the e-orders in the e-order consolidation pool until reaching the best batch release timing. To identify the best batch release timing to terminate the consolidation process of the e-orders and release the pending e-orders for the operators in the distribution centre to perform the subsequent order fulfillment process, the EBRM first predicts the arrival of e-orders for the next period. A single ANFIS model is used for predicting the arrival of e-orders, regardless of which e-retailer the e-order belongs to, as shown in Fig 5.9. Then, using the predicted e-order arrival figure, a “When to release” algorithm is adopted to compute the remaining time in which the company could still consolidate e-orders.

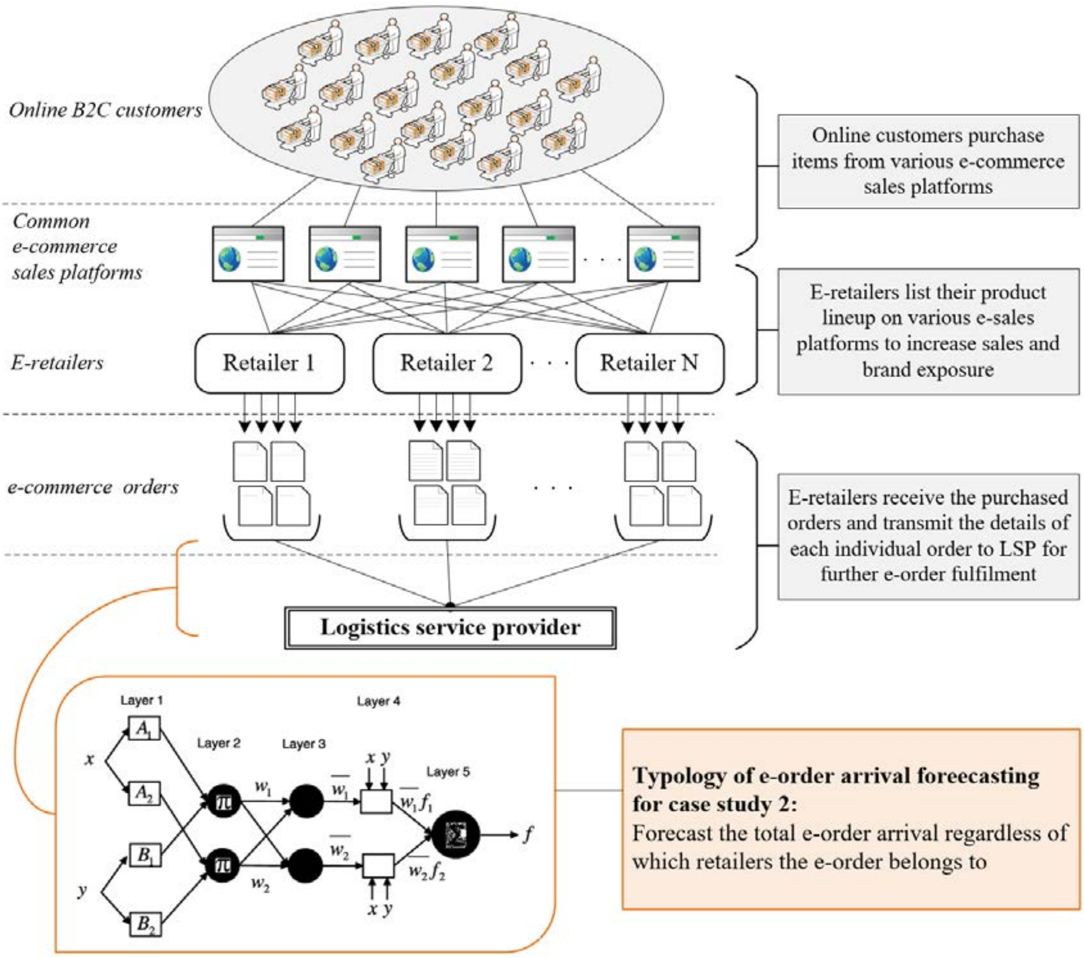


Fig. 5.9. Conceptual framework for ANFIS model construction for Case study 2

The ANFIS model construction, training and testing procedures applied in this case study are discussed below, and can be categorized into three separate stages, as introduced in Chapter 3.

- **Stage I – Design Consideration**

Step 1 – *Determine the cycle time for reviewing the e-order consolidation cut-off policy*

As introduced in Chapter 3, section 3.6.2.1, there are two factors for determining the cycle time for reviewing the e-order consolidation cut-off policy, they are: the maximum order handling capacity in the e-fulfilment distribution centres and the average number of orders (in kg) received per hour. Through the historical order arrival figures and the information regarding the order handling resource capacity provided by the management, the cycle time ("the period") for the company is set to be 2 hours. In other words, at the end of each "period", the management uses the EF-DSS to predict the e-order arrival of the next "period", so as to realize how much time is left for them to release the pending e-orders in a batch.

Step 2 – *Identify the input and output variables in the ANFIS models*

As the cycle time is set as two hours in Step 1, the output of the ANFIS model in this case study, $Q_d(t+1)$, denotes the predicted arrival of the e-orders (in kg) in the upcoming period $t+1$ in the current day d, i.e. the coming two hours. In this case study, two input variables are selected as the prediction indicators of the e-order arrival in the new 2-hour horizon, they are: the previous e-order arrival figures and the volatility of e-order arrival. This is the first study attempting to forecast the arrival of e-commerce order volume for managing the fluctuation of throughput in supply chains, as well as forecasting the subject through the integration of autoregressive models and ANFIS. Detailed explanations of the input variables are provided below.

(1) **Actual *n*-period e-order arrival**: Actual e-order arrival in the previous n periods, *i.e. period* $t, t-1, t-2, \ldots, t-n,$ are considered as essential indicators for predicting the e-order arrival figure at the upcoming period $t+1$. The identification of the lag length for a time series is especially essential. To address this issue and to identify the appropriate number of lag periods n that is the most fitting for the experimental dataset, an autoregressive (AR) model is formulated and estimated with the use of EViews software package. By using the least square method, we initially select 10 lag variables, i.e. $Q_d(t-n)$, where n=0, 1, …, 9, for testing. If the

p-value is less than the 0.05 significance level, then the null hypothesis is rejected. A four-week data set, which consists of a total of 336 observations of the e-order arrivals in each two-hour interval, are extracted. The first two-thirds of the observations, i.e. 223 observations, are selected to estimate and test the AR models. The lag test results, as shown in Fig. 5.10, reveal that both the one-order AR model (AR(1)) and the seven-order AR model (AR(7)) give the lowest p-values, which are both lower than 0.05. This indicates that both the inclusion of one lag variable and seven lag variables are the most appropriate AR model settings for the prediction of the e-order arrival figures. We then use the AR(1) and AR(7) models to forecast the remaining one-third of the observations and compare with the actual e-order arrival figures. Table 5.3 shows the test results of the AR(1) and AR(7) models measured by the root mean squared error (RMSE), and the coefficient of determinations (R^2), which are respectively measured by:

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(P_i - y_i)^2}{n}} \tag{33}$$

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}} \tag{34}$$

where y_i and P_i are respectively the actual arrival of e-order and predict arrival of e-order (in terms of weight in kg) at period t, and n is the number of data patterns in the independent data set. SS_{res} and SS_{tot} respectively represent the residual sum of square and the total sum of squares, calculated by:

$$SS_{res} = \sum_{i=1}^{n}(P_i - \bar{y})^2 \tag{35}$$

$$SS_{tot} = \sum_{i=1}^{n}(y_i - \bar{y})^2 \tag{36}$$

where $\bar{y}$ is the mean of the actual data. From Table 2, the AR(7) model performs slightly better in forecasting the e-order arrival than AR(1), as AR(7) gives a slightly lower values of RMSE and R^2. However, if the AR(7) model is to be adopted, a total of seven lag variables will be included in the ANFIS model. This will severely increase the computation time and requirements, as well as generate a large number of If-then rules in the inference engine of the ANFIS model. Therefore, taking these drawbacks into consideration in the ANFIS modelling, the AR(1) model is selected over the AR(7) model. In other words, the output variable $Q_d(t+1)$, is forecast based on only one lag variable $Q_d(t-n)$, for $n = 0$.

(2) **Volatility of previous e-order arrival:** The volatility of the previous e-order arrival (momentum) is an essential indicator of the trend of the time-series-based e-order arrival. This indicator has been used to predict stock prices. Tanaka-Yamawaki & Tokuoka (2007) introduced one and two-order momentum as one of the technical indicators of intra-day stock price prediction. Chang et al. (2011) also introduced one and two-order momentum for forecasting the stock prices. Thus, this study considers both one and two-order momentum of the e-order arrival as the input variables. For the current period t, one-order momentum, $Mo(t)$, and two-order momentum, $Mo(t-1)$, of e-order arrival are respectively calculated by:

$$Mo(t) = Q_d(t) - Q_d(t-1) \tag{37}$$

$$Mo(t-1) = Q_d(t-1) - Q_d(t-2) \tag{38}$$

Two separate ANFIS models, AR(1)MO(1) model and AR(1)MO(2), are built, one with one-order momentum as the input variable, and the other with both one-order and two-order momentum as the input variables. Evaluation and error analysis are performed to justify whether the inclusion of two-order momentum is suitable for the prediction of e-order arrival.

Dependent Variable: E_ORDER
Method: Least Squares
Date: 04/07/18 Time: 17:36
Sample (adjusted): 11 223
Included observations: 213 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	47.10833	8.442628	5.579819	0.0000
E_ORDER(-1)	0.641873	0.069258	9.267794	0.0000
E_ORDER(-2)	-0.114695	0.082467	-1.390800	0.1658
E_ORDER(-3)	-0.066403	0.082238	-0.807457	0.4204
E_ORDER(-4)	-0.202737	0.079726	-2.542930	0.0117
E_ORDER(-5)	-0.059809	0.080327	-0.744574	0.4574
E_ORDER(-6)	0.143427	0.080113	1.790300	0.0749
E_ORDER(-7)	-0.324318	0.079590	-4.074873	0.0001
E_ORDER(-8)	-0.102728	0.082577	-1.244028	0.2149
E_ORDER(-9)	0.044084	0.082702	0.533053	0.5946
E_ORDER(-10)	0.147582	0.068460	2.155751	0.0323

R-squared	0.716340	Mean dependent var	52.46948
Adjusted R-squared	0.702297	S.D. dependent var	23.03495
S.E. of regression	12.56837	Akaike info criterion	7.950505
Sum squared resid	31908.69	Schwarz criterion	8.124093
Log likelihood	-835.7288	Hannan-Quinn criter.	8.020658
F-statistic	51.01191	Durbin-Watson stat	2.051339
Prob(F-statistic)	0.000000		

Fig. 5.10. Lag test for identifying the number of lag length *n*

Table 5.3. Test results of AR(1) and AR(7) model

	RMSE	**R^2**
AR(1) model	15.43	0.52
AR(7) model	13.12	0.69

Step 3 – Select and extract dataset for model training and testing

A four-week real production data set from the beginning of January of 2018 is gathered and extracted from the case company's distribution centre where e-order fulfilment operations take place. With the management specifying a preferred cut-off review cycle of two working hours, the data sets are pre-processed and converted into useful input values for the proposed ANFIS models. Table 5.4 shows a data set regarding the actual four-week e-order arrival in a two-hour interval (measured by kg), which are used for performing lag testing to identify the appropriate number of lag periods *n*, as discussed in *Step 1*. In addition, in order to validate the neural system, the 4-week data set, comprised of 336 data pairs in total, is split into training and testing data sets. Usually, the training data set, contains 70% or 90% of all data and the remaining data serves as the testing data set (Sánchez et al., 2007), is used to train and build the adaptive network, whereas the testing data set is used to determine if any over fitting of the model occurs during training.

Table 5.4. Real four-week e-order arrival (in kg) data in 2-hour time interval

	Time											
Date	**0-2**	**2-4**	**4-6**	**6-8**	**8-10**	**10-12**	**12-14**	**14-16**	**16-18**	**18-20**	**20-22**	**22-24**
Week 1												
Mon	14	21	12	14	25	46	49	55	68	53	79	94
Tue	41	32	25	10	27	47	56	78	84	63	89	84
Wed	45	34	21	22	35	42	39	52	73	81	71	78
Thu	43	32	30	19	21	41	46	52	62	73	75	68
Fri	56	42	21	21	37	47	52	62	57	69	73	68
Sat	78	52	31	23	36	68	58	63	67	73	83	84
Sun	94	77	47	23	49	64	72	62	89	52	96	67
Week 2												
Mon	34	31	24	16	24	37	44	57	62	67	73	80
Tue	61	37	21	15	27	37	58	63	84	79	74	77
Wed	68	35	15	9	24	44	78	55	74	88	78	79
Thu	51	28	11	8	18	35	63	74	78	79	82	77
Fri	57	31	18	12	25	46	57	71	69	73	52	60
Sat	83	75	45	23	23	57	62	68	52	67	77	81
Sun	76	51	42	12	53	63	73	80	79	41	75	84
Week 3												
Mon	58	36	21	14	34	46	48	67	78	58	80	83
Tue	52	26	15	11	32	49	53	73	80	61	73	84
Wed	49	21	13	8	22	34	49	65	81	57	72	64
Thu	57	31	14	10	27	37	51	66	78	56	81	86
Fri	67	46	22	14	35	48	60	79	77	53	41	57
Sat	88	68	41	21	24	56	67	80	81	73	63	58
Sun	95	78	31	18	12	42	64	78	79	65	78	84
Week 4												
Mon	67	48	31	14	23	45	56	64	70	42	67	78
Tue	56	38	28	11	25	47	58	66	72	43	71	83
Wed	67	49	31	14	25	43	48	57	65	56	72	82
Thu	73	51	37	17	29	41	40	49	57	55	77	79
Fri	58	32	27	18	21	38	41	50	61	66	47	63
Sat	82	67	45	21	32	51	66	71	77	67	76	73
Sun	89	61	54	24	35	55	74	84	74	74	82	93

Step 4 – *Define the universe of disclosure for each input parameter*

To achieve the best result generated from the ANFIS model, system parameter modifications are critical. In the MATLAB's ANFIS editor, different types of membership functions (MFs), such as triangular (Tri), trapezoidal (Trap), generalized bell (Gbell), Gaussian curve (Guass), Gaussian combination, Π-shaped, difference between two sigmoid functions, and product of two sigmoid functions, are available for selection. In addition, the number of MFs for each input, and the types of output MFs (either constant or linear) can also be modified. Due to the large number of possible combinations of the parameter settings of the ANFIS model, the best combination of the ANFIS model needs to be identified. The model structure of AR(1)MO(1) and AR(1)MO(2), and a summary of the training parameters of the both models is presented and shown in Figs. 5.11, and 5.12 and Table 5.5 respectively.

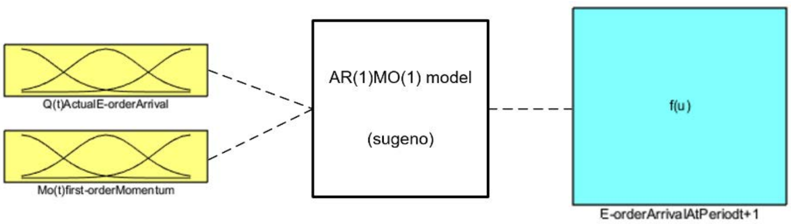


Fig. 5.11. AR(1)MO(1) model structure

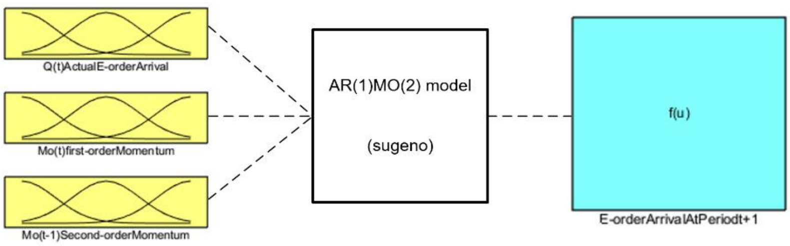


Fig. 5.12. AR(1)MO(2) model structure

Table 5.5. Training parameters of the ANFIS model

Parameters	Setting for AR(1)MO(1)	Setting for AR(1)MO(2)
Number of layers	5	5
Number of inputs	2	3
Number of output	1	1
Total number of data pairs	336+	336+
Size of data set:	1,008 observations in total (336 x 3)	1,344 observations in total (336 x 4)
- **Training data set**	906 observations (302 x 3)	1,208 observations (302 x 4)
- **Testing data set**	102 observations (34 x 3)	136 observations (34 x 4)
Initial FIS generation	Grid partitioning	Grid partitioning
Types of input MFs*	Tri/Trap/Gbell/Guass	Tri/Trap/Gbell/Guass
Number of MFs for each input*	2/3/4	2/3/4
Types of output function*	Constant /linear	Constant/linear
Learning algorithm	Least square method and Back-propagation gradient descent method	Least square method and Back-propagation gradient descent method
Number of epoch	40	40

+*The 336 data pairs are from a 4-week data set, with one data pair for every 2-hour time interval*

**Further experiments were made to identify the best MFs characteristics*

- ***Stage II – Model Training and Testing***

In order to check the generalization capability of the developed neural system and to avoid the model from overfitting the training data set, the trained fuzzy inference system under different combinations of settings is then applied using the testing data set. The training and testing environment in the MATLAB's Neuro-fuzzy designer toolbox is shown in Fig. 5.13. The training and testing results of the AR(1)MO(1) and AR(1)MO(2) models are respectively shown in **Appendix A and B**. The best setting for both the AR(1)MO(1) and AR(1)MO(2) model is identified based on the testing error (the lower the better) of each combination of setting for both models.

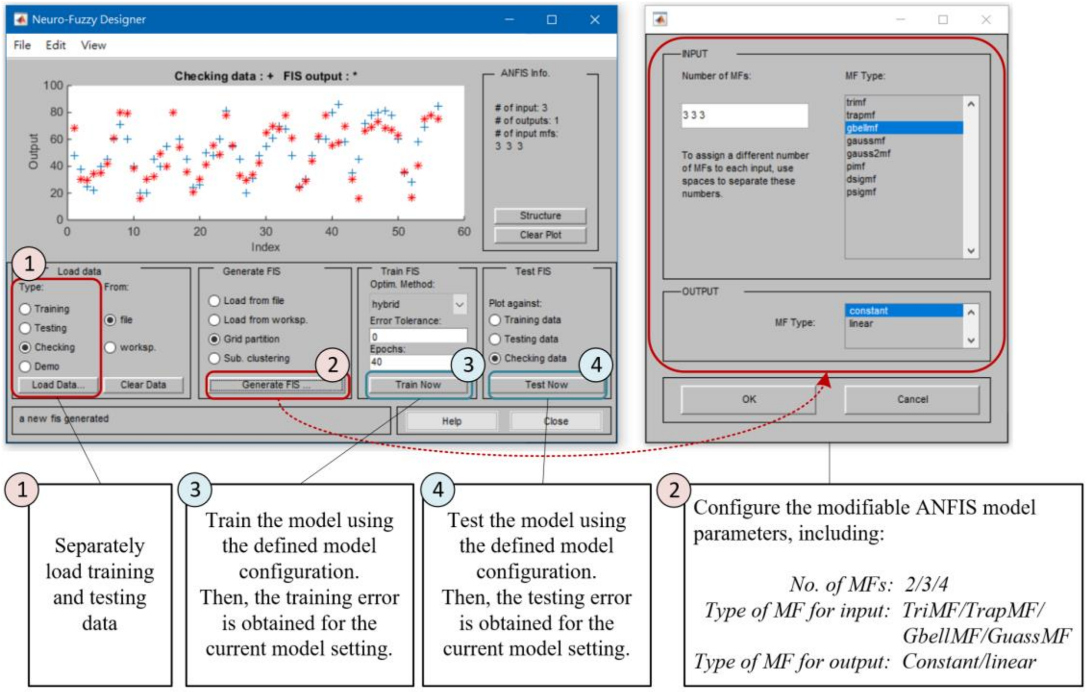


Fig. 5.13. ANFIS model training and testing environment in MATLAB's Neuro-fuzzy designer toolbox

- ***Stage III – Performance Evaluations***

With the best setting respectively obtained for both AR(1)MO(1) and AR(1)MO(2), these developed models are then compared with an autoregressive integrated moving average (ARIMA) model for further performance validation.

- The ARIMA model

In the ARIMA model, the predicted value of a variable is assumed to be a linear function of several past p observations and q random errors. A stationary ARIMA*(p,q)* model captures dependencies in the series in two parts, autoregressive (AR) and moving average (MA), in the form:

$$\begin{aligned} \mathrm{y(t)} &= a_0 + a_1 y(t-1) + a_2 y(t-2) + \cdots + a_p y(t-p) \\ &\quad + e(t) + b_1 e(t-1) + \ b_2 e(t-2) + \cdots + \ b_q e(t-q) \end{aligned} \tag{39}$$

where the autoregressive part is a linear combination of the past p observations $y(t-1)$, …, $y(t-p)$, weighted by p linear coefficients a_1, …, a_p, and a constant term a_0. The moving average part is a linear combination of the past q error terms $e(t-1)$, …, $e(t-q)$, weighted by q linear coefficients b_1, …, b_p, and the current error term $e(t)$. The error terms are assumed to be independently and identically distributed with a mean of zero and a constant variance of σ^2. Seasonal autoregressive (SAR) and seasonal moving average (SMA) term, r and s, may also be added to the ARIMA model, in case of having a periodic time series pattern.

To compare the model performance among the ANFIS models of AR(1)MO(1), AR(1)MO(2), and the ARIMA model, the root-mean square error (RMSE), mean absolute deviation (MAD), and mean absolute percentage error (MAPE) are used, which are respectively given by Eq. (25), (26), and (27), as shown in Section 3.6.2.3 on p. 98.

(iii) "When to release" algorithm development and implementation

With the developed ANFIS model with the best model setting through model training and testing, the output of the ANFIS model in EBRM of the EF-DSS, i.e. the predicted arrival of e-commerce orders in the upcoming period, measured by the weight in kg, is then used as one of the variables to generate decision support for logistics practitioners to adjust the cut-off frequency of releasing the grouped orders for actual order picking operations in a batch. To compute the cut-off time of the e-order grouping, the proposed approach in the EF-DSS suggests taking the maximum order handling capacity in the distribution centre into consideration, as discussed in Chapter 3, Section 3.6.3.

The maximum order handling capacity, Q_{max}, is obtained by identifying the total weight that can be handled by the resources for order handling, such as equipment and the order pickers, which are currently idle and available for performing picking operations of the e-orders. With the known constant value of Q_{max}, EF-DSS is able to automatically generate the cut-off time, denoted as T_{final}, with the notation definitions as shown in Table 5.6 (the same as in Section 3.6.3) and the underlying calculations as described below.

In order to avoid any potential over-utilization of the order handling resources, especially human resources, the maximum allowable order handling capacity (Q_{max}) is multiplied by a constant factor k (in %) to give an adjusted order handling capacity ($Q_{adjusted}$). For this case study, based on discussions with the management, the value of k is set to be 0.8. To obtain the current remaining order handling capacity ($Q_{remaining}$), the adjusted order handling capacity is subtracted by the total weight of pending orders in the e-order consolidate pool ($Q_{current}$), which is expressed as:

$$Q_{adjusted} = Q_{max} \times k \tag{40}$$

$$Q_{remaining} = Q_{adjusted} - Q_{current} \tag{41}$$

The predicted e-order arrival rate per minute (Q_t) is computed by dividing the predicted weight of the incoming e-orders in the upcoming period $t+1$ ($Q_d(t+1)$, the output of the ANFIS model), by the total duration in the specified period (in minutes) (n). It is expressed as:

$$Q_t = \frac{Q_d(t+1)}{n} \tag{42}$$

The optimal cut-off time for batch order release can then be computed by dividing Eq. (41) by Eq. (42), that is:

$$T_{optimal} = \frac{Q_{remaining}}{Q_t} \tag{43}$$

In order to avoid any e-order pending in the e-order consolidation pool for too long, an additional variable T_{max}, is introduced, defined as the maximum allowable waiting time of an e-order pending in the e-order consolidation pool. The purpose of introducing this variable is to govern the final suggested output of the EAPS, i.e. the cut-off time of e-orders (T_{final}), so that T_{final} would not exceed the maximum allowable waiting time of the e-order pending in the e-order consolidation pool. The logic is mathematically expressed as:

$$T_{final} = \begin{cases} \mathrm{T}_{optimal} & \text{for} \quad \mathrm{T}_{optimal} \leq T_{max} \\ \mathrm{T}_{max} & \text{for} \quad \mathrm{T}_{optimal} > T_{max} \end{cases} \tag{44}$$

The final output of the EBRM enables decision makers to realize how much longer the e-order consolidation pool can still collect the e-orders before they are released in a batch in the distribution centre for performing the subsequent batch order picking operations.

Table 5.6. Notation definitions for the cut-off frequency decision support in EBRM

Cut-off frequency decision support model:		
Notation	**Definition**	**Unit of measurement**
$\mathbf{Q_{max}}$	Maximum allowable order handling capacity	kg
$\mathbf{Q_{current}}$	Total weight of pending orders in the e-order consolidation pool	kg
$\mathbf{Q_d(t+1)}$	Predicted weight of incoming orders of the upcoming period *t+1 (Output of the ANFIS model)*	kg per period
$\mathbf{Q_t}$	Predicted e-order arrival rate per minute	kg per minute
n	Total minutes in the specified period	-
k	Constant factor for creating buffer for order handling	%
$\mathbf{T_{optimal}}$	Optimal cut-off time for batch order release	minutes
$\mathbf{T_{max}}$	Maximum allowable waiting time of an e-order pending in the e-order consolidation pool	minutes
$\mathbf{T_{final}}$	Suggested cut-off time remaining for batch order release *(Final output of the EAPS)*	minutes

(iv) Front-end user interface development

The ultimate goal of the development of EF-DSS is not only to predict the e-order arrival in the upcoming periods, but also to make use of such information to assist logistics practitioners in managing the received e-orders more effectively. This mission is accomplished by converting the output value generated by the proposed ANFIS model to the final output of the EF-DSS, that is, the remaining time to cut-off the currently pending e-orders, using the algorithm developed in section 3.6.3. In this sense, by taking both the real-time resource availability and the predicted e-order arrival rate into consideration, the EF-DSS suggests the optimal cut-off time of the pending e-orders. A system user interface in the form of a responsive web app, as shown in Fig. 5.14, was tailor-made by a team of software developers for assisting the management of the case company in managing the throughput rate of the e-order fulfilment operations through accurate prediction of the upcoming arrival frequency of the e-orders. Users in the case company are able to update the current resource availability, and obtain e-order cut-off frequency decision support. In other words, the user interface suggests to the users that they should release the consolidated e-orders at a specified time. Logistics operators can then allocate the resources and execute the batch order picking operations accordingly.

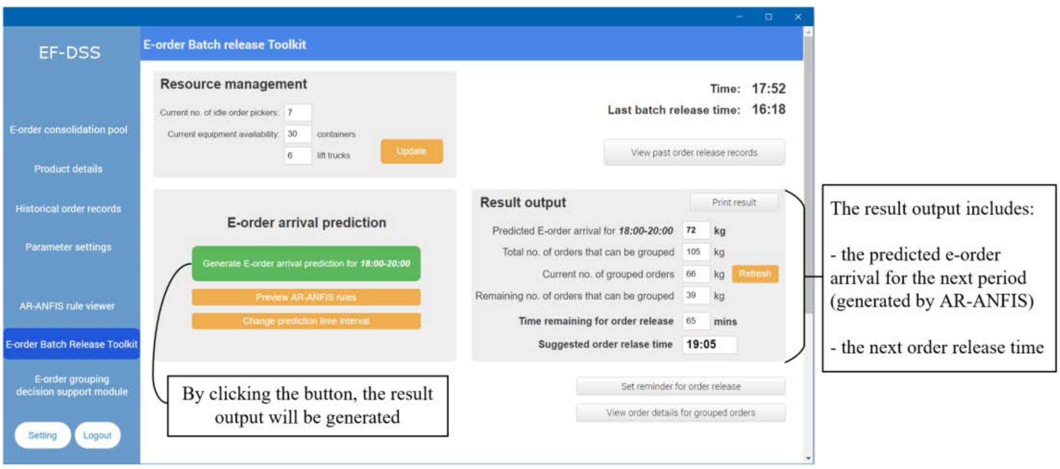


Fig. 5.14. User interface of the EF-DSS used in Case study 2

5.4 Case Study 3 – The Use of AR-MO-MA-ANFIS model for Generating "When to Release" Decision Support

In Case study 3, the ECM and the EBRM of the EF-DSS is deployed for assisting the logistics service provider in consolidating e-commerce orders and determining the best timing for batch release of the grouped e-orders. Same as in Case study 2, there are two essential features of the ECM and EBRM provided for facilitating the LSP in handling e-orders, they are:

- Facilitating the e-order consolidation process through the use of the e-order consolidation pool in the ECM, and
- Generating batch release decision support for predicting the e-order arrival rate in the coming period, thereby realizing the remaining time for them to continue consolidating e-commerce orders until being terminated in the order consolidation process and subsequently releasing the pending orders for immediate processing.

As both Case studies 2 and 3 deployed the ECM and EBRM, the implementation procedures of Case study 3 is the same as Case study 2, which are divided into four phases: (i) Database development, (ii) Identification of cut-off review cycle time and ANFIS model construction, training and testing, (iii) "When to release" algorithm development and implementation, and (iv) Front-end user interface development. For Phase 1, 3, and 4, the details of implementation are very similar. Therefore, they are not covered in this section. However, in Phase 2 – Identification of cut-off review cycle time and ANFIS model construction, training and testing, a more comprehensive ANFIS model construction methodology is developed in this case study, for the sake of undertaking more testing to justify which methodology is more suitable in predicting the e-order arrival. Therefore, in this section, the company background and problems encountered by the company are described, followed by a discussion of the ANFIS construction framework, ANFIS training and testing procedures that have been solely applied to this case study.

5.4.1 Company Background and Existing Problems Encountered

The case company in this case study is a Hong Kong-based logistics service provider that started the outsource e-commerce order fulfillment in 2015. It is a third-party logistics service provider, traditionally providing total logistics solutions including freight management, warehouse management, value-added logistics services, project-based cargo handling and local distribution of orders. Due to the growing trend of e-commerce business, it started offering logistics solutions for e-commerce retailers in 2015, through providing door-to-door order receive and delivery, e-commerce order consolidation and freight management, import and export declaration. In order to be capable of handling a significant number of e-commerce orders, the company has an 80,000 sq. ft. warehouse designated for day-to-day receive and delivery of e-commerce orders from retailers.

Due to the rapid expansion of the global e-commerce business, the throughput rate of the e-fulfillment distribution centre of the company for e-commerce order handling has been significantly increased since late 2015. With the drastic increase in the number of daily orders to be handled in the warehouse, the company has been facing several challenges which severely influence the warehouse operating efficiency in e-commerce order fulfillment. These include:

(i) *Overutilization of labor, particularly during receiving and put-away operations* – limited labor resources has become a major constraint in maintaining the same degree of operating and handling efficiency, as e-commerce orders involve more types of SKUs in comparison with traditional orders.

(ii) *Repetitive put-away operations being performed too frequently* – Given the irregular arrival of e-commerce orders at the inbound dock and a larger number of fragmented orders as compared with traditional orders, put-away operations are repeatedly undertaken throughout the working hours. Such operation inefficiency at the inbound area consequently leads to delays in performing the subsequent order fulfillment process especially outbound pick-and-pack and delivery operations.

As a result, the retailers have urged the company to improve the standard of e-commerce order fulfillment. In the light of this essential need to improve the warehouse internal e-commerce order processing efficiency, the company has trial launched EF-DSS to facilitate inbound operations of e-commerce orders.

5.4.2 Deployment of the ECM and EBRM

As suggested in Section 5.4, among the four phases of implementing ECM and EBRM, i.e. (i) Database development, (ii) Identification of cut-off review cycle time and ANFIS model construction, training and testing, (iii) "When to release" algorithm development and implementation, and (iv) Front-end user interface development, the discussion of this case study focuses on Phase 2 – Identification of cut-off review cycle time and ANFIS model construction, training and testing.

The conceptual framework for ANFIS model construction in this case study is presented in Fig. 5.15. Similar to the framework for Case study 2 (as shown in Fig. 5.9), e-retailers list their product lineup on various online sales platforms, allowing online customers to make purchases at anytime and anywhere. In this case study, the case company has partnership with three retailers. In other words, the case company receives e-order arrivals only from these three retailers. In this regard, **two typologies are developed with different sets of ANFIS models for prediction:**

Typology I – *Forecasting the total e-order arrival by aggregating e-order arrival from 3 retailers*

This typology is the same as the typology adopted in Case study 2, in which only one single ANFIS model is constructed for predicting the total e-order arrival, regardless of which retailer the e-orders belong to. This approach is comparatively straightforward but neglects the e-order arrival pattern of an individual retailer.

Typology II – *Separately forecasting the e-order arrival of each individual retailer*

This typology is specifically designed and applied to this case company as there are only three retailers, who have partnership with the company, to outsource the e-order fulfillment process. The idea of this typology is to construct three different ANFIS models to forecast the e-order arrival patterns of each individual retailer. By summing the predicted e-order arrival figures of each individual retailer, the total predicted e-order arrival can be obtained. The case company can also realize the e-order arrival of the next period. Additionally, this typology allows the company to realize the e-order arrival behavior of an individual retailer. Specialized or targeted operational strategies, such as resource re-allocation, can also be formulated for better handling of incoming e-commerce orders.

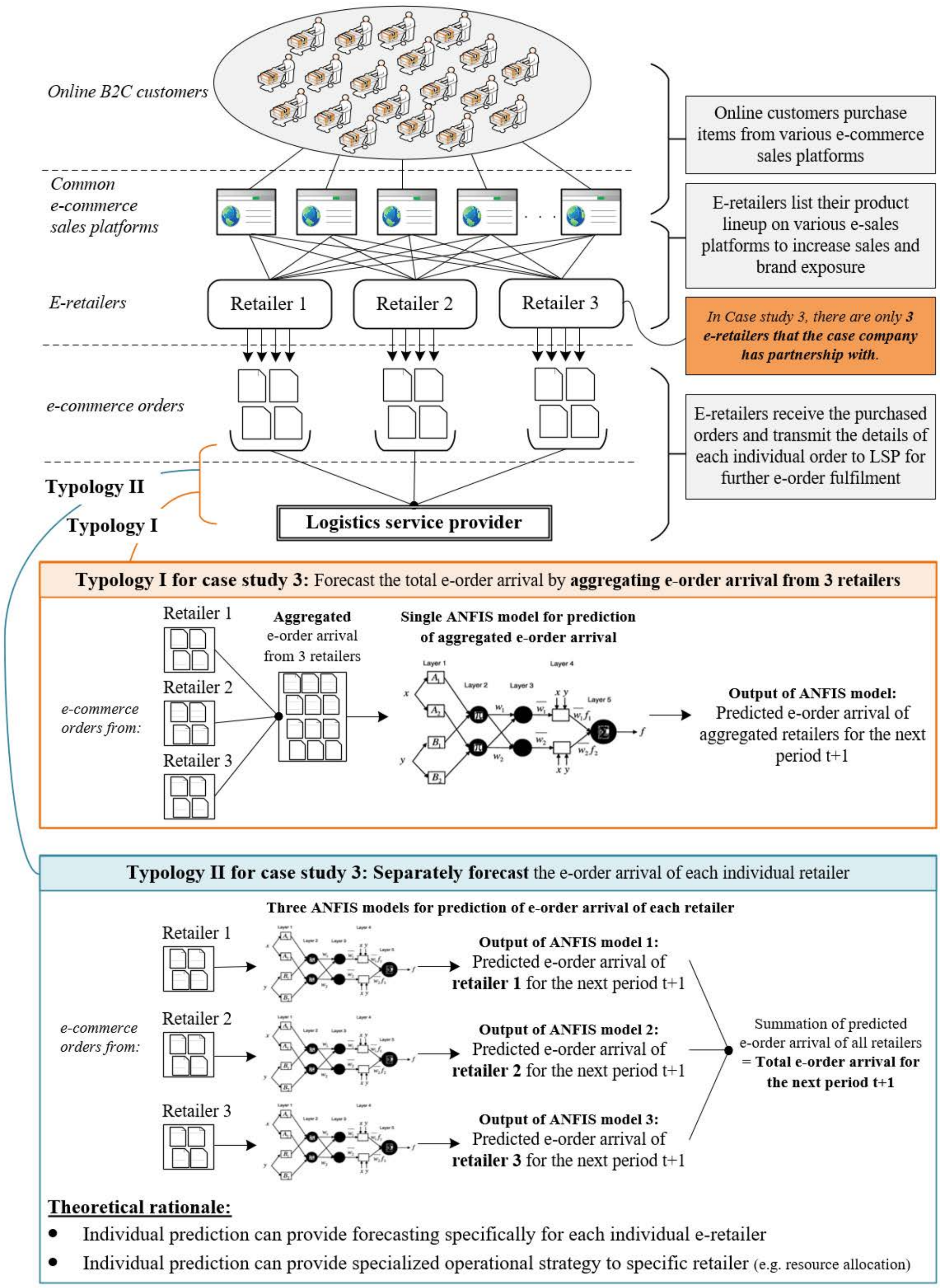


Fig. 5.15. Conceptual framework for ANFIS model construction for Case study 3

The ANFIS model construction, training and testing procedures applied in this case study are discussed below.

- **Stage I – Design Consideration**

Step 1 – *Determine the cycle time for reviewing the e-order consolidation cut-off policy*

Same as Case study 2, two factors for determining the cycle time for reviewing the e-order consolidation cut-off policy, i.e. the maximum order handling capacity in the e-fulfilment distribution centres and the average number of orders (in kg) received per hour, are considered. Through the historical order arrival figures and the information regarding the order handling resource capacity provided by the management, the cycle time (“the period”) for the company is set to be 3 hours. In other words, at the end of each “period”, the management is going to use the EF-DSS to predict the e-order arrival of the next “period”, so as to realize how much time is left for them to release the pending e-orders in a batch.

Step 2 – *Identify the input and output variables in the ANFIS models for both typologies*

As the cycle time is set as three hours in Step 1, the output of the ANFIS model in this case study, $Q_d(t+1)$, denotes the predicted arrival of the e-orders (in kg) in the upcoming period $t+1$ in the current day d, i.e. the coming three hours. In this case study, other than the two input variables introduced in Case study 2, i.e. the previous e-order arrival figures and the volatility of e-order arrival, a new input variable, i.e. the n-period moving average, which is also discussed in Chapter 3, Section 3.6.2.1, is added for further experiments to justify if the inclusion of moving average element can provide a better predicting performance. Hence, three input variables are selected as the prediction indicators of the e-order arrival in the new 3-hour horizon. Details of each input variable are discussed below.

(1) **Actual *n*-period e-order arrival**: Actual e-order arrivals in the previous *n* periods*, i.e. period t, t-1, t-2, …, t-n,* are considered as essential prediction indicators for predicting the e-order arrival figure in the upcoming period *t+1*. Same as in Case study 2, identifying the appropriate number of lag periods *n* that is the most fitting for the experimental dataset is required. An autoregressive (AR) model is formulated and estimated with the use of EViews software package. By using the least squares method, we initially select 10 lag variables for each reatailer's dataset, i.e. $Q_d(t-n)$, where n=0, 1, …, 9, for testing. If the p-value is less than the 0.05 significance level, then reject the null hypothesis. An eight-week data set, which consists of a total of 448 observations of the e-order arrivals in each three-hour interval, are extracted. The first two-thirds of the observations, i.e. 298 observations, are selected to estimate and test the AR models. The lag test results for the aggregated dataset in typology I and for each retailer's dataset in typology II are demonstrated:

Dataset for aggregated e-order arrival suggested in Typology I:

The lag test results, as shown in Fig. 5.16, reveal that both the one-order AR model (AR(1)) and the eight-order AR model (AR(8)) give the lowest p-values, which are both lower than 0.05. This indicates that both the inclusion of one lag variable and eight lag variables are the most appropriate AR model settings for the prediction of the e-order arrival figures. The AR(1) and AR(8) models are then used to forecast the remaining one-third of the observations and compare with the actual e-order arrival figures. Table 5.7 shows the test results of the AR(1) and AR(8) models measured by the root mean squared error (RMSE) and the coefficient of determinations (R^2). From Table 5.7, the AR(8) model performs better in forecasting the e-order arrival than AR(1), as AR(8) gives a lower value of RMSE and R^2. However, if the AR(8) model is to be adopted, a total of eight lag variables will be included in the in an ANFIS model. This will severely increase the computation time and requirements, as well as generate a large number of If-then rules in the inference engine of the ANFIS model. Therefore, taking these drawbacks into consideration in the ANFIS modelling, the AR(1) model is selected over the AR(8) model. In other words, the output variable $Q_d(t+1)$, is to be forecast based on only one lag variable $Q_d(t-n)$, for $n = 0$.

Dependent Variable: RETAILER123
Method: Least Squares
Date: 10/03/18 Time: 01:10
Sample (adjusted): 11 298
Included observations: 288 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	35.16887	9.209973	3.818563	0.0002
RETAILER123(-1)	0.748952	0.059712	12.54269	0.0000
RETAILER123(-2)	-0.083863	0.066378	-1.263416	0.2075
RETAILER123(-3)	0.031019	0.050913	0.609250	0.5429
RETAILER123(-4)	-0.051131	0.050764	-1.007234	0.3147
RETAILER123(-5)	0.005724	0.050745	0.112793	0.9103
RETAILER123(-6)	-0.061962	0.050906	-1.217194	0.2246
RETAILER123(-7)	0.067443	0.051063	1.320801	0.1877
RETAILER123(-8)	0.751757	0.051178	14.68894	0.0000
RETAILER123(-9)	-0.533852	0.068027	-7.847670	0.0000
RETAILER123(-10)	-0.080124	0.057626	-1.390410	0.1655

R-squared	0.884579	Mean dependent var	171.0347
Adjusted R-squared	0.880412	S.D. dependent var	65.63731
S.E. of regression	22.69834	Akaike info criterion	9.119907
Sum squared resid	142714.5	Schwarz criterion	9.259811
Log likelihood	-1302.267	Hannan-Quinn criter.	9.175972
F-statistic	212.2912	Durbin-Watson stat	2.003311
Prob(F-statistic)	0.000000		

Fig. 5.16. Lag test for identifying the number of lag lengths *n* for the aggregated dataset

Table 5.7. Test results of AR(1) and AR(8) model for aggregated dataset

	RMSE	**R^2**
AR(1) model	46.74	0.43
AR(8) model	32.90	0.72

Dataset for retailer 1 in Typology II:

The lag test results, as shown in Fig. 5.17, reveal that both the one-order AR model (AR(1)) and the eight-order AR model (AR(8)) give the lowest p-values, which are both lower than 0.05. This indicates that the inclusion of one lag variable and eight lag variables are the most appropriate AR model settings for the prediction of the e-order arrival figures. The AR(1) and AR(8) model are then used to forecast the remaining one-third of the observations and compare with the actual e-order arrival figures. Table 5.8 shows the test results of the AR(1) and AR(8) modeld measured by the root mean squared error (RMSE) and the coefficient of determinations (R^2). From Table 5.8, the AR(8) model performs slightly better in forecasting the e-order arrival than AR(1), as AR(8) gives slightly lower values of RMSE and R^2. However, if the AR(8) model is to be adopted, a total of eight lag variables will be included in the in an ANFIS model. This will severely increase the computation time and requirements, as well as generate a large number of If-then rules in the inference engine of the ANFIS model. Therefore, taking these drawbacks into consideration in the ANFIS modelling, the AR(1) model is selected over the AR(8) model. In other words, the output variable $Q_d(t+1)$, is to be forecast based on only one lag variable $Q_d(t-n)$, for $n = 0$.

Dependent Variable: RETAILER1
Method: Least Squares
Date: 10/03/18 Time: 00:48
Sample (adjusted): 11 298
Included observations: 288 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	12.91395	3.418183	3.778016	0.0002
RETAILER1(-1)	0.674426	0.059589	11.31789	0.0000
RETAILER1(-2)	-0.078556	0.068934	-1.139585	0.2554
RETAILER1(-3)	-0.078881	0.059243	-1.331480	0.1841
RETAILER1(-4)	0.076929	0.059307	1.297132	0.1957
RETAILER1(-5)	-0.088159	0.059453	-1.482833	0.1393
RETAILER1(-6)	-0.014926	0.059700	-0.250020	0.8028
RETAILER1(-7)	0.066830	0.059618	1.120971	0.2633
RETAILER1(-8)	0.616209	0.059529	10.35142	0.0000
RETAILER1(-9)	-0.324033	0.069965	-4.631356	0.0000
RETAILER1(-10)	-0.116267	0.058488	-1.987870	0.0478

R-squared	0.806802	Mean dependent var	48.37500
Adjusted R-squared	0.799828	S.D. dependent var	21.43376
S.E. of regression	9.589594	Akaike info criterion	7.396680
Sum squared resid	25473.00	Schwarz criterion	7.536585
Log likelihood	-1054.122	Hannan-Quinn criter.	7.452745
F-statistic	115.6765	Durbin-Watson stat	2.014015
Prob(F-statistic)	0.000000		

Fig. 5.17. Lag test for identifying the number of lag lengths *n* for retailer 1

Table 5.8. Test results of AR(1) and AR(8) model for retailer 1

	RMSE	**R^2**
AR(1) model	16.02	0.39
AR(8) model	12.20	0.65

Dataset for retailer 2 in Typology II:

Similarly, the lag test results for retailer 2, as shown in Fig. 5.18, reveal that both the one-order AR model (AR(1)) and the four-order AR model (AR(4)) give the lowest p-values, which are both lower than 0.05. Then, the AR(1) and AR(4) models are used to forecast the remaining one-third of the observations and compare with the actual e-order arrival figures. Table 5.9 shows the test results of the AR(1) and AR(4) models measured by root mean squared error (RMSE), and the coefficient of determinations (R^2). From Table 5.9, the AR(1) model performs even better than the AR(4) model as both the RMSE and R^2 values are better than those of the AR(4) model. Therefore, the AR(1) model is selected over the AR(4) model. In other words, the output variable $Q_d(t+1)$, is to be forecast based on only one lag variable $Q_d(t-n)$, for $n = 0$.

Dependent Variable: RETAILER2
Method: Least Squares
Date: 10/03/18 Time: 00:59
Sample (adjusted): 11 298
Included observations: 288 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	15.00175	3.981576	3.767793	0.0002
RETAILER2(-1)	0.561020	0.057623	9.736008	0.0000
RETAILER2(-2)	0.009730	0.064848	0.150048	0.8808
RETAILER2(-3)	0.131959	0.057160	2.308584	0.0217
RETAILER2(-4)	-0.162683	0.055432	-2.934842	0.0036
RETAILER2(-5)	0.112094	0.054962	2.039492	0.0423
RETAILER2(-6)	-0.206643	0.055008	-3.756618	0.0002
RETAILER2(-7)	0.264049	0.055645	4.745273	0.0000
RETAILER2(-8)	0.540065	0.057264	9.431069	0.0000
RETAILER2(-9)	-0.202701	0.065859	-3.077798	0.0023
RETAILER2(-10)	-0.279284	0.055371	-5.043883	0.0000

R-squared	0.848400	Mean dependent var	64.77778
Adjusted R-squared	0.842927	S.D. dependent var	23.09078
S.E. of regression	9.151438	Akaike info criterion	7.303145
Sum squared resid	23198.42	Schwarz criterion	7.443050
Log likelihood	-1040.653	Hannan-Quinn criter.	7.359210
F-statistic	155.0175	Durbin-Watson stat	1.967310
Prob(F-statistic)	0.000000		

Fig. 5.18. Lag test for identifying the number of lag lengths *n* for retailer 2

Table 5.9. Test results of AR(1) and AR(4) model for retailer 2

	RMSE	**R^2**
AR(1) model	16.63	0.40
AR(4) model	18.40	0.26

Dataset for retailer 3 in Typology II:

For retailer 3, the lag test results, as shown in Fig. 5.19, reveal that both the one-order AR model (AR(1)) and the eight-order AR model (AR(8)) give the lowest p-values, which are both lower than 0.05. Then, the AR(1) and AR(8) models are used to forecast the remaining one-third of the observations and compare with the actual e-order arrival figures. Table 5.10 shows the test results of the AR(1) and AR(8) models measured by the root mean squared error (RMSE), and the coefficient of determinations (R^2). From Table 5.10, same as the result for retailer 1's dataset, the AR(8) model performs slightly better in forecasting the e-order arrival than AR(1), as AR(8) gives slightly lower values of RMSE and R^2. However, if the AR(8) model is to be adopted, a total of eight lag variables will be included in the in an ANFIS model. Therefore, the AR(1) model is selected over the AR(8) model. In other words, the output variable $Q_d(t+1)$, is to be forecast based on only one lag variable $Q_d(t-n)$, for $n = 0$.

Dependent Variable: RETAILER3
Method: Least Squares
Date: 10/03/18 Time: 01:04
Sample (adjusted): 11 298
Included observations: 288 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	13.21755	3.517543	3.757607	0.0002
RETAILER3(-1)	0.711939	0.059891	11.88726	0.0000
RETAILER3(-2)	-0.085225	0.065729	-1.296609	0.1958
RETAILER3(-3)	0.032887	0.049703	0.661660	0.5087
RETAILER3(-4)	-0.060094	0.049657	-1.210178	0.2272
RETAILER3(-5)	-0.002540	0.049757	-0.051044	0.9593
RETAILER3(-6)	-0.040407	0.049864	-0.810332	0.4184
RETAILER3(-7)	0.045694	0.049839	0.916836	0.3600
RETAILER3(-8)	0.751857	0.049858	15.08001	0.0000
RETAILER3(-9)	-0.516789	0.067098	-7.701949	0.0000
RETAILER3(-10)	-0.065910	0.057884	-1.138650	0.2558

R-squared	0.853158	Mean dependent var	57.88194
Adjusted R-squared	0.847857	S.D. dependent var	22.44622
S.E. of regression	8.755274	Akaike info criterion	7.214635
Sum squared resid	21233.38	Schwarz criterion	7.354540
Log likelihood	-1027.908	Hannan-Quinn criter.	7.270701
F-statistic	160.9378	Durbin-Watson stat	1.993529
Prob(F-statistic)	0.000000		

Fig. 5.19. Lag test for identifying the number of lag lengths *n* for retailer 3

Table 5.10. Test results of AR(1) and AR(8) model for retailer 3

	RMSE	**R^2**
AR(1) model	16.57	0.41
AR(8) model	12.39	0.67

(2) **Volatility of previous e-order arrival:** The volatility of previous e-order arrival (momentum) is an essential indicator of the trend of the time-series-based e-order arrival. Differing from Case study 2, to avoid the problem of over-complexity in the input variable set, only one-order momentum, *Mo(t),* is used in this case study. Thus, for the current period *t*, the one-order momentum of e-order arrival is calculated by:

$$Mo(t) = Q_d(t) - Q_d(t-1) \tag{45}$$

(3) **n-period Simple moving average:** Simple moving average is another obvious figure that has been commonly introduced as a prediction indicator. Therefore, two-period and three-period simple moving average approaches are introduced as the input variables for ANFIS forecasting modelling. For the current period *t*, the two-period $MA_2(t)$ and three-period $MA_3(t)$ simple moving average of e-order arrivals are respectively calculated by:

$$\mathrm{MA}_2(t) = \frac{Q_d(t)+Q_d(t-1)}{2} \tag{46}$$

$$\mathrm{MA}_3(t) = \frac{Q_d(t)+Q_d(t-1)+Q_d(t-2)}{3} \tag{47}$$

In summary, with the two-period (MA(2)) and three-period (MA(3)) simple moving average being introduced in the case study, together with one-order AR model

(AR(1)) and the one-order momentum model (MO(1)), **two different sets of variables are identified for both typologies:**

- **Model A**: AR(1)MO(1)MA(2) model, i.e. ANFIS model with one-order AR, one-order momentum, and two-period simple moving average.
- **Model B**: AR(1)MO(1)MA(3) model, i.e. ANFIS model with one-order AR, one-order momentum, and three-period simple moving average.

In total, 8 ANFIS models are designed and built. A summary of ANFIS models designed for Typologies I and II are presented in Table 5.11.

Table 5.11. A summary of ANFIS models designed for Typologies I and II

	Model A AR(1)MO(1)MA(2)	**Model B AR(1)MO(1)MA(3)**
Typology I	Model 4A	Model 4B
Typology II:		
Retailer 1	Model 1A	Model 1B
Retailer 2	Model 2A	Model 2B
Retailer 3	Model 3A	Model 3B

Further experiments are performed to evaluate each model so as to justify whether the inclusion of two-period or three-period moving average momentum is suitable for the prediction of e-order arrival, in addition to the element of autoregressive and momentum that have been introduced in Case study 2.

Step 3 – *Select and extract dataset for model training and testing*

An eight-week real production data set is gathered and extracted from the case company's distribution centre where e-order fulfilment operations take place. With a cut-off review cycle of three working hours, the data sets are pre-processed and converted into useful input values for the proposed ANFIS models. Tables 5.12, 5.13, and 5.14 respectively show the dataset for the e-order arrival of retailers 1, 2, and 3 in a three-hour interval (measured by kg), which is comprised of 448 data pairs in total, is split into training and testing data sets. The first seven weeks of the datasets, i.e. 392 observations in total, are used to train and build the adaptive network. The remaining data, i.e. 56 observations, are used as the testing data set for determining whether any over fitting of the model occurs during training.

Table 5.12. Eight-week e-order arrival (in kg) data in 3-hour time interval for Retailer 1

	Time							
Date	**0-3**	**3-6**	**6-9**	**9-12**	**12-15**	**15-18**	**18-21**	**21-24**
				Week 1				
Mon	10	9	8	15	19	30	54	60
Tue	55	30	10	20	38	35	58	64
Wed	52	28	10	25	38	36	55	78
Thu	50	32	12	24	35	40	52	73
Fri	48	35	24	26	32	38	50	73
Sat	78	55	30	56	67	72	78	80
Sun	79	42	28	40	70	75	79	75
				Week 2				
Mon	50	28	15	18	35	40	55	78
Tue	58	29	12	18	36	34	50	70
Wed	45	25	13	20	40	42	60	82
Thu	48	35	10	25	32	45	55	75
Fri	50	38	12	30	28	35	45	82
Sat	80	48	13	35	65	70	75	81
Sun	80	45	15	35	65	71	75	80

				Week 3				
Mon	48	35	14	20	38	38	60	80
Tue	60	32	15	20	40	35	55	74
Wed	50	28	15	23	45	45	58	85
Thu	50	38	14	28	35	48	58	78
Fri	55	40	15	35	30	40	46	85
Sat	82	50	15	38	68	75	80	82
Sun	82	48	16	38	69	74	79	82
				Week 4				
Mon	50	38	15	22	40	45	58	75
Tue	64	35	18	25	45	38	53	78
Wed	58	30	13	26	50	48	60	85
Thu	50	42	18	30	45	52	60	85
Fri	65	45	18	42	35	45	54	88
Sat	85	55	20	45	72	78	85	85
Sun	85	54	22	42	70	76	82	88
				Week 5				
Mon	51	32	18	20	32	48	58	75
Tue	60	28	20	25	42	48	55	75
Wed	55	40	22	26	45	47	65	82
Thu	57	45	15	25	35	45	55	75
Fri	50	38	18	30	32	40	48	82
Sat	80	50	28	54	68	80	78	85
Sun	81	48	28	37	68	70	78	81
				Week 6				
Mon	58	32	18	28	32	48	64	71
Tue	75	45	28	25	48	45	55	75
Wed	65	48	30	28	45	51	69	80
Thu	60	45	20	24	38	45	58	78
Fri	58	41	18	30	32	40	54	82
Sat	80	61	32	51	70	79	84	82
Sun	81	53	32	45	70	75	71	85
				Week 7				
Mon	50	38	15	22	40	45	58	75
Tue	64	35	18	25	45	38	53	78
Wed	58	30	13	26	50	48	60	85
Thu	50	42	18	30	45	52	60	85

Fri	65	45	18	42	35	45	54	88
Sat	85	55	20	45	72	78	85	85
Sun	85	54	22	42	70	76	82	88
				Week 8				
Mon	48	38	25	22	40	45	60	71
Tue	60	40	20	20	45	40	55	80
Wed	60	45	24	26	50	48	60	81
Thu	55	45	20	31	48	55	61	70
Fri	68	48	25	30	48	60	60	80
Sat	86	58	35	45	72	78	80	81
Sun	78	60	35	28	58	69	78	85

Table 5.13. Eight-week e-order arrival (in kg) data in 3-hour time interval for Retailer 2

				Time				
Date	**0-3**	**3-6**	**6-9**	**9-12**	**12-15**	**15-18**	**18-21**	**21-24**
				Week 1				
Mon	18	15	12	12	28	45	69	80
Tue	75	55	21	28	58	54	68	81
Wed	78	52	25	30	52	58	75	95
Thu	74	50	25	34	55	60	74	93
Fri	72	54	25	32	56	61	85	98
Sat	95	78	45	68	85	82	95	98
Sun	96	69	35	50	88	85	98	97
				Week 2				
Mon	70	58	22	25	60	50	65	90
Tue	70	58	28	25	60	50	70	85
Wed	80	56	28	28	50	55	71	90
Thu	70	48	26	20	58	58	70	90
Fri	70	58	27	30	54	67	80	90
Sat	91	68	30	45	90	85	90	95
Sun	95	70	40	45	90	86	95	96
				Week 3				
Mon	85	57	26	30	65	55	65	98
Tue	75	46	18	30	65	55	75	86
Wed	85	60	25	30	45	58	75	90
Thu	70	48	18	20	58	58	70	92

Fri	80	60	20	35	55	68	82	92
Sat	91	68	20	45	94	88	92	98
Sun	98	72	45	50	91	90	93	94
				Week 4				
Mon	89	70	18	25	58	89	68	95
Tue	80	58	25	33	68	60	80	90
Wed	92	65	30	40	48	62	80	95
Thu	78	50	22	30	60	65	75	98
Fri	85	65	25	40	60	78	88	96
Sat	96	72	68	54	88	92	90	95
Sun	95	78	48	48	89	95	95	98
				Week 5				
Mon	75	51	28	30	58	56	70	89
Tue	65	56	32	30	58	68	75	90
Wed	73	55	35	32	53	58	75	91
Thu	75	57	28	20	48	59	75	85
Fri	75	68	30	35	58	70	78	95
Sat	94	71	42	68	91	88	91	94
Sun	98	78	45	69	89	89	95	96
				Week 6				
Mon	78	58	35	41	58	58	75	85
Tue	78	67	45	38	60	65	78	90
Wed	84	60	45	40	58	61	78	95
Thu	78	60	30	35	54	65	78	90
Fri	71	68	31	38	54	75	80	95
Sat	97	78	45	70	89	89	95	98
Sun	98	80	54	78	85	91	98	98
				Week 7				
Mon	89	70	18	25	58	89	68	95
Tue	80	58	25	33	68	60	80	90
Wed	92	65	30	40	48	62	80	95
Thu	78	50	22	30	60	65	75	98
Fri	85	65	25	40	60	78	88	96
Sat	96	72	68	54	88	92	90	95
Sun	95	78	48	48	89	95	95	98
				Week 8				
Mon	80	60	58	25	58	79	71	91

Tue	85	60	42	50	68	58	78	91
Wed	90	70	50	45	48	62	85	98
Thu	80	51	35	40	58	68	78	91
Fri	90	68	40	48	58	80	90	98
Sat	95	75	58	60	88	95	91	96
Sun	90	76	50	45	78	90	96	98

Table 5.14. Eight-week e-order arrival (in kg) data in 3-hour time interval for Retailer 3

				Time				
Date	**0-3**	**3-6**	**6-9**	**9-12**	**12-15**	**15-18**	**18-21**	**21-24**
				Week 1				
Mon	15	13	11	11	25	40	63	78
Tue	69	48	15	25	45	40	62	78
Wed	60	50	18	28	52	56	70	85
Thu	58	49	23	30	48	54	68	88
Fri	54	50	23	28	45	52	75	93
Sat	88	61	38	59	78	79	88	94
Sun	89	58	32	45	85	80	89	92
				Week 2				
Mon	70	50	18	30	48	37	60	75
Tue	70	50	25	22	48	38	60	75
Wed	55	45	25	28	50	59	65	84
Thu	60	50	18	28	46	51	65	87
Fri	58	48	15	30	42	50	79	95
Sat	90	58	20	40	75	75	85	90
Sun	85	60	25	40	82	79	85	90
				Week 3				
Mon	75	48	15	25	50	40	58	73
Tue	75	51	15	25	50	40	58	73
Wed	58	48	16	30	51	60	69	88
Thu	64	58	20	30	50	58	67	90
Fri	68	53	17	28	45	58	85	93
Sat	92	64	22	45	80	78	88	95
Sun	94	70	28	45	85	80	88	94
				Week 4				
Mon	98	62	20	25	45	38	58	84
Tue	78	55	18	18	45	48	60	78

Wed	64	50	20	28	55	58	65	85
Thu	79	64	22	35	48	64	60	85
Fri	78	60	25	32	48	65	90	95
Sat	89	69	25	48	88	85	81	90
Sun	89	75	35	48	88	85	90	91
				Week 5				
Mon	68	48	22	35	50	40	58	78
Tue	69	48	30	28	45	50	65	85
Wed	74	54	30	28	54	61	70	86
Thu	69	50	25	28	41	51	68	87
Fri	65	54	22	32	48	68	68	90
Sat	88	67	32	58	78	79	88	91
Sun	86	68	30	50	78	80	88	89
				Week 6				
Mon	69	51	25	35	50	53	68	75
Tue	71	54	38	35	54	51	65	85
Wed	75	55	35	35	54	58	75	85
Thu	70	54	28	29	45	58	70	85
Fri	64	61	22	32	48	68	72	88
Sat	90	71	38	60	75	85	90	90
Sun	88	78	48	70	80	84	80	90
				Week 7				
Mon	98	62	20	25	45	38	58	84
Tue	78	55	18	18	45	48	60	78
Wed	64	50	20	28	55	58	65	85
Thu	79	64	22	35	48	64	60	85
Fri	78	60	25	32	48	65	90	95
Sat	89	69	25	48	88	85	81	90
Sun	89	75	35	48	88	85	90	91
				Week 8				
Mon	71	56	40	25	45	70	62	82
Tue	75	51	31	25	45	50	68	80
Wed	65	51	30	35	55	58	70	89
Thu	75	61	25	38	55	61	65	81
Fri	80	61	35	45	50	70	85	91
Sat	90	65	45	48	80	90	85	89
Sun	85	70	45	35	65	88	89	90

Step 4 – *Define the universe of disclosure for each input parameter*

To achieve the best result generated from the ANFIS model, system parameter modifications are critical. Consequently, a summary of the training parameters for Models A and B, i.e. AR(1)MO(1)MA(2) and AR(1)MO(1)MA(3) respectively, as well as their model structure, are presented and shown in Table 5.15, Figs. 5.20, and 5.21.

Table 5.15. Training parameters of the ANFIS model in Case study 3

Parameters	**Setting for both AR(1)MO(1)MA(2) and AR(1)MO(1)MA(3)**
Number of layers	5
Number of inputs	3
Number of output	1
Total number of data pairs	448+
Size of data set:	1,792 observations in total (448 x 4)
- **Training data set**	1,568 observations (392 x 4)
- **Testing data set**	224 observations (56 x 4)
Initial FIS generation	Grid partitioning
Types of input MFs*	Tri/Trap/Gbell/Guass
Number of MFs for each input*	2/3/4
Types of output function*	Constant
Learning algorithm	Least square method and Back-propagation gradient descent method
Number of epoch	40

+*The 448data pairs are an 8-week data set, with one data pair for every 3-hour time interval*

**Further experiments were made to identify the best MFs characteristics*

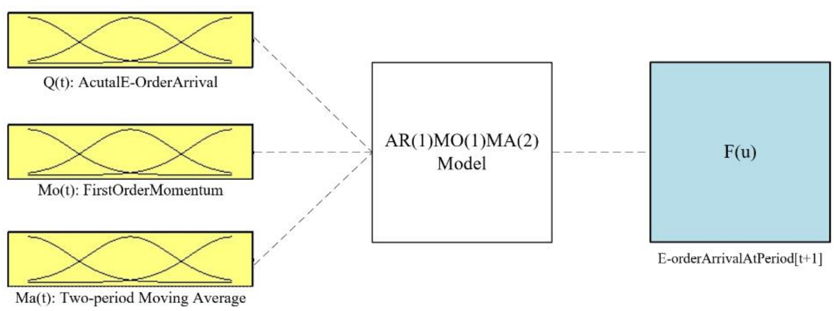


Fig. 5.20. AR(1)MO(1)MA(2) model structure

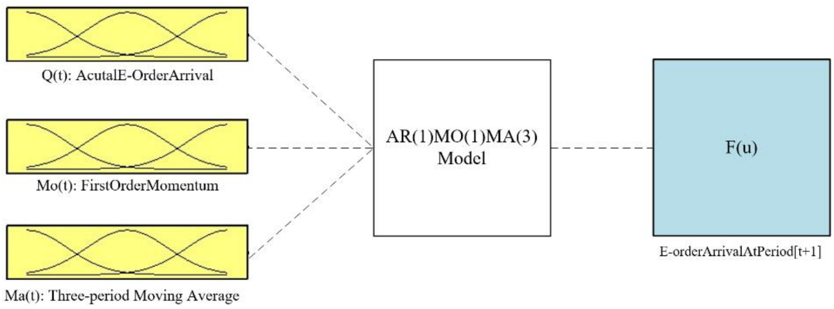


Fig. 5.21. AR(1)MO(1)MA(3) model structure

- **Stage II – Model Training and Testing**

Same as Case study 2, different types of membership functions (MFs) and numbers of MFs for each input are tested so as to identify which combination of system parameter gives the lowest testing error. During the model training and testing for models 1A, 1B, 2A, 2B, 3A, 3B, 4A and 4B, it is observed that when the output function is selected as “Linear”, a lower training error is often obtained, as compared with the output function being selected as “Constant”. However, though the training error is lower, the testing error is most of the time much higher than when the output function is “Constant”. Therefore, the “Linear” output function is not considered for further testing. The training and testing results for models 1A, 1B, 2A, 2B, 3A, 3B, 4A and 4B are respectively shown in **Appendices C to J**, as summarized in Table 5.16. With the testing results displayed in the Appendices section, the best combination of the model characteristics for each model is obtained based on the one that gives the lowest testing error, as discussed and presented in the next chapter.

Table 5.16. A summary of the ANFIS model training and testing results

Typology	Retailer	Model	Appendix
II	1	1A	C
		1B	D
	2	2A	E
		2B	F
	3	3A	G
		3B	H
I	Aggregated e-order arrival of retailer 1, 2 and 3	4A	I
		4B	J

- **Stage III – Performance Evaluations**

To evaluate the feasibility of the developed ANFIS model for forecasting the e-order arrival, the same as in Case study 2, with the best model setting identified for each model (Models 1A, 1B, 2A, 2B, 3A, 3B, 4A and 4B) in Stage II, these developed ANFIS models are then compared with an autoregressive integrated moving average (ARIMA) model for further performance validation. However, as two different typologies are introduced in this case study, performance evaluations are not undertaken to compare the ANFIS model and the ARIMA model only. Instead, performance evaluation consists of four major comparisons. A model comparison framework, as shown in Fig. 5.22, is constructed to better illustrate the performance evaluation process adopted. The four prediction performance comparisons are:

(i) **Comparison 1 – Model A vs Model B**: Model A and B comparison for each individual retailer's ANFIS model

(ii) **Comparison 2 – Typology 1 vs Typology 2 for ANFIS model**: ANFIS model prediction performance comparison between typologies 1 and 2

(iii) **Comparison 3 – Typology 1 vs Typology 2 for ARIMA model**: ARIMA model prediction performance comparison between typologies 1 and 2

(iv) **Comparison 4 *(the ultimate comparison)* – ANFIS vs ARIMA**: Prediction performance comparison between the best ANFIS model and the best ARIMA model.

5.5 Summary

In this chapter, three case studies are presented. The three modules of the EF-DSS are separately deployed for different logistics service providers according to their existing operational bottlenecks and needs. The ECM and EGM are applied in Case study 1, whereas the ECM and EBRM are applied in Case Studies 2 and 3. As the implementation of the EF-DSS in Case studies 2 and 3 are different in terms of: (i) the methodologies adopted for ANFIS model construction, (ii) the dataset used for model training and testing, and (iii) the set of input variables introduced in the ANFIS models for order arrival prediction, the results upon the implementation of EF-DSS in Case study 2 and 3 are discussed and compared in the next chapter. Furthermore, with the EF-DSS deployed in three different case companies, the performance of the EF-DSS, as well as the operating performance of each case company upon the system implementation, are thoroughly discussed in the next chapter.

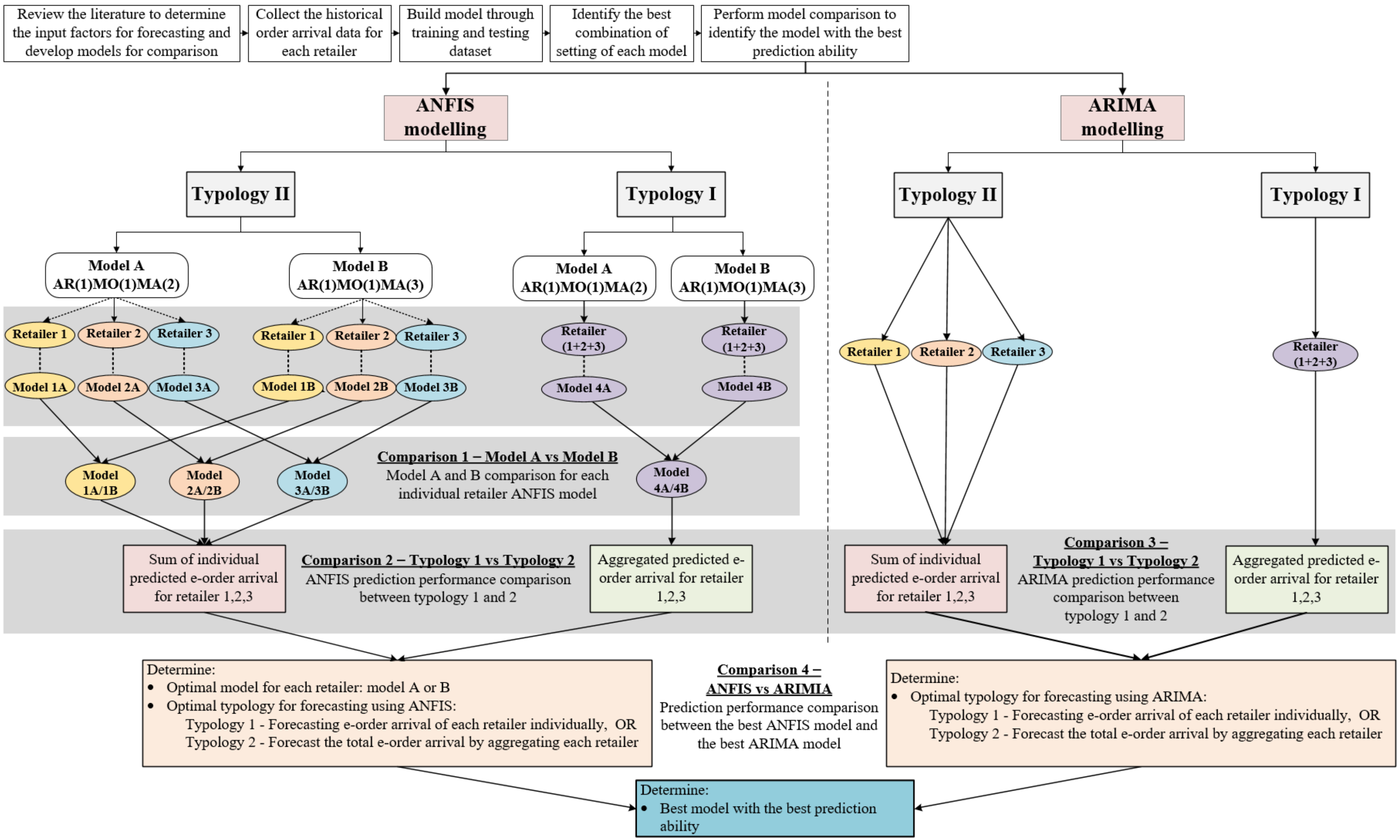


Fig. 5.22. Model performance comparison framework

Chapter 6 – Results and Discussion

6.1 Introduction

In this research, the Warehouse Postponement Strategy is proposed to streamline the e-fulfillment operations of e-commerce order handling in distribution centres. To deploy the proposed operational strategy, two critical decisions, i.e. How to group e-orders, and when to release the grouped orders, need to be made manually by the logistics service providers. Therefore, the EF-DSS is proposed and developed in this research to support the logistics service providers in implementing WPS with the relevant decision support. EF-DSS adopts the GA technique, rule-based inference engine, autoregressive models and ANFIS models to group the e-orders based on their similarity of storage locations, and identify the optimal cut-off time for releasing the grouped e-orders. In this chapter, the results and discussion of the research is presented in two areas: (i) Experimental results and discussion of the system based on the three case studies, and (ii) Research, managerial, and practical implications.

6.2 Experimental Results and Discussion of the System

Three case studies are conducted to implement the EF-DSS, which consists of the E-order Consolidation Module (ECM), E-order Grouping Module (EGM) and E-order Batch Releasing Module (EBRM). The first case study implemented the ECM and EGM of the EF-DSS for solving the problem of order grouping. The second and the third case study implemented the ECM and EBRM of the EF-DSS for identifying the timing for releasing the grouped orders for performing e-order fulfilment operations in a batch. In this section, the experimental results and discussion of the system in the three case studies are presented separately.

6.2.1 Results and Discussion of the GA Parameter Settings in the EGM from Case Study 1

The e-fulfilment process in warehouses or distribution centers is re-engineered. Logistics service providers no longer perform e-order fulfilment operations immediately after orders are received online. Instead, e-orders, which are placed by B2C customers from various online sales platforms, and usually small in lot-size, are consolidated in a cloud database for further order grouping. In addition to the order grouping decision support by separating pending to-be-picked SKUs into several order grouping lists based on storage locations dissimilarity, the operating procedures and appropriate material handling equipment are further suggested for ease of e-order fulfilment process execution. The improvement is not only beneficial to the case company, but also its downstream logistics service providers along the supply chain. In this section, the GA optimal parameter setting is first reported, followed by an analysis of the key performance improvement areas found in the case company.

(i) Parameter settings of the Genetic Algorithm

The GA parameter settings are required to be defined prior to implementation in an actual production environment. Specifically, the crossover rate and mutation rate, ranging from 0 to 1, are defined by the users. A trial-and-error approach is used to determine an appropriate crossover and mutation rates that best suit the GA mechanism developed. In Case Study 1, a crossover rate of 0.7 and 0.9, and a mutation rate of 0.1 and 0.25, are selected for testing in a population size of 2000 and with the number of generations set as 50,000. Using different combinations of the crossover and mutation rate, as specified in Table 6.1, it is found that, after pair-wise executing 10 times, a GA parameter setting with a crossover rate of 0.9 and a mutation rate of 0.1 gives the lowest fitness value, as summarized and shown in Fig. 6.1. The more storage locations to be visited, a greater number of trials is preferred, so as to obtain a better nearly-optimal solution.

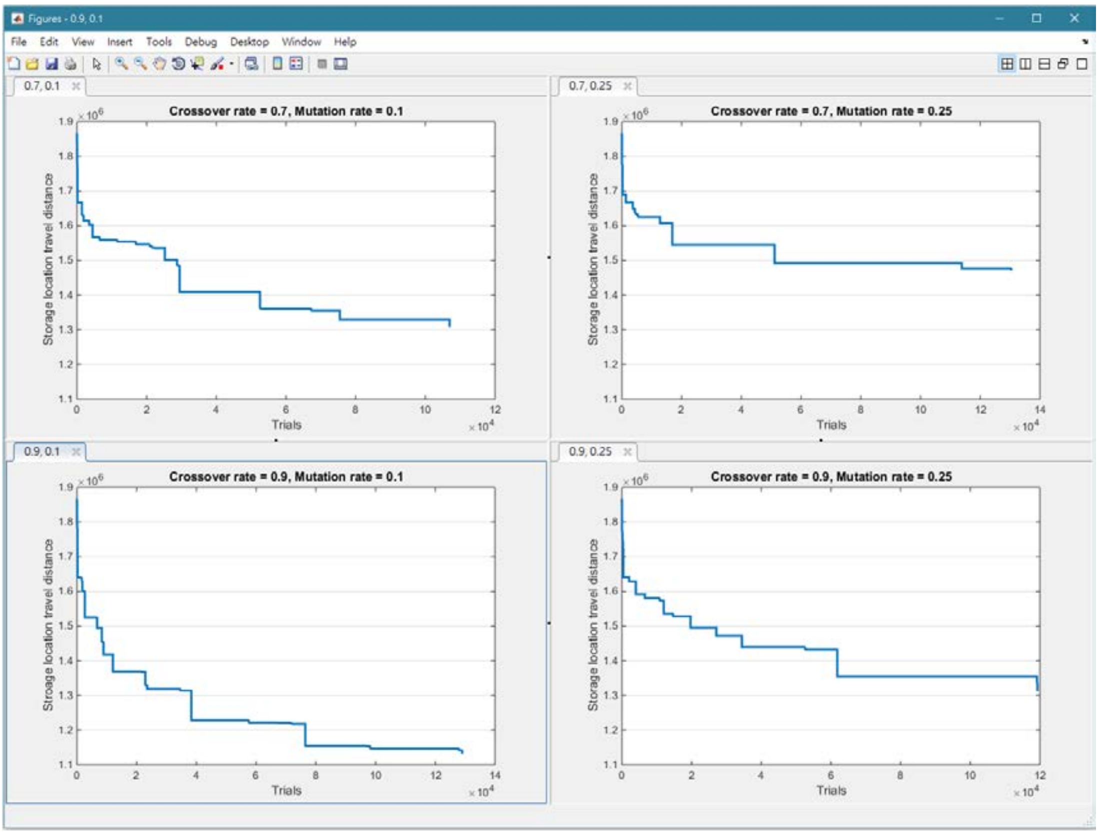


Fig. 6.1. Graphical comparison of the results under different combinations of GA parameter setting

Table 6.1. Optimal parameter settings for the Genetic Algorithm

Parameter	**Settings**
Crossover rate	0.7/0.9
Mutation rate	0.1/0.25
Population size	2000
Termination criteria	Stops if: (1) the number of generations reach 50,000; or (2) the target cell has an improvement of less than 0.01% in the last 10,000 trials.

(ii) Key operating performance improvements

The performance improvement in the order fulfilment operations in the e-fulfilment centres of Case Study 1 can be found in terms of two measurable areas, namely: Reduction of total order processing time, and reduction of total traveling distance of a customer order.

- *Reduction of total order processing time*

The total order processing time in handling an e-order in e-fulfillment centers involves the following sequential operations:

I. Order planning – Consolidate e-orders and print relevant documents for warehouse operators to execute accordingly;

II. Order picking – Travel to storage locations and pick the required items;

III. Order packing and consolidation – Allocate the picked items to the designated customer order and pack the items in a carton box; and

IV. Labeling – Print and stick the required label(s) on the packed carton box.

Before the implementation of EF-DSS, e-orders were processed individually without any grouping of orders in advance for future batch processing. Therefore, the order processing operation did not consist of any order planning operation that consolidated e-orders before process execution. E-orders are immediately picked by assigning a worker to travel to the specified storage locations to pick up the required items. After the picked items are inspected, the items are loaded into a carton box at the packing area, followed by placing the shipping and precaution labels on the packed carton box. According to previous time measurement conducted by the case company, the total e-order processing time of an order, involving the operations mentioned above, was 9.33 minutes on average, as shown in Table 6.2.

With the implementation of EF-DSS, the e-orders are consolidated before processing in a batch. On average, each batch consist of 30 individual online customer orders. Through time measurement over a 3-month period, for a batch order processing operation, it takes 13.5 minutes for order planning operations, followed by 37 minutes for picking the grouped e-orders by visiting the storage locations once, 52 minutes for allocating the required items to the customers and packing the 30 carton boxes, and 10 minutes for labelling all the packed boxes. On a per-order basis, the total e-order processing time is 2.68 minutes on average, showing a 70% reduction of the total processing time as compared to the performance before the implementation of the proposed system. A graphical comparison of the time spent on each order processing operation is shown in Fig. 6.2.

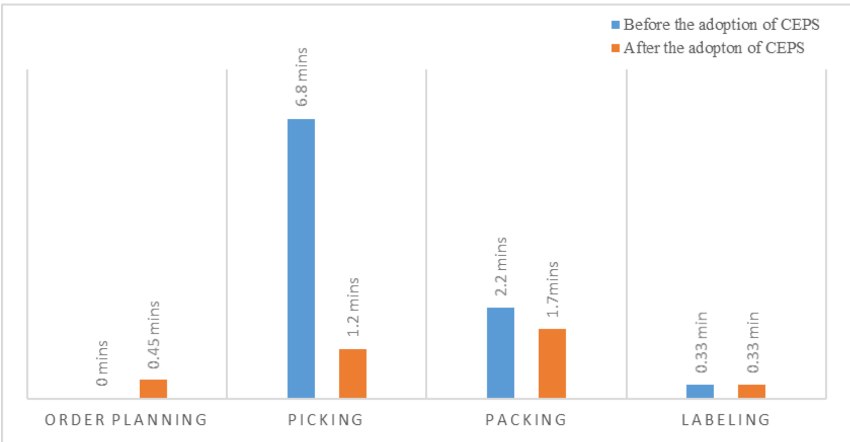


Fig. 6.2. Improvement in terms of order processing time

Table 6.2. A before-and-after comparison in terms of order processing time

Operation	Before	After	After (per batch)	Difference
Order planning	*0 min*	*0.45 mins*	*13.5 mins*	-
Picking	*6.8 mins*	*1.2 mins*	*37 mins*	-82.4%
Packing	*2.2 mins*	*1.7 mins*	*52 mins*	-22.7%
Labeling	*0.33 min*	*0.33 min*	*10 mins*	0%
Total	***9.33 mins***	***2.68 mins***	*112.5 mins*	-71.3%

- *Reduction of total traveling distance of a customer order*

The total travelling distance is another noticeable improvement area. The adoption of EF-DSS has reduced the traveling distance of an e-order, as storage locations are visited only once for a batch of consolidated customer orders, instead of conventionally visiting storage locations repeatedly throughout the working hours for each particular customer order. Before the re-engineered order fulfilment operations, the items purchased in an e-commerce order were picked by visiting the storage locations once, which, on average, required a travel distance of 68 meters. With the implementation of EF-DSS, a batch, which consists of 30 individual online customer orders on average, requires a total travel distance of 397 meters. In other words, a travel distance of only 13.2 meters is required for an order, yielding a 81% reduction of total traveling distance in handling a customer order. In the long run, the re-engineered e-order process reduces the workload of employees working in e-fulfilment operations. The saved time for repeated visits to storage locations enables managers to flexibly reallocate the human resources to handle other operations, such as put-away and cargo loading or unloading operations.

6.2.2 Results and Discussion of the AR-MO-ANFIS Model Parameter Settings in the EBRM from Caste Study 2

In Case Study 2, two ANFIS-based models, AR(1)MO(1) and AR(1)MO(2) model, are developed for forecasting the arrival frequency of e-commerce orders in the case company's distribution centres. The output of the ANFIS-based models, i.e. the predicted volume of e-commerce order arrival (in terms of kg) for the upcoming two-hour period in the distribution centres, serves as one of the inputs of another proposed algorithm in the EBRM of the EF-DSS, so as to identify the optimal cut-off time for releasing the grouped orders that are currently consolidated in the E-order consolidation pool of the ECM of the EF-DSS, and pending for batch release to the distribution centres for actual process execution. As the prediction ability of the two developed ANFIS-based models have a significant effect on identifying the final output of EBRM, i.e. the optimal cut-off time of releasing the grouped orders, model evaluation and comparison must be performed.

In this section, the ANFIS model comparison and evaluations are first reported. The performance of the ANFIS models are compared in two separate stages. First, various combination settings for the AR(1)MO(1) and AR(1)MO(2) models are tested, so as to obtain the best setting that gives the highest prediction accuracy. Second, the optimized setting of the AR(1)MO(1) and AR(1)MO(2) models is further compared with ARIMA model to evaluate the performance of the ANFIS model in the prediction of e-order arrival. Evaluation of the performance of the ANFIS models in the first stage and second stage is discussed in (i) Performance comparison of the ANFIS system parameters and (ii) Performance comparison of the developed ANFIS and ARIMA models respectively. Lastly, an analysis of the key performance improvement areas found in the case company is presented in (iii) Order handling performance comparison.

(i) Performance comparison of the ANFIS system parameters

Various settings, regarding the types of MFs, the number of MFs, and the types of output function, are evaluated for the two proposed ANFIS models, the AR(1)MO(1) and AR(1)MO(2) models. The best combination of settings for the AR(1)MO(1) and AR(1)MO(2) models, as depicted in Table 6.3, is obtained through a comprehensive evaluation and error analysis for each of the models, as shown in the Appendices A and B. One of the noticeable issues during the evaluation of the models is the problem of model over fitting during training. In the Appendices A and B, especially for the

AR(1)MO(2) model, it is found that a lower training error is often obtained when the output function is set as linear, and when the number of membership functions is larger. However, the testing error of these settings (for example, the number of MFs for each input is four, in Gbell-shape, and the output function is set as linear) is very large. These are perfect examples where the model over fits the training data. To avoid the model from over fitting, we determine the best combination of settings based on the one that gives the lowest testing error. The corresponding ANFIS information for both models under the best structure is respectively shown in Table 6.3, which confirms that the total number of parameters in the network is fewer than the number of training data pairs. With the best combination of the setting obtained for AR(1)MO(1) and AR(1)MO(2), their network structure and test results are respectively shown in Figs. 6.3 to 6.6. Then, error analysis is performed for evaluating and comparing the prediction performance of these models under their corresponding best setting with the ARIMA model.

Table 6.3. The characteristics of the best structure of AR(1)MO(1) and AR(1)MO(2) model and their corresponding ANFIS information

Characteristics of the best structure of the ANFIS for:		
	AR(1)MO(1)	**AR(1)MO(2)**
Number of MFs for each input	*4, 4*	*2, 4, 3*
Types of input MFs	*Guass*	*Gbell*
Types of output function	*Constant*	*Constant*
The corresponding ANFIS information		
Number of nodes	53	72
Number of linear parameters	16	24
Number of nonlinear parameters	16	27
Total number of parameters	32	51
Number of training data pairs	302	302
Number of checking data pairs	34	34
Number of fuzzy rules	16	24

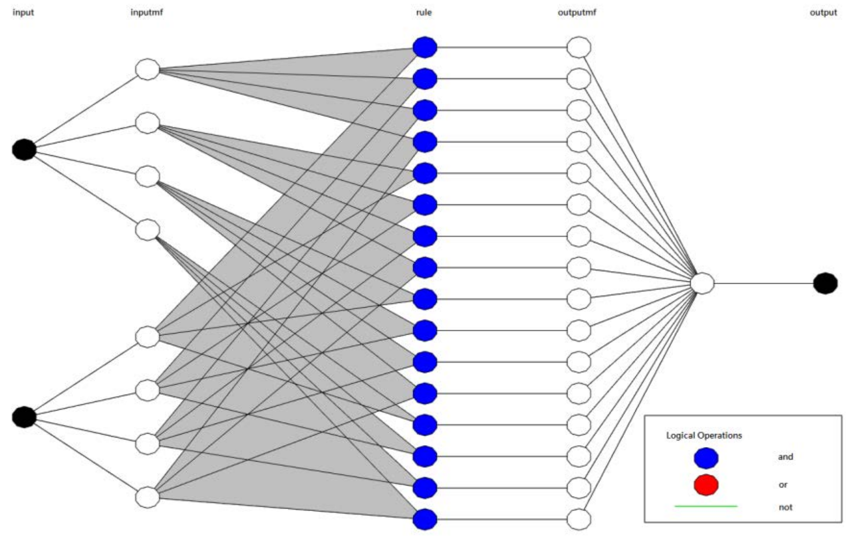


Fig. 6.3. Network frame of AR(1)MO(1) model using the best structure

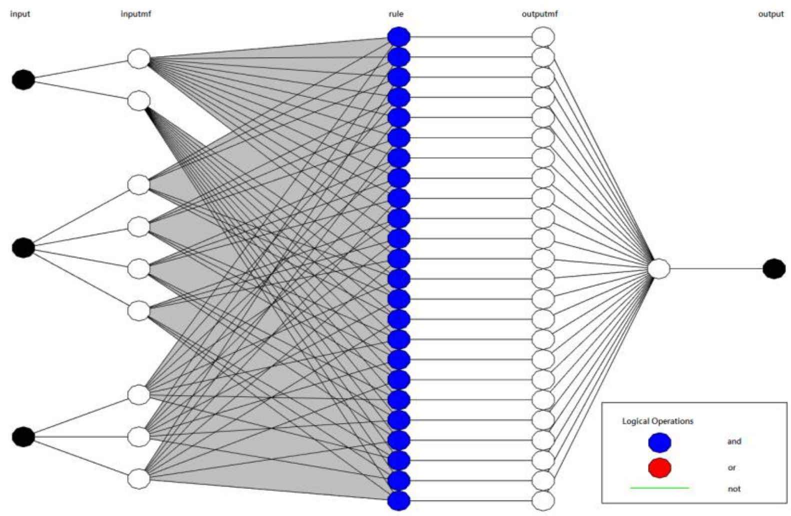


Fig. 6.4. Network frame of AR(1)MO(2) model using the best structure

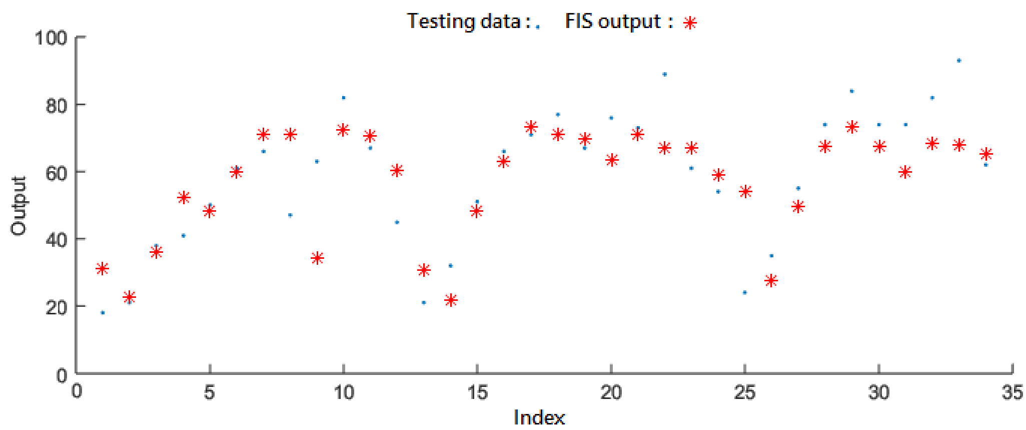


Fig. 6.5. Test results of AR(1)MO(1) model using the best structure

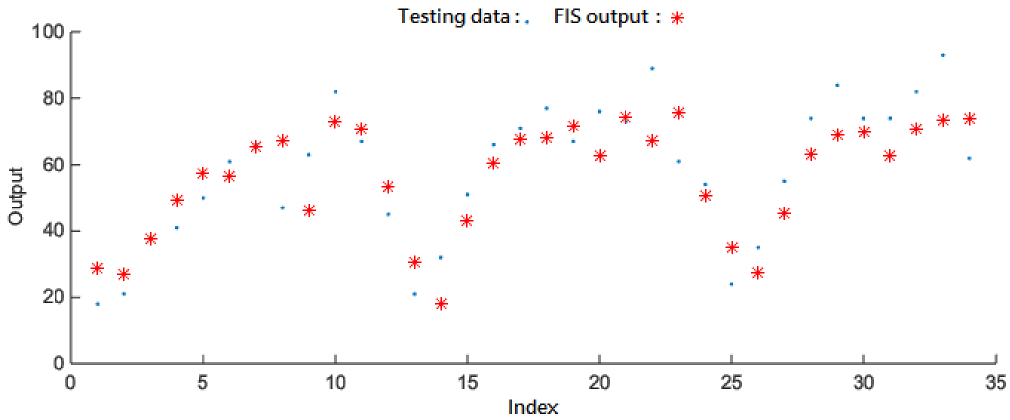


Fig. 6.6. Test results of AR(1)MO(2) model using the best structure

(ii) Performance comparison of the developed ANFIS and ARIMA models

The AR(1)MO(1) and AR(1)MO(2) models are compared with the ARIMA model to evaluate the predicting ability of the developed ANFIS models. The same four-week data set, which is used for training and testing the AR(1)MO(1) and AR(1)MO(2) models, is also used for building the ARIMA(p,q)(r,s) model. By selecting the maximum number of the autoregressive (AR), moving average (MA), seasonal autoregressive (SAR) and seasonal moving average (SMA) terms, say p, q, r, s, of the ARIMA model, as well as the periodicity of the seasonal terms using thte EViews software package, an ARIMA(3,2)(1,1) model, which obtains the lowest Akaike information criterion (AIC) value, is selected after generating 100 ARMA models, as shown in Figs. 6.7 and 6.8. Then, another one-week historical data set, consisting of a total of 84 e-order arrival figures in a two-hour interval, is used for comparison of the AR(1)MO(1), AR(1)MO(2), and ARIMA(3,2)(1,1) models. Table 6.4 shows the test results of the three models with respect to RMSE, MAD, and MAPE, as introduced in section 3.6.2.3. Figs. 6.9 and 6.10 show a comparison of the actual and predicted e-order arrival figures using the AR(1)MO(1), AR(1)MO(2) and ARIMA(3,2)(1,1) models for the 84 observations. It is shown that both AR(1)MO(1) and AR(1)MO(2) outperform ARIMA in predicting the e-order arrival. In addition to these error measures, the accuracy of each prediction value is also considered. The case company management suggests that a predicted e-order arrival with ±10kg error is generally acceptable. Thus, by counting the number of accurate items (the difference between predicted value and actual value being less than 10) in the 84 observations, the item accuracy of AR(1)MO(1) and AR(1)MO(2) achieves levels of 85.7% and 86.9% respectively, which is better than that of ARIMA model (79.8%), as depicted in Table 6.5. This further confirms the satisfactory predicting ability of the proposed ANFIS models.

Automatic ARIMA Forecasting
Selected dependent variable: LOG(EORDER)
Date: 04/07/18 Time: 18:07
Sample: 1 336
Included observations: 336
Forecast length: 84

Number of estimated ARMA models: 100
Number of non-converged estimations: 0
Selected ARMA model: (3,2)(1,1)
AIC value: -0.022905573286

Fig. 6.7. Automatic ARIMA model selection result for case study 1

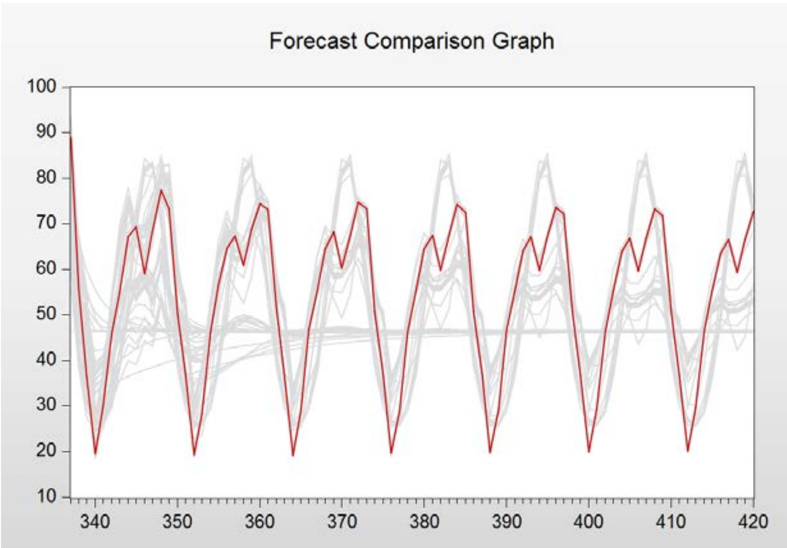


Fig. 6.8. Forecast comparison graph showing the selected model (in red) and other ARIMA models (in grey) for case study 1

Table 6.4. Error analysis for model comparison for case study 1

	Model comparison		
Error measures:	AR(1)MO(1)	AR(1)MO(2)	ARIMA
RMSE	6.79	7.40	9.56
MAD	4.66	5.20	6.54
MAPE (%)	10.65%	11.79%	14.79%

Table 6.5. Item accuracy comparison for case study 1

	Model comparison		
	AR(1)MO(1)	AR(1)MO(2)	ARIMA
No. of accurate items	72	73	67
No. of inaccurate items	12	11	17
Total number of items	84	84	84
Item accuracy	85.7%	86.9%	79.8%

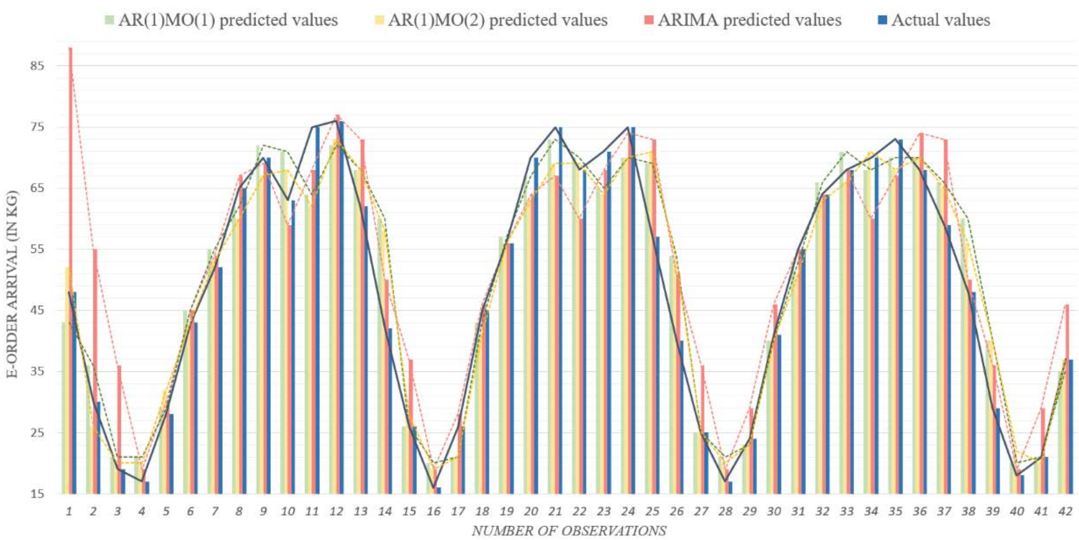


Fig. 6.9. Comparison of actual and predicted e-order arrival using AR(1)MO(1), AR(1)MO(2) and ARIMA model for observation no. 1-42

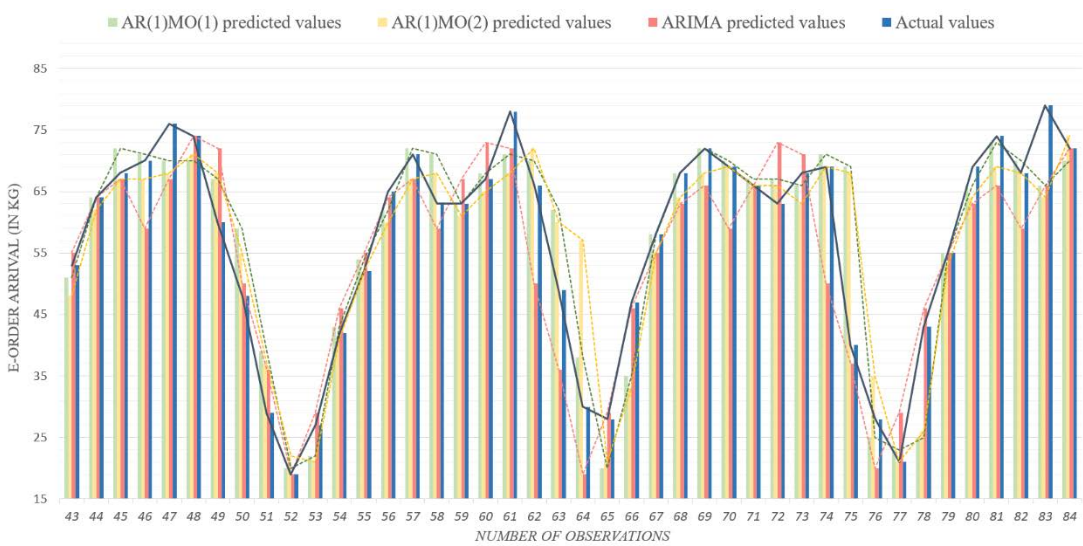


Fig. 6.10. Comparison of actual and predicted e-order arrival using AR(1)MO(1), AR(1)MO(2) and ARIMA model for observation no. 43-84

(iii) Order handling performance comparison

The deployment of EF-DSS, integrating the AR(1)MO(2) ANFIS models, improves the order handling performance in terms of the order handling efficiency and resource management, which are respectively measured by the number of e-orders processed within a designated period, and the traveling distance per worker. The results of a before-and-after comparison of the e-order handling performance in the e-fulfilment centres is shown in Table 6.6. Before the introduction of EF-DSS, e-orders were processed individually upon receiving notification from the retailers. The number of processed orders within a half working day is, on average, 362 orders. After the implementation of EF-DSS, the average number of processed orders within a half working day is 569 orders, a 57% improvement of the order handling efficiency. Besides, better resource management is achieved as the traveling distance per worker per working day is reduced from 978 meters to 467 meters, a 52% reduction. The number of visits to the storage area per day for a worker is also reduced from 16 times to only 5 times. The reduction of traveling distance is credited to the re-engineered flow of e-order handling, in which an e-order is no longer picked from its storage location immediately upon being received from the retailer, but is consolidated in the e-order consolidation pool of the EF-DSS for batch release and picking. Therefore, the total traveling distance and the number of visits to storage locations per day have been drastically reduced.

Table 6.6. A before-and-after comparison of e-order handling and resource management

Order handling and resource allocation improvement	Without EAPS	With EAPS	% of improvement
No. of processed orders (per 0.5 working day)	362 orders	569 orders	57%
Traveling distance per worker (per working day)	978 meters	467 meters	52%
No. of visits to the storage area per worker (per working day)	16 times	5 times	69%

6.2.3 Results and Discussion of the AR-MO-MA-ANFIS Model Parameter Settings in the EBRM from Case Study 3

In Case Study 3, a total of 8 ANFIS-based models are developed under two typologies, as summarized in Table 6.7, for forecasting the arrival frequency of e-commerce orders in the case company's distribution centres. The output of the ANFIS-based models, i.e. the predicted volume of e-commerce order arrivals (in terms of kg) for the upcoming three-hour period in the distribution centres, serves as one of the inputs of another algorithm in the EBRM of the EF-DSS, so as to identify the optimal cut-off time for releasing the grouped orders that are currently consolidated in the E-order consolidation pool of the ECM of the EF-DSS, and pending for batch release to the distribution centres for actual process execution.

Table 6.7. A summary of the ANFIS models developed in Case study 3

Typology	Retailer	Model	Set of input variables
II	1	1A	AR(1), MO(1), MA(2)
		1B	AR(1), MO(1), MA(3)
	2	2A	AR(1), MO(1), MA(2)
		2B	AR(1), MO(1), MA(3)
	3	3A	AR(1), MO(1), MA(2)
		3B	AR(1), MO(1), MA(3)
I	Aggregated e-order arrival of retailer 1, 2 and 3	4A	AR(1), MO(1), MA(2)
		4B	AR(1), MO(1), MA(3)

As discussed in the previous chapter, a model performance comparison framework, which consists of 4 comparisons, is formulated for systematically evaluating the prediction ability of each model and typology. This section provides error analysis of each model for making model comparisons, thereby providing implications through each comparison. **In total, 10 findings are generated using the model performance comparison framework presented in Fig. 5.22.**

(i) ***Comparison 1 – Model A vs Model B****: Model A and B comparison for each individual retailer's ANFIS model*

Through the model training and testing processes for each model developed in Case study 3, the performance of each model under different combinations of model setting is identified and presented in Appendices C to J, where the best model setting is one that gives the **minimum testing error**. A summary of the best model setting for each model, i.e. Models 1A, 1B, 2A, 2B, 3A, 3B, 4A, and 4B, is shown in Table 6.8. Using the corresponding training dataset for each retailer, each model is then tested with the testing dataset. The test results of the best models for each retailer's dataset and for the dataset aggregating all retailers are respectively depicted in Figs. 6.11 to 6.14. Several findings can be obtained from observing Table 6.8, they are:

Finding 1 (Output function) – *"Constant" output function is far better than the "Linear" funcation:* When the training error is very low and the testing error extremely high, the model is said to be overfitting with the training data. That means the model is a good forecasting model. In performing model training and testing in this case study, overfitting training dataset is an obvious problem found in models with "Linear" output function. This finding is consistent with the model training and testing results in Case study 2 in which, the problem of overfitting with training dataset also exists when the output function is set as "Linear". Therefore, setting the output function as "Constant" when deploying the EF-DSS is more appropriate.

Finding 2 (Types of MFs) – *No specific type of membership function gives a better predicting performance:* Triangle (Tri), trapezoid (Trap), Gbell, and Guass membership functions have been used for model training and testing. The results, as shown in Table 6.8, indicate that there is no specific type of membership function that outperforms the others. In this regard, different types of MFs should be tested during the model training and testing process.

Finding 3 (No. of MFs) – Input with two membership functions generally gives better predicting performance: During the model training and testing process, the number of MFs for an input variable is set as either 2, 3, or 4. MFs higher than 4 would hugely increase the computation time, require stronger computation power, and require a larger training dataset. Results shown in Table 6.8 reveal that the majority of the time, the best model can be obtained with some of the input variables with 2 MFs. Therefore, in deploying EF-DSS, to minimize the effort and time spent in the model and training process, configuring the inputs to have two MFs is good enough.

Finding 4 (Model A vs B) – Model B performs better than Model A in all retailer's models: By investigating the overall performance between model A (AR(1)MO(1)MA(2)) and model B (AR(1)MO(1)MA(3)), it is found that model B outperforms model A in all the retailer's dataset, as well as in the aggregated retailer's e-order arrival dataset. This suggests that configuring a three-period moving average input variable gives a better prediction performance than that of a two-period moving average. Models 1B, 2B, 3B and 4B are found to be the best models for the prediction of the e-order arrival of retailers 1, 2, 3 and the aggregated dataset respectively.

Table 6.8. Best model setting for each ANFIS model

Typology	**Retailer**	**Model**	**Testing error**	**No. of MFs respectively for AR,MO,MA**	**Types of MFs**	**Output function**
II	1	1A	10.1776	2,2,3	Gbell	Constant
		1B*	9.2656	2,4,2	Tri	Constant
	2	2A	11.5383	2,2,2	Tri	Constant
		2B*	11.1557	2,2,2	Tri	Constant
	3	3A	10.8748	3,2,2	Guass	Constant
		3B*	10.3066	4,2,2	Gbell	Constant
I	Aggregated e-order arrival of retailer 1, 2 and 3	4A	28.2246	2,2,4	Gbell	Constant
		4B*	27.4482	4,2,2	Gbell	Constant

**represents the best model for each retailer's dataset (based on testing error)*

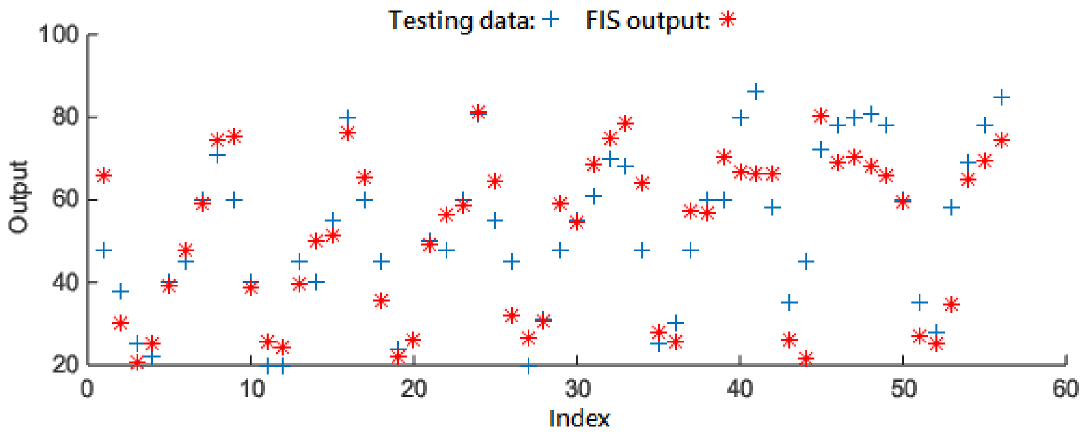


Fig. 6.11. Test results of the best model (Model 1B) for retailer's 1 dataset

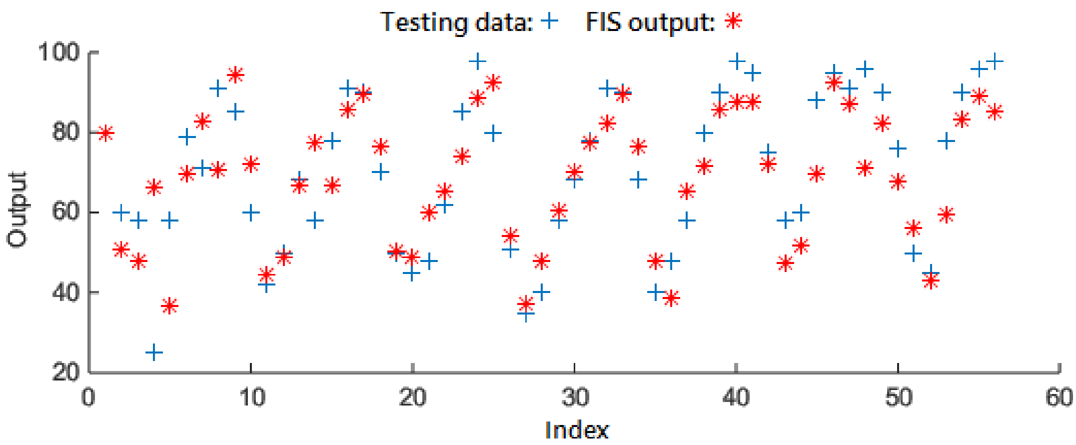


Fig. 6.12. Test results of the best model (Model 2B) for retailer's 2 dataset

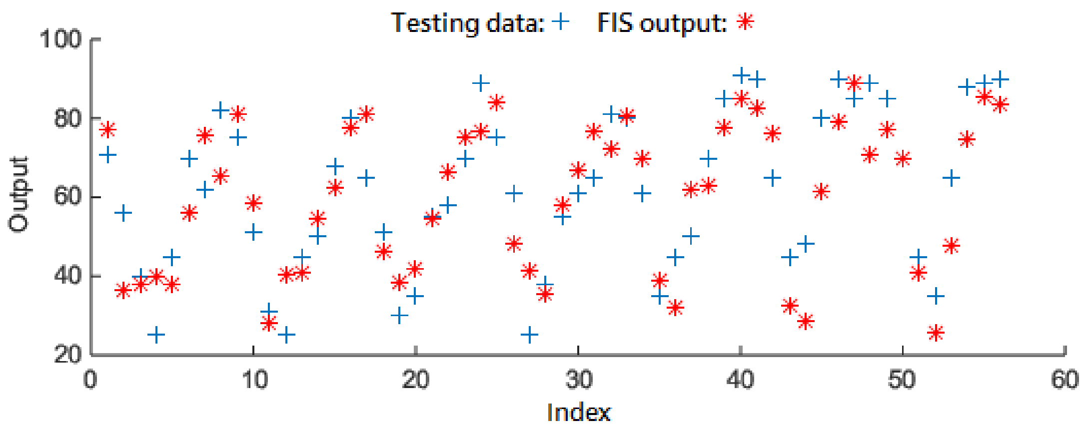


Fig. 6.13. Test results of the best model (Model 3B) for retailer's 3 dataset

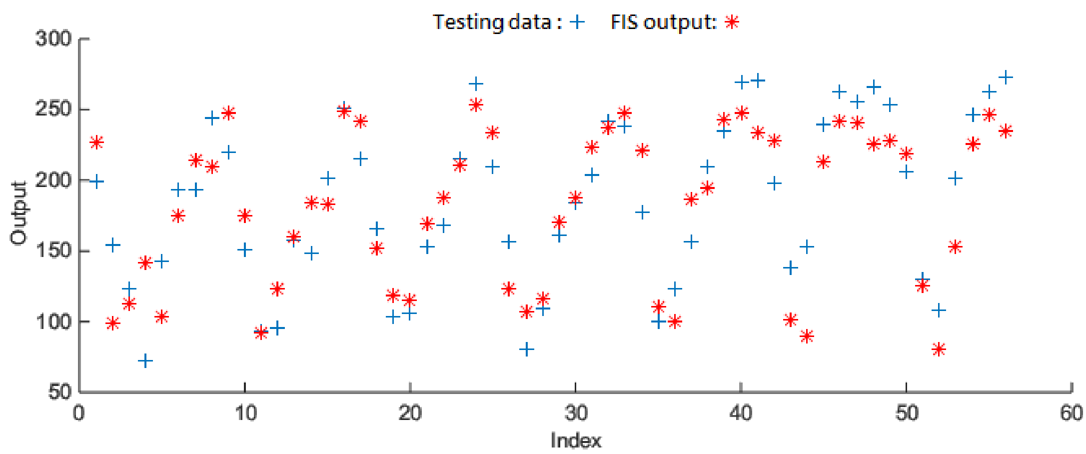


Fig. 6.14. Test results of the best model (Model 4B) for the dataset aggregating retailers 1, 2 and 3

(ii) ***Comparison 2 – Typology 1 vs Typology 2 for ANFIS model****: ANFIS model prediction performance comparison between typology 1 and 2*

With the best model setting determined for each model, the prediction performance of models A and B under each retailer's dataset and the aggregated dataset is compared. Based on the training error (the lower the better), the best model for each retailer's dataset is identified as summarized in Table 6.8. **In this comparison, to compare the prediction performance between typology I (aggregating all retailers for the prediction) and II (Separately predicting each individual retailer), another set of real data, which consists of one-week e-order arrivals in a three-hour horizon, is gathered in the distribution centre of the case company.** The best model for retailers 1, 2, and 3, as well as for the aggregated dataset, i.e. Models 1B, 2B, 3B and 4B respectively, are used to predict a one-week actual e-order arrivals data. The one-week of data for each retailer for performance evaluations of Models 1B, 2B, 3B is respectively shown in Tables 6.9 to 6.11. By summing up the one-week data of each retailer, an aggregated dataset for all retailers is formulated as shown in Table 6.12, for performance evaluation of Model 4B.

Table 6.9. Another one-week e-order arrival dataset for Retailer 1

				Time				
Date	0-3	3-6	6-9	9-12	12-15	15-18	18-21	21-24
				Week 1				
Mon	62	33	20	26	45	52	68	79
Tue	69	41	25	17	37	49	61	77
Wed	65	38	19	30	59	70	74	81
Thu	63	37	21	31	55	64	73	79
Fri	68	41	30	32	55	66	74	81
Sat	64	35	28	39	56	68	79	84
Sun	65	31	30	46	64	70	79	77

Table 6.10. Another one-week e-order arrival dataset for Retailer 2

				Time				
Date	0-3	3-6	6-9	9-12	12-15	15-18	18-21	21-24
				Week 1				
Mon	77	55	29	38	52	69	81	92
Tue	76	57	41	43	66	79	94	96
Wed	83	52	28	45	60	79	88	90
Thu	75	50	29	45	67	79	93	95
Fri	83	50	37	56	73	78	89	95
Sat	97	72	43	44	65	78	89	92
Sun	89	79	49	38	48	65	83	90

Table 6.11. Another one-week e-order arrival dataset for Retailer 3

				Time				
Date	0-3	3-6	6-9	9-12	12-15	15-18	18-21	21-24
				Week 1				
Mon	77	52	27	44	57	77	81	83
Tue	68	48	32	46	56	77	83	89
Wed	72	51	24	36	55	74	84	90
Thu	70	45	25	41	62	78	83	91
Fri	79	48	18	33	56	65	77	82
Sat	72	61	40	38	57	70	83	89
Sun	80	61	38	29	51	66	79	87

Table 6.12. The one-week e-order arrival dataset that aggregates e-order arrival for Retailer 1, 2 and 3

	Time							
Date	**0-3**	**3-6**	**6-9**	**9-12**	**12-15**	**15-18**	**18-21**	**21-24**
				Week 1				
Mon	216	140	76	108	154	198	230	254
Tue	213	146	98	106	159	205	238	262
Wed	220	141	71	111	174	223	246	261
Thu	208	132	75	117	184	221	249	265
Fri	230	139	85	121	184	209	240	258
Sat	233	168	111	121	178	216	251	265
Sun	234	171	117	113	163	201	241	254

Using the one-week dataset for performance evaluation, the prediction performance of Models 1B, 2B, 3B and 4B, in terms of RMSE, MAD and MAPE error measures is summarized in Table 6.13. The same as in Case study 2, item accuracy is also calculated to identify the percentage of observations that is within a specified range of error. For the individual datasets of retailers 1, 2 and 3, an observation with mean absolute deviation (MAD) less than 10 is considered to be accurate. As the dataset that aggregates the three retailer's dataset sums up three individual datasets for retailers 1, 2 and 3, an observation with mean absolute deviation (MAD) less than 30 is considered to be accurate. A model comparison in terms of item accuracy is shown in Table 6.14. Graphical comparisons between the predicted and actual e-order arrival for Models 1B, 2B, 3B and 4B are respectively shown in Figs. 6.15 to 6.18.

Several findings can be deduced from Tables 6.13 and 6.14:

Finding 5 (Model performance in Typology II) – From Table 6.13, for each individual retailer's dataset, models 1B, 2B and 3B performs well in forecasting the e-order arrival of retailers 1, 2 and 3 respectively. For instance, as the value of MAD indicates the average absolute error between the predicted and actual e-order arrival figure (in kg), the MAD values of 4.67, 6.11, and 4.26 respectively for models 1B, 2B and 3B indicates that there is only 4 to 6 kilograms of forecasting error in predicting the next three-hour e-order arrival. Furthermore, as shown in Table 6.14, the overall item accuracy is found to be more than 85%. Models 1B and 3B even surpass 90% item accuracy, as less than 4 out of 56 items in total are inaccurate. Such prediction performance is very satisfactory.

Finding 6 (Model performance in Typology I) – From Table 6.13, the MAD for Model 4B is relatively larger than that in Models 1B, 2B and 3B. However, it is noted that this phenomenon is justifiable because the dataset for model 4B is an aggregated dataset that sums up the datasets of retailers 1, 2, and 3. As displayed in Table 6.12 – the one-week e-order arrival dataset that aggregates e-order arrivals for retailers 1, 2 and 3, it is obvious that the range of values is much larger than that in each individual dataset shown in Tables 6.9 to 6.11. Thus, larger values of RMSE and MAD do not imply poor prediction performance for Model 4B where the e-order arrival figures are aggregated. In addition, the mean absolute percentage error (MAPE) is only 6%, which is even lower than in Models 1B, 2B and 3B. This suggests that, in such a large range of values in the dataset, the mean percent deviation from the actual figures is even smaller than Models 1B, 2B and 3B, which respectively have MAPE values of 10.95%, 11.13% and 7.29%. Hence, in terms of MAPE, typology I (aggregating e-order arrival for prediction) is statistically better than typology II.

Table 6.13. Error analysis for model comparison for Model 1B to 4B

Model performance comparison				
Typology	I	II	II	II
Error measures:	4B	1B	2B	3B
RMSE	12.73	5.42	7.42	5.14
MAD	9.92	4.67	6.11	4.26
MAPE (%)	6.00%	10.95%	11.13%	7.29%

Table 6.14. Item accuracy comparison for Model 1B to 4B

Model performance comparison				
Typology	I	II	II	II
Model	4B	1B	2B	3B
No. of accurate items	56*	53+	49+	52+
No. of inaccurate items	0	3	7	4
Total number of items	56	56	56	56
Item accuracy	**100%**	**94.6%**	**87.5%**	**92.9%**

+ There are a total of 56 observations in a one-week dataset. For individual dataset for each retailer, an observation with MAD less than 10 is considered to be accurate.
** An observation with MAD less than 30 is considered to be accurate for Model 4B as the dataset aggregates 3 retailer's data.*

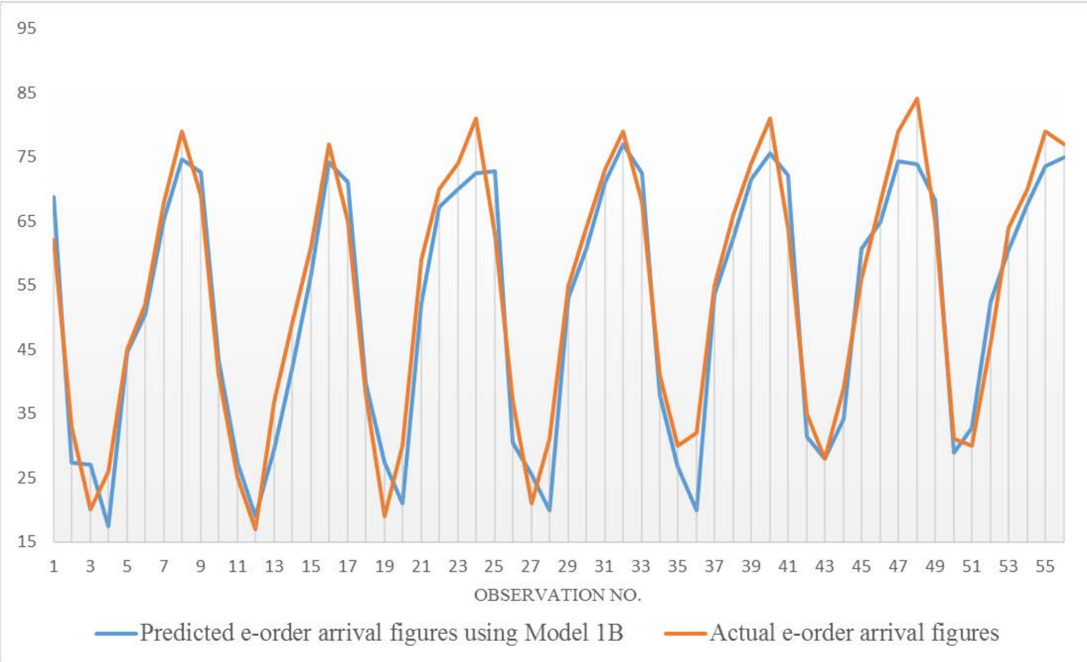


Fig. 6.15. A graphical comparison between actual and predicted e-order arrival figures for retailer 1 under Typology II

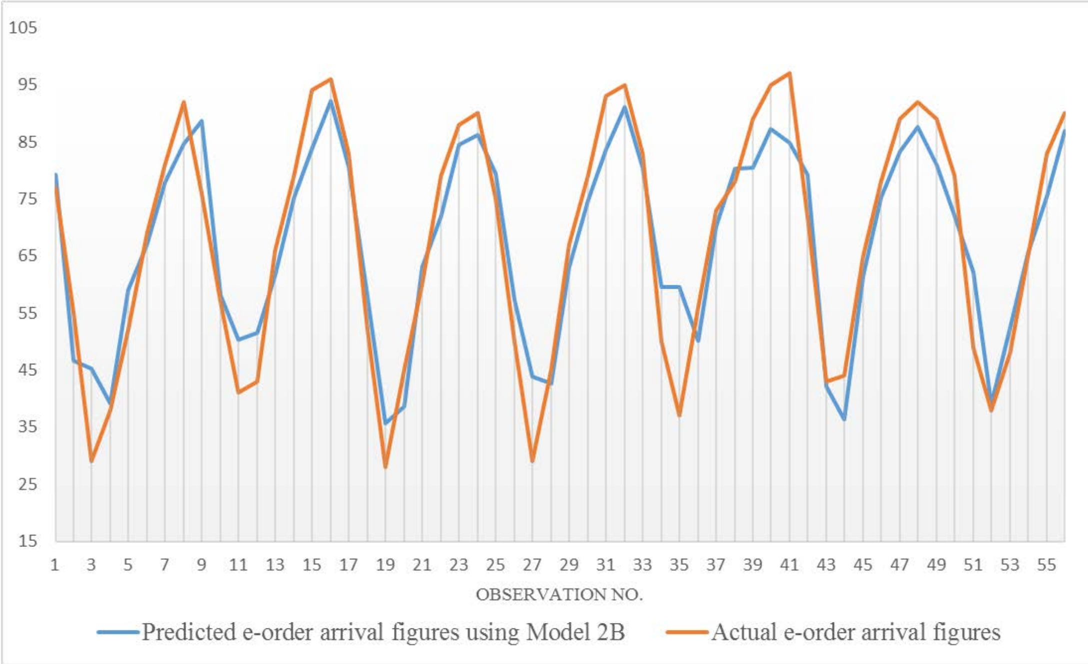


Fig. 6.16. A graphical comparison between actual and predicted e-order arrival figures for retailer 2 under Typology II

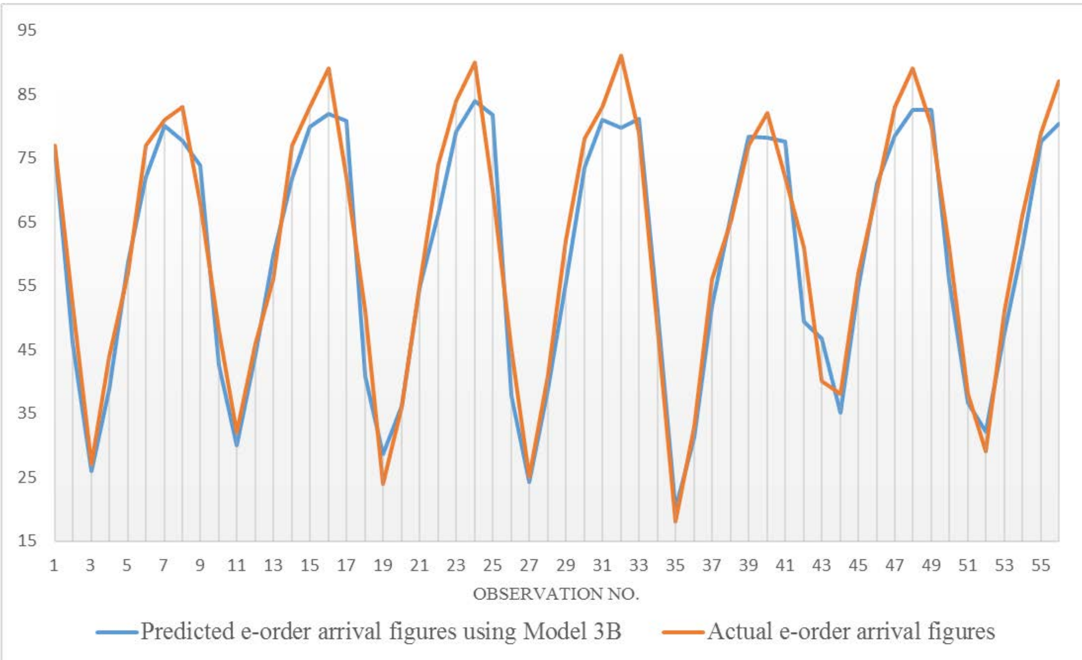


Fig. 6.17. A graphical comparison between actual and predicted e-order arrival figures for retailer 3 under Typology II

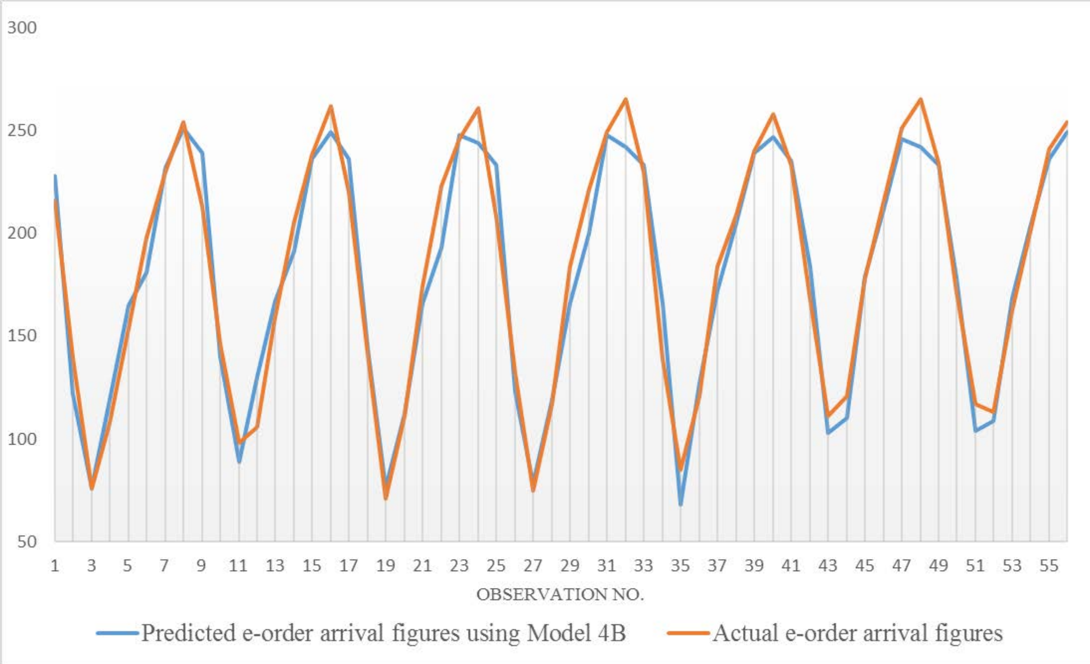


Fig. 6.18. A graphical comparison between actual and predicted e-order arrival figures for aggregated dataset under Typology I

Finding 7 (Typology I vs II) – Recall that, in typology I, model 4B already predicts the total e-order arrival figures in the coming period, disregarding how many orders are from a specific retailer. In typology II, the e-order arrival figures for retailers 1, 2, and 3 are separately predicted by models 1B, 2B, and 3B. Therefore, to compare the prediction performance between typologies I and II, the total e-order arrival figures have to be computed by summing up the individual e-order arrival figures predicted for retailers 1, 2 and 3, and separately predicted by models 1B, 2B and 3B in Typology II, as illustrated in Fig. 5.22. Then, the prediction accuracy using typologies I and II can be compared with respect to the one-week actual e-order arrival data that aggregates the e-order arrivals for retailers 1, 2, and 3, as shown in Table 6.12. The error analysis results in Table 6.15 show that typology I (using one aggregated dataset) has a lower error in terms of RMSE, MAD, and MAPE than that of typology II (using three separate datasets and then adding up each predicted value). Nevertheless, it is noticeable that the error produced by typologies I and II are actually very close, and both typologies give a small error, reflecting a generally high precision in forecasting the e-order arrival of the next period using both typologies. Furthermore, the item accuracy comparison, as shown in Table 6.16, indicates that among the 56 observations in the one-week dataset, none of the observation has an error of more than 30kg. Thus, both typologies give 100% item accuracy. Based on this finding, a more in-depth discussion on the selection of an appropriate typology for e-order arrival is provided in Section 6.3.2 Managerial and Practical Implication – (i) On the selection of typology I or II for e-order arrival prediction in real practice.

Table 6.15. Error analysis for model comparison for typology I and II

Model performance comparison		
Typology	I	II
Error measures:	4B	Summation of predicted e-order arrival of each retailer by Model 1B, 2B, 3B
RMSE	12.73	13.47
MAD	9.92	11.91
MAPE (%)	6.00%	7.82%

Table 6.16. Item accuracy comparison for typology I and II

Model performance comparison		
Typology	I	II
Model	4B	Summation of predicted e-order arrival of each retailer by Model 1B, 2B, 3B
No. of accurate items	56	56
No. of inaccurate items	0	0
Total number of items	56	56
Item accuracy	**100%**	**100%**

(iii) ***Comparison 3 – Typology 1 vs Typology 2 for ARIMA model****: ARIMA model prediction performance comparison between typology 1 and 2*

For effective prediction performance comparison between the ANFIS and ARIMA approaches, the same eight-week data set used for training and testing the ANFIS models, is also used for building the ARIMA*(p,q)(r,s)* model. The same as in Case study 2, by selecting the maximum number of the autoregressive (AR), moving average (MA), seasonal autoregressive (SAR) and seasonal moving average (SMA) terms, say *p, q, r, s,* of the ARIMA model, as well as the periodicity of the seasonal terms using EViews software package, one ARIMA model is built under typology I for predicting the total e-order arrival, and three ARIMA models are built under typology II for predicting the e-order arrival of retailers 1, 2, and 3 separately.

The best ARIMA model is automatically generated by the E-views software package under each typology setting. Then, with the best ARIMA model generated, another one-week historical data set, identically used in the ANFIS model evaluations, which consists of a total of 56 e-order arrival figures in a three-hour interval, is used for comparison of the ANFIS Models 1B, 2B, 3B, 4B and the ARIMA models. Prediction performance of the ARIMA models are discussed below.

- **Typology I – Dataset aggregated all retailers' data:**

An ARIMA(4,4)(1,1) model, which obtains the lowest Akaike information criterion (AIC) value, is selected after assessing 100 ARMA models, as shown in Fig. 6.19. Dependent variables and the corresponding coefficients of the ARIMA(4,4)(1,1) model are shown in Fig. 6.20. The ARIMA(4,4)(1,1) model is marked in red and is graphically compared with the other ARMA models generated, as shown in Fig. 6.21. A graphical comparison between actual and predicted e-order arrival figures of the one-week dataset using ARIMA is presented in Fig. 6.22.

Automatic ARIMA Forecasting
Selected dependent variable: D(RETAILER123_AGGREGATED)
Date: 11/23/18 Time: 22:18
Sample: 1 448
Included observations: 447
Forecast length: 56

Number of estimated ARMA models: 100
Number of non-converged estimations: 0
Selected ARMA model: (4,4)(1,1)
AIC value: 8.94793147085

Fig. 6.19. Automatic ARIMA model selection result for the dataset aggregating all retailers' data

Dependent Variable: D(RETAILER123_AGGREGATED)
Method: ARMA Maximum Likelihood (BFGS)

Sample: 2 448
Included observations: 447
Convergence achieved after 182 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.939045	13.45029	0.069816	0.9444
AR(1)	-0.270121	0.055517	-4.865554	0.0000
AR(2)	1.247702	0.047002	26.54560	0.0000
AR(3)	0.026832	0.053566	0.500923	0.6167
AR(4)	-0.687363	0.045863	-14.98746	0.0000
SAR(8)	0.999398	0.000679	1472.303	0.0000
MA(1)	0.031256	0.034093	0.916770	0.3598
MA(2)	-1.499515	0.034748	-43.15453	0.0000
MA(3)	0.106959	0.029821	3.586703	0.0004
MA(4)	0.936689	0.033574	27.89889	0.0000
SMA(8)	-0.928088	0.030335	-30.59509	0.0000
SIGMASQ	396.8557	27.50470	14.42865	0.0000

R-squared	0.862432	Mean dependent var	0.514541
Adjusted R-squared	0.858953	S.D. dependent var	53.77043
S.E. of regression	20.19414	Akaike info criterion	8.947281
Sum squared resid	177394.5	Schwarz criterion	9.057417
Log likelihood	-1987.717	Hannan-Quinn criter.	8.990702
F-statistic	247.9152	Durbin-Watson stat	2.011289
Prob(F-statistic)	0.000000		

Fig. 6.20. Details of the ARIMA model selection result for the dataset aggregating all retailers' data

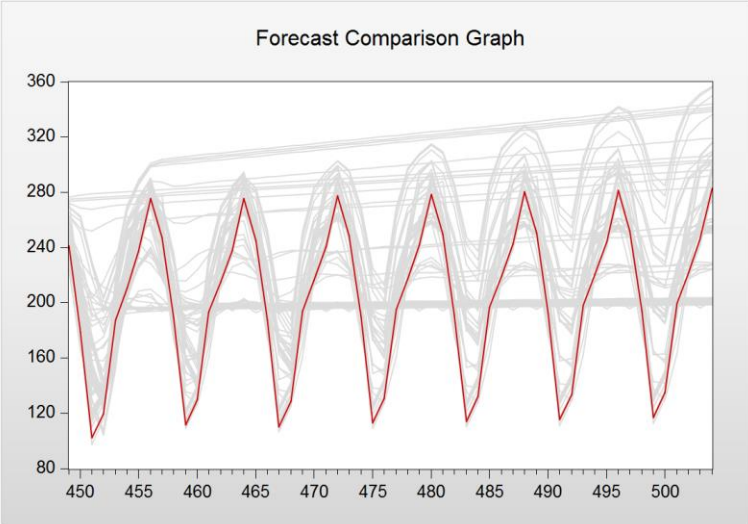


Fig. 6.21. Forecast comparison graph showing the selected model (in red) and other ARIMA models (in grey) (for the dataset aggregating all retailers' data)

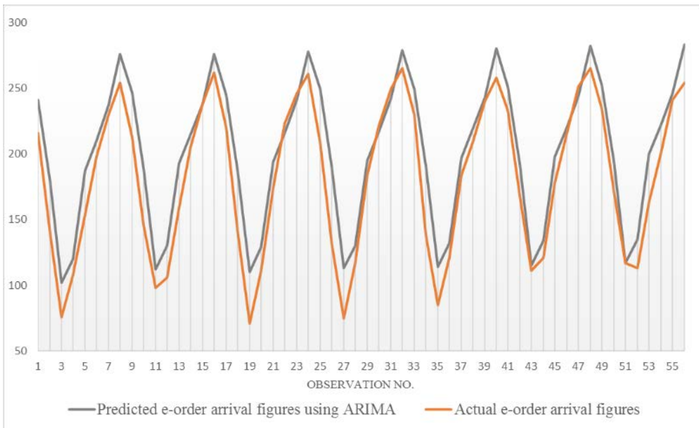


Fig. 6.22. A graphical comparison between actual and predicted e-order arrival figures using ARIMA for the dataset aggregating all retailers' data

- **Typology II – Retailer 1's dataset:**

The same procedures as previously discussed apply to the other datasets. An ARIMA(4,1)(1,1) model, which has the lowest Akaike information criterion (AIC) value, is selected for retailer 1's dataset after assessing 100 ARMA models, as shown in Fig. 6.23. Dependent variables and the corresponding coefficients of the ARIMA(4,1)(1,1) model are shown in Fig. 6.24. The ARIMA(4,1)(1,1) model is marked in red and is graphically compared with other ARMA models generated, as shown in Fig. 6.25. A graphical comparison between actual and predicted e-order arrival figures of the one-week dataset using ARIMA is presented in Fig. 6.26.

Automatic ARIMA Forecasting
Selected dependent variable: D(RETAILER1)

Sample: 1 448
Included observations: 447
Forecast length: 56

Number of estimated ARMA models: 100
Number of non-converged estimations: 0
Selected ARMA model: (4,1)(1,1)
AIC value: 7.13425105392

Fig. 6.23. Automatic ARIMA model selection result for retailer 1's dataset

Dependent Variable: D(RETAILER1)
Method: ARMA Maximum Likelihood (BFGS)

Sample: 2 448
Included observations: 447
Failure to improve objective (non-zero gradients) after 55 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.034842	0.021434	1.625532	0.1048
AR(1)	0.612844	0.046869	13.07561	0.0000
AR(2)	0.012809	0.057612	0.222332	0.8242
AR(3)	-0.021863	0.057814	-0.378158	0.7055
AR(4)	0.191871	0.043258	4.435519	0.0000
SAR(8)	1.000000	3.27E-06	305614.8	0.0000
MA(1)	-0.999778	0.002758	-362.5222	0.0000
SMA(8)	-0.999665	9.26E-05	-10798.84	0.0000
SIGMASQ	64.16831	4.223632	15.19269	0.0000

R-squared	0.804507	Mean dependent var	0.167785
Adjusted R-squared	0.800936	S.D. dependent var	18.13764
S.E. of regression	8.092394	Akaike info criterion	7.134677
Sum squared resid	28683.24	Schwarz criterion	7.217279
Log likelihood	-1585.600	Hannan-Quinn criter.	7.167242
F-statistic	225.3109	Durbin-Watson stat	1.970148
Prob(F-statistic)	0.000000		

Fig. 6.24. Details of the ARIMA model selection result for retailer 1's dataset

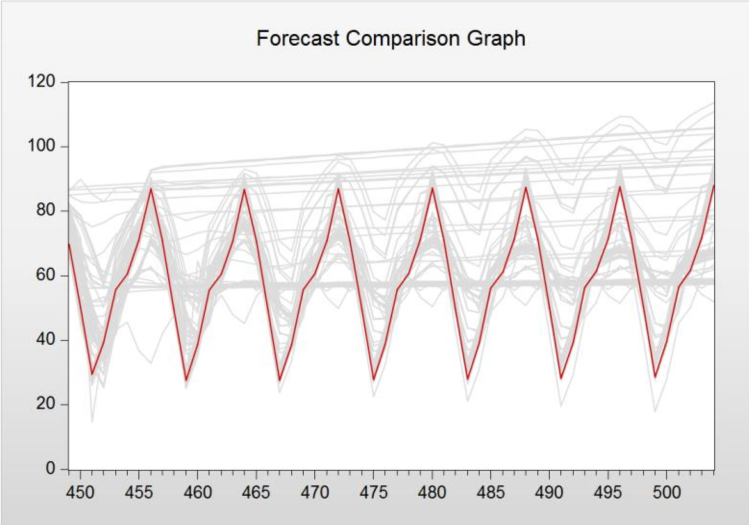


Fig. 6.25. Forecast comparison graph showing the selected model (in red) and other ARIMA models (in grey) (for retailer 1's dataset)

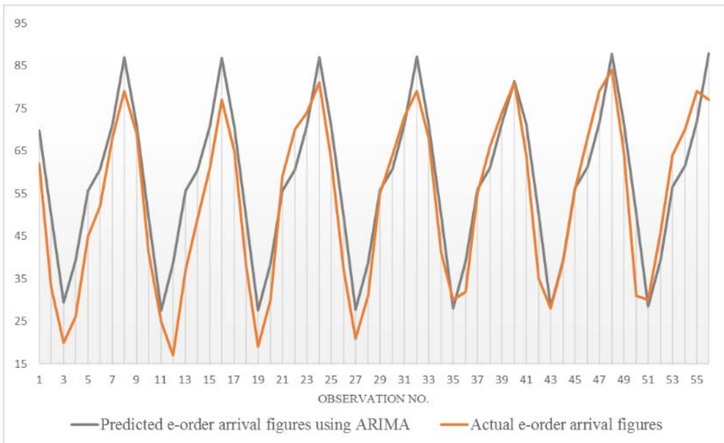


Fig. 6.26. A graphical comparison between actual and predicted e-order arrival figures using ARIMA for retailer 1

- **Typology II – Retailer 2's dataset:**

Similarly, an ARIMA(3,4)(1,1) model is generated and found to be the best one for retailer's 2 dataset. Details are shown in Figs. 6.27 to 6.30.

Automatic ARIMA Forecasting
Selected dependent variable: D(RETAILER2)

Sample: 1 448
Included observations: 447
Forecast length: 56

Number of estimated ARMA models: 100
Number of non-converged estimations: 0
Selected ARMA model: (3,4)(1,1)
AIC value: 7.22365552504

Fig. 6.27. Automatic ARIMA model selection result for retailer 2's dataset

Dependent Variable: D(RETAILER2)
Method: ARMA Maximum Likelihood (BFGS)

Sample: 2 448
Included observations: 447
Convergence achieved after 73 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.329401	4.412525	0.074651	0.9405
AR(1)	0.711363	0.044929	15.83293	0.0000
AR(2)	0.814445	0.032024	25.43194	0.0000
AR(3)	-0.856836	0.044020	-19.46455	0.0000
SAR(8)	0.999313	0.000675	1480.540	0.0000
MA(1)	-1.167189	0.093775	-12.44669	0.0000
MA(2)	-0.569822	0.077280	-7.373431	0.0000
MA(3)	1.267778	0.109807	11.54550	0.0000
MA(4)	-0.329588	0.063648	-5.178330	0.0000
SMA(8)	-0.918333	0.027787	-33.04951	0.0000
SIGMASQ	72.02771	4.259937	16.90816	0.0000

R-squared	0.807776	Mean dependent var	0.178971
Adjusted R-squared	0.803367	S.D. dependent var	19.37902
S.E. of regression	8.593307	Akaike info criterion	7.223656
Sum squared resid	32196.39	Schwarz criterion	7.324613
Log likelihood	-1603.487	Hannan-Quinn criter.	7.263458
F-statistic	183.2181	Durbin-Watson stat	1.940395
Prob(F-statistic)	0.000000		

Fig. 6.28. Details of the ARIMA model selection result for retailer 2's dataset

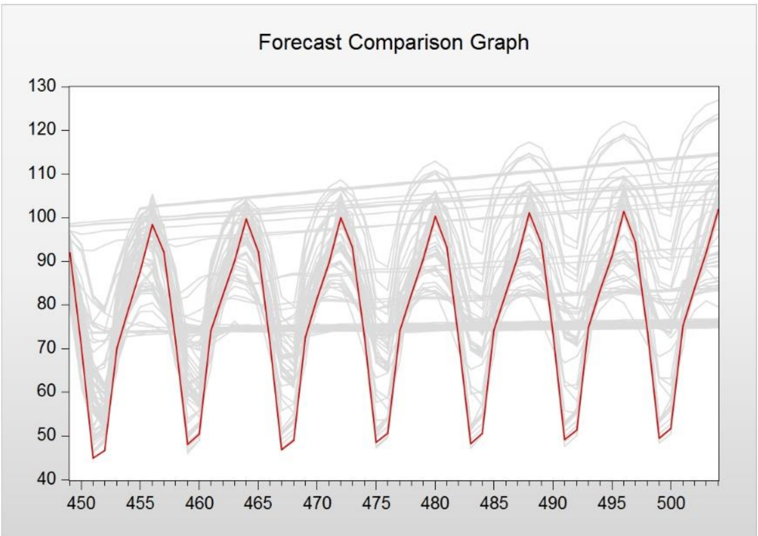


Fig. 6.29. Forecast comparison graph showing the selected model (in red) and other ARIMA models (in grey) (for retailer 2's dataset)

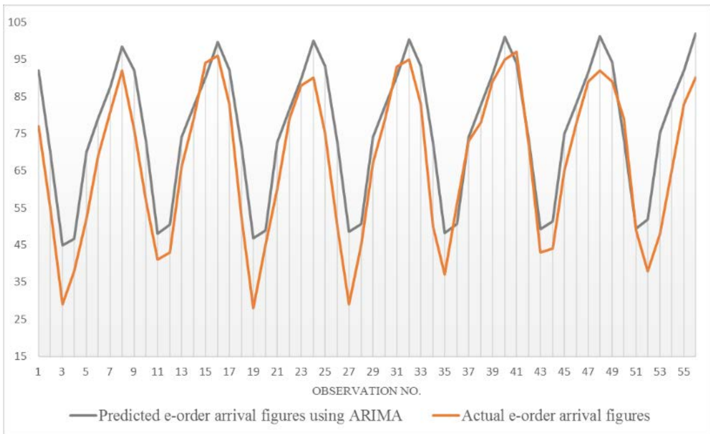


Fig. 6.30. A graphical comparison between actual and predicted e-order arrival figures using ARIMA for retailer 2

- **Typology II – Retailer 3's dataset:**

Lastly, an ARIMA(3,4)(1,1) model is generated and found to be the best one for retailer's 3 dataset. Details are shown in Figs. 6.31 to 6.34.

Automatic ARIMA Forecasting
Selected dependent variable: D(RETAILER3)
Date: 11/23/18 Time: 22:05
Sample: 1 448
Included observations: 447
Forecast length: 56

Number of estimated ARMA models: 100
Number of non-converged estimations: 0
Selected ARMA model: (3,4)(1,1)
AIC value: 7.07473644801

Fig. 6.31. Automatic ARIMA model selection result for retailer 3's dataset

Dependent Variable: D(RETAILER3)
Method: ARMA Maximum Likelihood (BFGS)

Sample: 2 448
Included observations: 447
Convergence achieved after 170 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.038992	0.038687	1.007879	0.3141
AR(1)	-1.048651	0.047895	-21.89478	0.0000
AR(2)	0.620789	0.076317	8.134388	0.0000
AR(3)	0.775231	0.042227	18.35853	0.0000
SAR(8)	0.999171	0.000647	1543.436	0.0000
MA(1)	0.741454	0.694351	1.067836	0.2862
MA(2)	-1.106388	0.501530	-2.206026	0.0279
MA(3)	-0.824062	0.378265	-2.178534	0.0299
MA(4)	0.189002	0.050929	3.711110	0.0002
SMA(8)	-0.911654	0.029264	-31.15233	0.0000
SIGMASQ	62.52567	54.41702	1.149010	0.2512

R-squared	0.826620	Mean dependent var	0.167785
Adjusted R-squared	0.822643	S.D. dependent var	19.01147
S.E. of regression	8.006445	Akaike info criterion	7.089729
Sum squared resid	27948.98	Schwarz criterion	7.190686
Log likelihood	-1573.554	Hannan-Quinn criter.	7.129531
F-statistic	207.8703	Durbin-Watson stat	1.945942
Prob(F-statistic)	0.000000		

Fig. 6.32. Details of the ARIMA model selection result for retailer 3's dataset

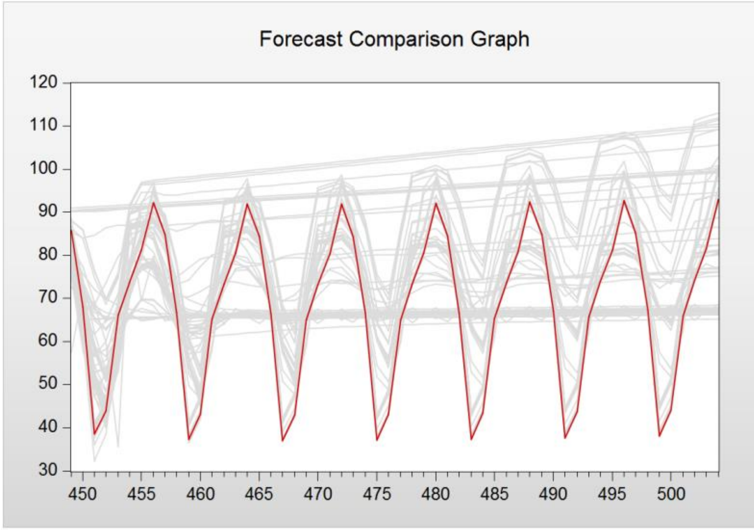


Fig. 6.33. Forecast comparison graph showing the selected model (in red) and other ARIMA models (in grey) (for retailer 3's dataset)

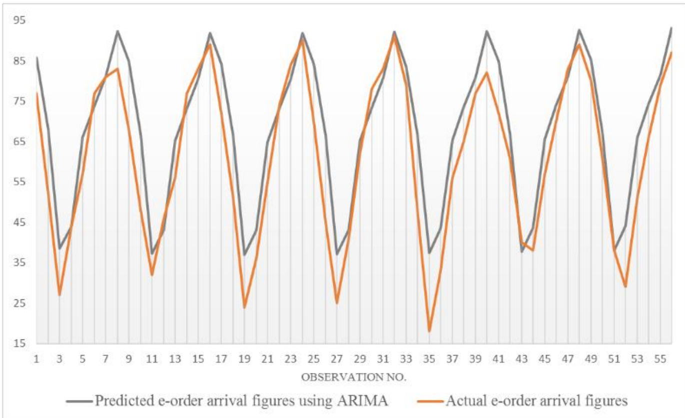


Fig. 6.34. A graphical comparison between actual and predicted e-order arrival figures using ARIMA for retailer 3

With the ARIMA models developed for each typology, error analysis is then performed by comparing the predicted e-order arrival figures with respect to the one-week actual dataset. The findings are discussed below.

Finding 8 (Typology I vs II in ARIMA) – In typology I, one ARIMA model is generated using the dataset that aggregates all retailer's e-order arrival data. In typology II, three different ARIMA models are generated using each retailer's dataset to predict the e-order arrival figures of the corresponding retailers.

Therefore, to compare the prediction performance between typologies I and II, the total e-order arrival figures have to be computed by summing up the individual e-order arrival figures for retailers 1, 2 and 3 separately predicted by ARIMA(4,1)(1,1), ARIMA(3,4)(1,1), and ARIMA(3,4)(1,1) in typology II. Then, the prediction accuracy using typologies I and II can be compared with respect to the one-week actual e-order arrival data that aggregates the e-order arrival for retailers 1, 2 and 3, as shown in Table 6.12.

The error analysis results in Table 6.17 shows that typology I (using one aggregated dataset) has a lower error in terms of RMSE, MAD, and MAPE than that of typology II (using three separate datasets and then adding up each predicted value), though it is noticeable that the errors produced by typologies I and II are actually very close. Furthermore, the item accuracy comparison in Table 6.18 also shows that typology I provides a slightly higher item accuracy. Therefore, statistical error analysis suggests that typology I has a slightly better prediction performance.

Table 6.17. Error analysis for ARIMA model comparison

	Model performance comparison				
Typology	I	II	II	II	II
ARIMA model:	ARIMA(4,4)(1,1) for dataset aggregated all retailers	Summation of separated forecasting figures	ARIMA(4,1)(1,1) for Retailer 1	ARIMA(3,4)(1,1) for Retailer 2	ARIMA(3,4)(1,1) Retailer 3
RMSE	24.27	25.08	8.72	11.33	9.55
MAD	20.23	21.03	7.23	9.36	7.74
MAPE	13.82%	14.56%	18.41%	17.43%	16.81%

Table 6.18. Item accuracy comparison for ARIMA models

	Model performance comparison				
Typology	I	II	II	II	II
ARIMA model:	ARIMA (4,4)(1,1) for dataset aggregated all retailers	Summation of separated forecasting figures	ARIMA (4,1)(1,1) for Retailer 1	ARIMA (3,4)(1,1) for Retailer 2	ARIMA (3,4)(1,1) for Retailer 3
No. of accurate items	44*	43*	45^{+}	35^{+}	40^{+}
No. of inaccurate items	12	13	11	21	16
Total number of items	56	56	56	56	56
Item accuracy	78.6%	76.8%	80.4%	62.5%	71.4%

+ There are a total of 56 observations in a one-week dataset. For individual dataset for each retailer, an observation with MAD less than 10 is considered to be accurate.
** An observation with MAD less than 30 is considered to be accurate for Model 4B as the dataset aggregates 3 retailer's data.*

(iv) ***Comparison 4 (the final comparison) – ANFIS vs ARIMA****: Prediction performance comparison between the ANFIS and ARIMA approaches*

Finally, to compare the prediction performance between the proposed ANFIS and the conventional ARIMA approach, several findings are identified, as discussed below:

Finding 9 (Model 1B to 4B vs ARIMA models in Typology II) – In typology II, when retailers' e-order arrival figures are separately forecasted by their corresponding ANFIS and ARIMA models, the error analysis shown in Tables 6.19 and 6.20 clearly indicates that the ANFIS-based approach outperforms the ARIMA-based approach, in terms of all error measures, i.e. RMSE, MAD, MAPE, and item accuracy. Therefore, ANFIS is statistically proven to be a better e-order arrival prediction model for predicting individual retailer's e-order arrival.

Table 6.19. Error analysis for ANFIS and ARIMA model comparison in typology II

Model performance comparison						
	Retailer 1		Retailer 2		Retailer 3	
Model:	1B	ARIMA (4,1)(1,1)	2B	ARIMA (3,4)(1,1)	3B	ARIMA (3,4)(1,1)
RMSE	5.42	8.72	7.42	11.33	5.14	9.55
MAD	4.67	7.23	6.11	9.36	4.26	7.74
MAPE	10.95%	18.41%	11.13%	17.43%	7.29%	16.81%

Table 6.20. Item accuracy comparison for ANFIS and ARIMA model comparison in typology II

	Model performance comparison					
	Retailer 1		Retailer 2		Retailer 3	
Model:	1B	ARIMA (4,1)(1,1)	2B	ARIMA (3,4)(1,1)	3B	ARIMA (3,4)(1,1)
No. of accurate items	53	45	49	35	52	40
No. of inaccurate items	3	11	7	21	4	16
Total number of items	56	56	56	56	56	56
Item accuracy	94.6%	80.4%	87.5%	62.5%	92.9%	71.4%

Finding 10 (ANFIS vs ARIMA) – Statistically, typology I (aggregating all retailer's datasets for prediction) has a slightly better prediction result than typology II in both the ANFIS-based and ARIMA-based approaches. Therefore, the ultimate comparison between ANFIS and ARIMA is by comparing the prediction performance of ANFIS model in typology I with that of ARIMA model in typology I. In other words, model 4B is compared with ARIMA(4,4)(1,1).

As shown in Table 6.21, the error using ANFIS (Model 4B) is much lower than that of ARIMA(4,4)(1,1), in terms of all error measures, i.e. RMSE, MAD and MAPE. Interestingly, the RMSE, MAD and MAPE using ARIMA(4,4)(1,1) are double of those using the ANFIS-based approach. Hence, the proposed ANFIS-based approach gives a statistically 200% better prediction performance than the conventional ARIMA model in forecasting e-order arrivals. As for item accuracy comparison, as shown in Table 6.22, the ARIMA model also bares no comparison with the proposed ANFIS model with only 78% item accuracy for ARIMA and 100% item accuracy for ANFIS.

All in all, the proposed ANFIS approach that integrates the elements of autoregressive (AR), momentum (MO) and moving average (MA) for model construction is far better than the conventional ARIMA approach in forecasting e-order arrival in distribution centres.

Table 6.21. Error analysis for ANFIS and ARIMA model comparison in typology I

Model performance comparison		
Approach	ANFIS	ARIMA
Model	4B	ARIMA(4,4)(1,1)
RMSE	12.73	24.27
MAD	9.92	20.23
MAPE (%)	6.00%	13.82%

Table 6.22. Item accuracy comparison for ANFIS and ARIMA model comparison in typology I

Model performance comparison		
Approach	ANFIS	ARIMA
Model	4B	ARIMA(4,4)(1,1)
No. of accurate items	56	44
No. of inaccurate items	0	12
Total number of items	56	56
Item accuracy	**100%**	**78.6%**

6.3 Implications of the Research

6.3.1 Research Implications

The research implications are discussed in four aspects: (i) the selection of forecasting techniques, (ii) the selection of typologies 1 or II for e-order arrival prediction in real practice, (iii) the selection of variables for forecasting e-order arrival figures, and (iv) the process of identifying the best parameter setting of the ANFIS model.

(i) On the selection of forecasting techniques

The framework of the ANFIS model facilitates machine learning and adaptation using various data sets, and has been established as one of the most popular forecasting tools. The results from the error analysis given in this chapter confirm the superiority of the proposed ANFIS-based models over the ARIMA model, indicating better predicting ability of the e-order arrival figures using the ANFIS framework. The error analysis results are consistent with a number of previous studies, in which the ANFIS model was proven to outperform other approaches, such as multiple linear regression (MLR), artificial neural networks (ANN), autoregressive integrated moving average (ARIMA) model and fuzzy logic. For example, Masoudi et al. (2018) found that

ANFIS models in general are more accurate than ANN in modelling manufacturing processes and reflect the benefits of combining fuzzy systems capabilities with neural networks. Tabrizi & Sancar (2017) compared three estimation models, MLR, ANN and ANFIS. The results indicated that the ANFIS model for predicting Body Mass Index is more feasible than the other two models. For instance, the ANFIS model also performs well in handling time-series data. In this research, e-order arrival figures in the distribution centre, as the prediction subject of this research, are time series data. The prediction performance of the proposed ANFIS models suggests the suitability of the ANFIS technique for the prediction of time series data. This indication is consistent with a study performed by Efendigil et al. (2009), in which time series-type demand in a supply chain was forecast using both artificial neural networks (ANN) and ANFIS, and the ANFIS method was found to perform more effectively than the ANN approach in the estimation of such time series data. This study, in conjunction with other ANFIS literature, suggests that the ANFIS model is feasible for handling both time series and non-time series data with accurate prediction performance.

(ii) On the selection of typologies I or II for e-order arrival prediction in real practice

Finding 7 presented in the results and discussion part for Case study 3 (Section 6.2.3) shows that both typologies give an MAD of less than 12 kg. This indicates that the difference in the actual and predicted e-order arrival figures for each three-hour period is, on average, less than 12 kg. From the statistical point of view, typology I (aggregating individual data for each retailer for prediction) performs slightly better than typology II, with lower MAD, MAPE and RMSE error, as shown in Table 6.15. However, both typologies in fact give very good prediction performance as both typologies achieve 100% item accuracy (as shown in Table 6.16) and the error difference between typologies I and II is very small, i.e. only an MAD of 2.01 kg, for the e-order arrival figures (in kg) for the coming three-hour time interval.

From the statistical point of view, constructing one single ANFIS model for aggregating e-order arrival figures is statistically justifiable for forecasting the e-order arrival in distribution centres. Therefore, it can be concluded that aggregating e-order arrivals for using one single ANFIS model for prediction provides a better prediction accuracy.

In reality, managerial and practical implications of both prediction typologies (I and II) need to be taken into consideration. It is noticeable that there are some drawbacks of aggregating e-order arrival figures for prediction that cannot be ignored from a practical perspective. In real practice, using only one single ANFIS model to forecast the total e-order arrival disregards which retailer an e-order belongs to. Without predicting an individual retailer's e-order arrival, a logistics practitioner may not be able to accurately allocate the right amount of resources to a specified zone location in the distribution centre where the stock for a specific retailer is stored. Therefore, this research suggests that, if there is a large number of retailers that the logistics service provider has partnerships with, aggregating all retailers' e-order arrivals for forecasting a total e-order arrival (Typology I) in the coming period is more appropriate, so as to reduce the effort in model construction, training and testing. Otherwise, separately forecasting the e-order arrival of each retailer (Typology II) for operational decision support for specific retailers enables the logistics service providers to receive more benefits in ANFIS modelling. A summary of the practical recommendation of the deployment of ANFIS forecasting models for e-order arrival prediction is presented in Table 6.23.

Table 6.23. A summary of the practical recommendation of the deployment of ANFIS forecasting models for the e-order arrival prediction

		Suggested approach for ANFIS construction for e-order arrival prediction:
If there is a large number of retailers that the logistics service provider has partnership with:	*More than 5*	**Typology I** – Aggregating all retailers' e-order arrival for forecasting a total e-order arrival
	Less than 5	**Typology II** – Separately forecasting e-order arrival of each retailer for operational decision support for specific retailers, enabling the logistics service providers to receive more benefits in ANFIS modelling

(iii) On the selection of variables for forecasting e-order arrival figures

The e-order arrival figure of the previous period, the volatility (or momentum) of e-order arrival, and the moving average of the previous two or three periods are selected as the input variables for the ANFIS model to predict the e-order arrival in the upcoming period. The selection of these variables is consistent with a study performed by Chang et al. (2011), in which a hybrid ANFIS model was built based on AR and volatility to forecast stock price problems of the Taiwan stock exchange capitalization weighted stock index (TAIEX). Our error analysis results based on RMSE, MAD and MAPE suggest that these variables are the essential indicators that are able to forecast e-order arrival figures. Therefore, the introduction of autoregressive lag variables, the volatility of data and moving average as the input variables of ANFIS models should enable the forecasting of other types of time series data across various industries.

(iv) On the process of identifying the best parameter setting of the ANFIS model

For practical deployment of the proposed ANFIS-based approach for order arrival prediction, though industry practitioners are able to use autoregressive lag variables and the volatility and moving average of data as the input parameters suggested in this study to build their own ANFIS models for forecasting the order arrival rate in their distribution centre, the best parameter settings for their own ANFIS models still need to be identified through undergoing the five steps discussed in section 3.6.2 – ANFIS Model Construction. Due to the fact that an ANFIS model can be built with a large number of combination of settings, such as the type of membership function (MF), the number of MFs for each input and the type of output function, ANFIS models under different parameter settings can achieve very different results. Hence, identifying the best parameter setting is a critical process when building an ANFIS model. To address the essence of this process, this research presents a step-by-step framework for the identification of the input variables, followed by how data sets are selected and split into training and testing data sets, subsequently obtaining the best parameter setting using the training and testing data sets. A detailed evaluation and error analysis of the various settings is also presented in this chapter. Therefore, it is emphasized that there is a crucial need to present not only the theoretical framework, but also the process of obtaining the best parameter combination in detail for each of the proposed ANFIS models, which is lacking in most of the ANFIS literature.

6.3.2 Managerial and Practical Implications

The managerial and practical implications are discussed in two aspects: (i) the essence of reengineering the logistics flow for handling today's e-commerce logistics orders, (ii) the essence of integrating Information and Communication Technology (ICT) for assisting logistics practitioners in the decision-making process for efficient e-order handling.

(i) The essence of reengineering the logistics flow for handling today's e-commerce logistics orders

Making timely and accurate decisions depend not only on the availability of information, but also how this is managed so as to select the proper data analytic tool for extracting useful knowledge through gathering the raw data. The warehouse postponement strategy, i.e. delaying the execution of a logistics process until the last possible moment, can be executed in the real logistics environment only if an appropriate data analytic tool provides industry practitioners with decision support for determining the cut-off time of e-order groupings. Without such decision support, industry practitioners are required to manually decide when to stop the consolidation of e-commerce orders and subsequently release the consolidated orders for batch processing in the distribution centre. It is a difficult decision to make in the absence of any decision support, not to mention that the quality of such a manual decision cannot be guaranteed. Worse still, improper timing in releasing grouped e-orders can severely affect the efficiency in order handling and can create other resource allocation problems, as shown in Table 6.24. For example, if the consolidated orders are released too late, in other words, there are too many orders being grouped in this batch, the grouped orders might need to be separated into more sub-batches as they cannot be processed together at one time. Therefore, the proper timing for batch release is critical for deploying an effective warehouse postponement strategy.

This study presents an ANFIS framework that is able to utilize the raw data of historical e-order arrivals for forecasting the rate of e-order arrival in the upcoming periods. By realizing the e-order arrival rate, the proposed system further generates the optimal cut-off time of the pending e-orders, i.e. the remaining time to stop consolidating discrete, small lot-sized e-commerce orders and release the consolidated orders for processing in bulk in the distribution centre. In fact, apart from the optimal cut-off time that can be generated based on the predicted e-order arrival rate, such prediction can be further used for generating other types of decision support for enhancing a firm's operating performance or business competence. For example, logistics practitioners can use the predicted e-order arrival figures for making other warehouse related decisions, such as resource allocation decisions. Online retailers can perform target marketing or design new promotional strategies, as they can now realize the predicted number of e-orders that are to be placed by end consumers in the e-marketplace in the upcoming time period.

Table 6.24. Various scenarios of ineffective warehouse postponement strategy

		Consequences in the perspective of:	
		Order handling	*Resource management*
If the consolidated orders were released:	*Too early*	- Too few e-orders being grouped - Lose the original idea of warehouse postponement - Need to re-visit the same item storage location for many times due to a large number of order batches created	- Excessive resources remain idle
	Too late	- Too many e-orders being grouped - Unable to process the grouped orders at one time - Need to separate the grouped orders into two or more batches	- Excessive workload of workers

(ii) The essence of integrating Information and Communication Technology (ICT) for assisting logistics practitioners in the decision-making process for efficient e-order handling

The rise of e-commerce, O2O retailing, and direct-to-consumer last-mile delivery has positioned e-fulfilment distribution centers at the very heart of what end consumers perceive as good service. Aggressive, guaranteed delivery dates are often provided for addressing customer demands. The increasing convenience of online shopping has redefined the way we shop; the customer demands, on the other hand, are reshaping e-fulfilment. In the e-commerce marketplace, customer segmentation is a known market opportunity enabling retailers to reach a wider customer base. However, it is also one of the biggest challenges in e-commerce. The e-order fulfilment of logistics service providers has to be very efficient in handling e-orders, which are received from the internet at any time, and are to be delivered to a vast number of locations worldwide by the guaranteed delivery dates. In the absence of decision support systems facilitating the e-order internal processing operations in e-fulfilment centers, logistics practitioners, especially those SME-sized organizations that often handle orders without comprehensive IT support, experience obstacles in maintaining the same level of efficiency as they had in handling traditional orders in warehouses or distribution centers.

The evolution of information and communication technology (ICT) services with cloud computing and mobile technologies has offered enterprises not only more sales channels and effective formulation of target marketing strategies through big data analytics, but also better internal and external information and communication management solutions for integration into daily business for operational excellence. However, with the slow pace of new technology adoption and innovation in the logistics and distribution sector (Evangelista & Sweeney, 2006; European

Commission, 2012), logistics practitioners manage e-orders in a conventional flow of operations, which affects their e-order handling capability and prolongs the e-fulfilment lead time. The results from the case studies indicates that light-weight IT applications that integrate artificial intelligence techniques and state-of-the-art cloud computing technologies enable logistics practitioners to improve their internal order processing in a cost effective manner. Software and solution providers should take e-fulfilment requirements into consideration when designing and developing competitive ICT solutions, with the integration of artificial intelligence techniques for providing decision support and e-commerce logistics process re-engineering and automation.

6.4 Summary

In this chapter, the results and discussion of the research are presented. Experiments were performed for:

- Identifying the best parameter settings for the GA algorithm in EGM of the EF-DSS (Section 6.2.1),
- Determining the best structure for the AR(1)MO(1) model and AR(1)MO(2) models, and comparing the performance of the AR(1)MO(1) and AR(1)MO(2) models with the traditional ARIMA (Section 6.2.2),
- Determining the best structure for the AR(1)MO(1)MA(2) model and AR(1)MO(1)MA(3) models, and comparing the performance of the AR(1) MO(1)MA(2) and AR(1) MO(1)MA(3) models with the AR(1)MO(1) and AR(1)MO(2) models and the traditional ARIMA (Section 6.2.3).

Finally, a number of significant implications in research, managerial, and practical perspective are presented in this chapter.

Chapter 7 – Conclusions

7.1 Summary of the Research

The capability of logistics service providers in e-order fulfilment is one of the key factors affecting the growth of the online retail business. This research study develops an E-order Fulfilment Decision Support System (EF-DSS), which integrates: (i) the genetic algorithm technique and the rule-based inference engine for logistics service providers to effectively plan for the upcoming internal processing operations of received orders before actual process execution, and (ii) ANFIS-based prediction models for forecasting the arrival frequency of e-commerce orders so as to determine the optimal timing for batch release of grouped orders. To provide the above-mentioned decision support, the EF-DSS consists of three modules, namely E-order Consolidation Module (ECM), E-order Grouping Module (EGM), and E-order Batch Releasing Module (EBRM).

In ECM, an e-order consolidation pool is built using a cloud database for consolidating pending e-orders. In EGM, an optimal internal order processing plan is justified by the genetic algorithm approach. Essential operating guidance is provided through the rule-based inference engine for order processing execution. With this hybrid GA-rule-based approach enabling logistics service providers to determine "How to group e-orders", discrete e-orders are no longer required to be processed immediately after they are received. The e-commerce internal order processing flow is therefore streamlined and re-designed. The improved e-order handling capability of logistics service providers eventually reduces the processing time in e-fulfilment centers, thereby meeting the ever tighter delivery requirements of online customers. Ultimately, the intelligent system presented in this research contributes to the development of the e-commerce business environment from the perspective of the interconnected parties. Logistics service providers become more capable in capturing the logistics of the e-commerce business. Retailers can build brand images and loyalty by satisfying the consumers' needs and expectations, especially considering the timeliness of the last-mile e-order delivery, one of the most critical e-fulfilment processes. End consumers can receive their purchased items without a long waiting time.

In EBRM, a novel ANFIS-based approach is proposed and developed with the inclusion of the autoregressive, momentum and moving average characteristics of time series data for the prediction of e-order arrival in distribution centres. Two typologies are introduced to identify the best approach and set of ANFIS models for making accurate prediction.

In summary, three case studies are undertaken to validate the performance of the EF-DSS. Results upon implementation of EF-DSS in the case studies reveal the feasibility of the EF-DSS in handling e-orders efficiently, and the superiority of ANFIS models for forecasting the arrivals of e-orders in distribution centres.

7.2 Contributions of the Research

There are unprecedented pressures on companies to improve their operational efficiency for enhanced competitiveness and overall business performance. Under the fierce competition in the e-commerce operating environment, e-retailers are striving to survive by attracting potential customers and retaining existing ones. To sustain their core business, e-retailers who could also be the manufacturers of their listed products, attempt to improve their competitive advantages by focusing on their core business activities and outsourcing the non-core business functions, such as the logistics and delivery segment to third-party logistics service providers (3PLs). This has been a common phenomenon in the past decades. The essence of supply chain integration in improving overall supply chain performance has been addressed in both the academic and practitioner literature (Nguyen et al., 2018; Akter & Wamba, 2016; Yu et al., 2016; Mellat-Parast & Spillan, 2014). In today's fast-changing e-commerce environment with tight customer requirements, particularly on speedy last-mile delivery and the product availability, close connections and coordination must be established among the stakeholders in the supply chain. For the outsourced functions to be performed efficiently, e-retailers and 3PLs must closely co-operate. A standard protocol for order information synchronization among e-retailers and 3PLs ought to be established so as to streamline the information transmission process, increase the information transparency, and extend the degree of information sharing, thus achieving supply chain network excellence. 3PLs, on the other hand, need to utilize the information shared by the e-retailers for effective order management. With the e-commerce orders being fundamentally different from the conventional large lot-sized stock replenishing orders in nature, and the fact that online customers are increasingly emphasizing on order processing and delivery timeliness, the reputation of both the 3PL and the e-retailer hinges on the operating performance of the 3PL in handling the e-orders in distribution centres.

In view of the need to streamline the e-commerce order fulfilment process, this research provides a generic methodology for the development of an operation planning system for effective order management under today's e-commerce operating environment. In general, the contributions of the research are threefold. They are:

(i) WPS – A novel operational methodology proposed in this research

The conventional product-oriented postponement strategy suggests practitioners to "delay the production process until the last possible moment", such as postponing the product assembling operations for better product customization and meeting local customer needs. The proposed operational strategy that should be applied in distribution centres and warehouses, namely the Warehouse Postponement Strategy, transforms the conventional product-oriented strategy into a process-oriented operational strategy that is specifically designed for logistics practitioners. The proposed strategy introduces the need to consolidate orders so as to delay the subsequent order handling process, such as order pick-and-pack operations, until the last possible moment. Such operational strategy is particularly applicable to LSPs who handle a large number of e-commerce orders on a daily basis.

In the mainstream literature, research conducted in managing e-commerce order fulfilment activities has been lacking (Nguyen et al., 2018). The environmental implications and impact of e-commerce business on the related logistics activities have not yet been studied in detail as well (Mangiaracina et al., 2015). The proposed WPS fills the gap in the literature by introducing an operational strategy that takes the environmental implications of e-commerce business into consideration in streamlining e-order fulfillment activities. It is strongly recommended that more studies be undertaken to remove the existing bottlenecks of e-commerce order fulfillment operations, thereby proposing state-of-the-art solutions to tackle the problems specifically found in e-fulfilment distribution centres where e-commerce orders are processed.

(ii) EF-DSS – An intelligent decision support system developed in this research that specifically take e-commerce operating bottlenecks into account

For effective execution of the proposed WPS, logistics practitioners are required to consolidate orders with considerations of “How can the orders be grouped” and “When should the grouped orders be released to distribution centres for batch processing”. To provide a total solution for logistics practitioners to execute WPS in real practice, this research combines the genetic algorithm technique, rule-based inference engine, autoregressive modeling, and adaptive neuro-fuzzy inference system (ANFIS). The EF-DSS developed in this research simultaneously tackles the problem of "How to group the e-orders" and "When to release the grouped e-orders in a batch" as identified at the beginning of this research, and is the first published study that proposes the need to delay the execution of the order processes due to the fundamental differences between e-order and conventional logistics order handling. It pinpoints the two essential decisions to be made, i.e. how to group, and when to group e-orders, under the wider concept of warehouse postponement, and thus provides specific decision support for each of these decisions using artificial intelligence and machine learning tools. The results upon deployment of the EF-DSS in three case studies in the logistics service providers based in Hong Kong also indicate remarkable system and operating performance.

(iii) Wide applicability of the proposed typologies for forecasting other time-series data

This research takes the *n*-period autoregressive (AR), momentum (MO), moving average (MA) indicators of time-series data into the account in the input variables selection process of ANFIS forecasting models in the EBRM of the EF-DSS. These input factors are generic characteristics of time-series data. Therefore, the proposed ANFIS model typologies that integrate these generic characteristics of time-series data suggest that the typologies proposed in this research and applied in the field of order management in an e-commerce scenario may be appropriate for applications in predicting subjects in other fields or industries. There is a wide range of potential areas of application, where time-series data exist and can be used for prediction, thereby generating knowledge and decision support in a particular field. A list of potential application areas of the proposed AR-MO-MA-based ANFIS forecasting approach is depicted in Table 7.1. They include, but are not limited to, the following: property price prediction, stock price prediction, GDP and CPI prediction, patient arrival prediction in hospitals, etc.

Table 7.1. A list of potential application areas of the proposed AR-MO-MA-based ANFIS forecasting approach

In the fields of Supply Chain Management:
1. In retailer perspective – product category sales trend prediction 2. In a product category – sales trend prediction of a list of products under the same product category 3. In manufacturer perspective – Order arrival prediction
Other fields:
Macro/Micro economics:
1. Property price prediction 2. Stock price prediction 3. GDP and CPI prediction
Hospitality industry:
4. Tourists arrival prediction 5. Hotel booking prediction
Medical industry:
6. Patient arrival prediction in hospitals

7.3 Limitations of the Research and Suggestions for Future Work

Although this research makes significant contributions to both academia and the logistics industry in today's e-commerce business environment, there are some limitations in the research and suggestions for future work as addressed below.

(i) Further strengthen the decision support algorithm "how to group" decision decision using GA mechanism

In this research, the problem of grouping similar e-commerce orders is tackled through the use of a GA algorithm. Depending on the operating parameters and complexity of the e-order handling process of a logistics service provider, the GA algorithm for generating "how to group" decision support can be strengthened in future research.

(ii) Take more time-series characteristics into the consideration of process in identifying the input variables of ANFIS forecasting technique

This research integrates n-period autoregressive (AR), momentum (MO), moving average (MA) feature of time-series data for the modeling and construction of the ANFIS forecasting approach for e-order arrival prediction. Despite this research provides in-depth model comparison and evaluation using various time-series-type input variables, and confirm their superiority over traditional forecasting approaches in predicting e-commerce order arrival frequency, the inclusion of input variables other than AR, MO and MA element is possible and can be considered in future.

Appendices

Appendix A.
Evaluation and error analysis of various settings for AR(1)MO(1) model

			Types of output function:			
No. of MFs for each input:			***Constant***		***Linear***	
$Q_d(t)$	***Mo(t)***		Training error	Testing error	Training error	Testing error
2	**2**	TriMF	14.4271	14.427	14.0196	14.0196
		TrapMF	14.0285	14.0278	13.0508	13.0507
		GbellMF	13.8738	13.871	12.9082	12.9076
		GuassMF	14.1305	14.1301	13.0306	13.0305
	3	TriMF	14.3528	14.3527	13.7032	13.7032
		TrapMF	14.8937	14.8926	12.8537	12.8535
		GbellMF	14.2018	14.1988	12.5944	12.5939
		GuassMF	14.2235	14.223	12.6902	12.6901
	4	TriMF	14.2067	14.2066	13.4862	13.4862
		TrapMF	13.7043	13.7038	12.4777	12.4771
		GbellMF	13.6382	13.6361	12.3906	13.0284
		GuassMF	13.895	13.8946	12.5762	12.5761
3	**2**	TriMF	13.9494	13.3703	12.8565	13.7287
		TrapMF	14.7074	14.8646	12.8531	13.7465
		GbellMF	14.1565	13.8674	12.7886	13.0672
		GuassMF	14.0092	13.5464	12.8578	13.2057
	3	TriMF	13.905	13.3784	12.5795	13.6921
		TrapMF	15.6599	14.9848	12.8011	13.5483
		GbellMF	14.5204	14.1298	12.6536	12.8613
		GuassMF	14.1749	13.6863	12.5763	12.8562
	4	TriMF	13.7233	13.263	12.3038	23.9326
		TrapMF	14.7052	14.7565	12.5637	13.1572
		GbellMF	14.1169	13.718	12.1552	14.5842
		GuassMF	13.8971	13.3738	12.1517	13.818
4	**2**	TriMF	13.6765	13.0518	12.8329	13.4665
		TrapMF	13.5524	13.0605	12.7256	13.3196
		GbellMF	13.3704	12.961	12.6322	13.3313

		GuassMF	13.4527	12.9446	12.7332	13.4938
	3	TriMF	13.481	12.7301	12.5223	13.3808
		TrapMF	14.4935	13.5589	12.3381	14.8454
		GbellMF	13.5491	12.8844	12.0301	13.4427
		GuassMF	13.392	12.7344	12.1564	13.5443
	4	TriMF	13.1496	12.9454	12.0825	14.0868
		TrapMF	13.1139	13.1222	11.8162	13.4292
		GbellMF	12.8147	12.6959	11.5945	14.8787
		GuassMF	12.8882	**12.4506**	11.6623	15.4905

Appendix B.

Evaluation and error analysis of various settings for AR(1)MO(2) model

				Types of output function:			
No. of MFs for each input:				***Constant***		***Linear***	
$Q_d(t)$	***Mo(t)***	***Mo(t-1)***		Training error	Testing error	Training error	Testing error
2	2	2	TriMF	13.648	13.0506	12.1941	11.2498
			TrapMF	13.1712	12.3447	12.0434	11.52
			GbellMF	13.1095	12.2946	11.7826	13.6268
			GuassMF	13.3291	12.6148	11.8675	12.1885
		3	TriMF	13.3267	12.8819	11.7977	13.0101
			TrapMF	12.9524	12.6099	11.3156	14.7978
			GbellMF	12.6675	12.1999	11.2045	10.9757
			GuassMF	12.9037	12.3952	11.353	12.6964
		4	TriMF	12.7593	13.0327	11.3698	11.7819
			TrapMF	12.6124	11.8264	11.3551	12.5201
			GbellMF	12.3754	12.6664	10.5341	14.4348
			GuassMF	12.5097	12.7147	10.6357	14.1913
	3	2	TriMF	13.358	12.3665	11.8545	11.6334
			TrapMF	13.6353	13.6395	11.2878	11.5755
			GbellMF	13.0861	12.1361	11.2439	13.1096
			GuassMF	13.1414	12.0106	11.3146	12.3522
		3	TriMF	12.9708	12.0729	10.921	12.7947
			TrapMF	13.6294	14.1152	11.0043	17.3381
			GbellMF	12.7659	12.6429	10.3535	20.3293

			GuassMF	12.7768	12.0162	10.2943	24.7081
		4	TriMF	12.5171	12.1613	10.2778	88.8763
			TrapMF	13.019	13.723	10.3095	10.3089
			GbellMF	12.3796	12.8098	9.7701	20.3497
			GuassMF	12.4086	12.1948	9.8448	41.1734
	4	**2**	TriMF	13.2067	12.7526	11.5058	11.8889
			TrapMF	13.0572	12.1285	10.8629	12.5343
			GbellMF	12.9407	11.9633	10.659	18.9192
			GuassMF	13.0399	12.0798	10.908	15.1604
		3	TriMF	12.5434	11.6178	10.1685	14.6075
			TrapMF	12.7133	12.6576	10.2591	50.241
			GbellMF	12.2494	**10.7138**	9.7835	18.0167
			GuassMF	12.4931	13.0532	9.7674	39.9658
		4	TriMF	11.9871	13.0099	9.7076	53.3982
			TrapMF	12.2787	11.4872	10.2052	13.5434
			GbellMF	11.9786	11.814	8.9751	41.2609
			GuassMF	12.0132	12.0237	9.1399	34.2902
3	**2**	**2**	TriMF	12.6372	11.4093	11.841	11.3663
			TrapMF	13.2946	13.1338	11.3888	13.5707
			GbellMF	12.8018	11.7959	11.3258	13.2054
			GuassMF	12.7122	11.5076	11.5012	13.0584
		3	TriMF	12.5288	11.5165	10.539	13.361
			TrapMF	13.8182	13.6098	10.9889	16.5444
			GbellMF	12.8064	11.7791	10.4109	19.9308
			GuassMF	12.6498	11.5885	10.477	16.0153
		4	TriMF	12.0985	12.2545	10.3217	21.2293
			TrapMF	12.9041	12.9515	10.5969	13.3959
			GbellMF	12.179	12.5397	9.638	30.1391
			GuassMF	12.2005	12.4879	9.7942	22.6588
	3	**2**	TriMF	12.3814	10.8512	11.034	15.3558
			TrapMF	14.1579	13.7458	10.7286	15.457
			GbellMF	12.8705	11.8443	10.418	13.9859
			GuassMF	12.5728	11.2266	10.6243	13.2457
		3	TriMF	12.2508	10.9525	9.8349	28.373
			TrapMF	14.1483	13.9558	10.5902	26.0203
			GbellMF	12.605	11.7161	9.6435	25.5912
			GuassMF	12.344	11.1118	9.4599	25.165

		4	TriMF	11.5327	12.0992	9.4474	112.5874
			TrapMF	13.6513	13.3607	10.085	35.4727
			GbellMF	12.1045	12.85	8.7143	44.4161
			GuassMF	11.8335	12.345	8.8267	56.6004
	4	2	TriMF	12.1411	11.494	10.3637	12.3726
			TrapMF	13.108	12.8297	10.1621	14.2853
			GbellMF	12.3941	11.4939	9.7251	19.947
			GuassMF	12.2553	11.233	9.8308	17.612
		3	TriMF	11.9198	11.7827	8.8172	59.6185
			TrapMF	13.7173	13.5359	9.5687	19.1148
			GbellMF	12.2087	11.7067	8.7993	38.2297
			GuassMF	11.9789	11.1917	8.7822	21.1079
		4	TriMF	11.0019	14.5003	8.0621	77.1304
			TrapMF	12.4708	11.9993	9.7111	14.0735
			GbellMF	11.0135	12.8894	7.7649	45.2788
			GuassMF	10.9409	14.0037	7.6939	63.4831
4	2	2	TriMF	12.7785	11.7943	11.1416	14.2183
			TrapMF	12.6632	11.8873	10.9002	12.9608
			GbellMF	12.5438	11.4684	10.8556	12.408
			GuassMF	12.6088	11.4774	10.8669	12.9636
		3	TriMF	12.5166	12.3103	10.1946	17.5911
			TrapMF	12.5877	27.7602	10.4653	26.7841
			GbellMF	12.1888	11.8186	9.9073	14.8401
			GuassMF	12.2967	11.9344	9.8293	14.578
		4	TriMF	11.9887	12.7546	9.4991	103.2905
			TrapMF	11.7943	11.8035	10.0132	19.5224
			GbellMF	11.6816	11.7824	9.1191	13.6296
			GuassMF	11.7453	12.0145	9.1221	30.9574
	3	2	TriMF	12.5321	11.4699	10.5653	13.1735
			TrapMF	12.9196	13.6187	10.6645	19.6589
			GbellMF	12.1674	11.8331	9.7487	15.1379
			GuassMF	12.2793	11.4137	9.7912	17.4592
		3	TriMF	12.1349	12.479	9.1298	16.1905
			TrapMF	13.1509	14.9089	10.0839	212.4286
			GbellMF	12.1281	12.3467	8.7511	31.7854
			GuassMF	11.9803	12.1791	8.5484	20.2353
		4	TriMF	11.4632	12.4465	8.1913	211.2479

			TrapMF	12.1351	13.8907	9.2266	24.4161
			GbellMF	11.3689	12.3765	7.9522	28.2303
			GuassMF	11.3871	12.3166	7.9432	55.6645
		2	TriMF	12.0962	11.4785	9.5274	20.9748
			TrapMF	12.1757	11.5894	9.5329	11.3579
			GbellMF	11.7884	11.3832	8.809	37.5127
			GuassMF	11.9376	11.3563	8.9022	39.3995
	4	**3**	TriMF	11.3632	12.5853	8.4819	23.2367
			TrapMF	12.216	12.9003	9.4688	19.4579
			GbellMF	11.2423	11.5943	7.4807	153.9597
			GuassMF	11.2532	11.3237	7.5101	131.812
		4	TriMF	11.0229	13.6062	7.1499	116.0546
			TrapMF	11.6497	11.1396	9.1704	36.1136
			GbellMF	10.8655	13.3523	6.9615	383.8571
			GuassMF	10.7958	17.0555	7.047	154.5012

Appendix C.

Evaluation and error analysis of various settings for Model 1A, i.e. AR(1)MO(1)MA(2) model for Retailer 1

No. of MFs for each input:				***Types of output function: Constant***	
$Q_d(t)$	***Mo(t)***	***$Ma_2(t)$***		Training error	Testing error
2	**2**	**2**	TriMF	13.1515	12.0092
			TrapMF	12.1802	11.0776
			GbellMF	11.7153	10.6506
			GuassMF	11.9304	10.8256
		3	TriMF	12.9603	12.4173
			TrapMF	12.634	18.2435
			GbellMF	11.9175	**10.1776**
			GuassMF	12.4813	10.7293
		4	TriMF	12.5757	12.286
			TrapMF	11.6692	11.327
			GbellMF	11.2622	10.412
			GuassMF	11.6554	10.7576
	3	**2**	TriMF	11.128	13.3142
			TrapMF	12.1274	11.7528

			GbellMF	10.899	11.4099
			GuassMF	10.8047	10.7944
		3	TriMF	10.5988	12.7924
			TrapMF	13.1783	12.4371
			GbellMF	11.164	11.4898
			GuassMF	10.8635	11.4871
		4	TriMF	10.6055	11.9072
			TrapMF	12.348	14.5436
			GbellMF	10.4755	11.7601
			GuassMF	10.3144	11.4805
	4	2	TriMF	10.4257	11.1526
			TrapMF	11.6572	11.8984
			GbellMF	10.8819	11.2482
			GuassMF	10.7219	10.9287
		3	TriMF	9.9282	11.9901
			TrapMF	11.8873	12.2233
			GbellMF	10.4572	10.5226
			GuassMF	10.14	10.4463
		4	TriMF	9.6213	10.3641
			TrapMF	10.9503	12.7916
			GbellMF	9.9397	10.5753
			GuassMF	9.7447	10.6237
3	2	2	TriMF	12.6862	16.933
			TrapMF	11.5498	11.6985
			GbellMF	11.2636	10.7782
			GuassMF	11.5786	11.1326
		3	TriMF	12.0104	13.6739
			TrapMF	12.3511	12.4265
			GbellMF	11.1276	10.4194
			GuassMF	11.4077	11.1987
		4	TriMF	11.6155	15.3247
			TrapMF	11.5002	12.3691
			GbellMF	10.8989	10.6987
			GuassMF	10.8466	11.1444
	3	2	TriMF	10.7745	13.0429
			TrapMF	13.5635	14.2505
			GbellMF	11.8629	11.5446

			GuassMF	11.4221	11.2065
		3	TriMF	10.513	12.7352
			TrapMF	13.9237	13.534
			GbellMF	9.9116	10.9391
			GuassMF	9.9572	11.0661
		4	TriMF	10.188	13.149
			TrapMF	13.3765	13.747
			GbellMF	10.003	11.5982
			GuassMF	9.7191	11.541
	4	**2**	TriMF	10.1108	11.3868
			TrapMF	11.3256	12.6428
			GbellMF	10.3489	11.4931
			GuassMF	10.1335	11.0989
		3	TriMF	9.8575	12.5177
			TrapMF	11.7065	12.784
			GbellMF	10.0124	10.2791
			GuassMF	9.8481	10.976
		4	TriMF	9.4146	11.1793
			TrapMF	11.0384	13.3904
			GbellMF	9.5685	11.7293
			GuassMF	9.3202	10.9694
4	**2**	**2**	TriMF	12.252	17.4954
			TrapMF	11.6383	10.6519
			GbellMF	11.2983	10.945
			GuassMF	11.7551	11.6921
		3	TriMF	11.5353	13.4882
			TrapMF	11.6656	11.785
			GbellMF	10.5958	11.376
			GuassMF	11.1847	10.6469
		4	TriMF	11.6471	14.6402
			TrapMF	11.0396	10.3426
			GbellMF	10.2729	10.9845
			GuassMF	10.2085	11.512
	3	**2**	TriMF	10.6523	12.4104
			TrapMF	11.9161	11.4996
			GbellMF	10.9488	10.9648
			GuassMF	10.6944	10.7899

		3	TriMF	10.3846	11.7688
			TrapMF	12.0481	12.8981
			GbellMF	10.3459	10.9339
			GuassMF	10.3035	10.4624
		4	TriMF	10.1513	12.8004
			TrapMF	11.898	11.6072
			GbellMF	9.6358	11.5273
			GuassMF	9.5179	10.7315
	4	2	TriMF	9.7469	10.8029
			TrapMF	11.9913	11.4631
			GbellMF	9.888	11.2058
			GuassMF	9.8168	11.0841
		3	TriMF	9.6253	12.7955
			TrapMF	10.4063	12.5755
			GbellMF	9.7064	11.7942
			GuassMF	9.5378	12.0416
		4	TriMF	9.3787	10.8492
			TrapMF	10.2823	13.0534
			GbellMF	9.382	12.9238
			GuassMF	9.2407	11.7103

Appendix D.
Evaluation and error analysis of various settings for Model 1B,
i.e. AR(1)MO(1)MA(3) model for Retailer 1

No. of MFs for each input:				***Types of output function: Constant***	
$Q_d(t)$	***Mo(t)***	***$Ma_3(t)$***		Training error	Testing error
2	2	2	TriMF	13.3285	11.6771
			TrapMF	12.1317	10.3485
			GbellMF	12.2179	10.5321
			GuassMF	12.747	11.0181
		3	TriMF	11.9845	11.8622
			TrapMF	11.7481	10.4343
			GbellMF	11.6044	10.4971
			GuassMF	11.8187	10.8128
		4	TriMF	12.382	11.8486

			TrapMF	11.619	11.4573
			GbellMF	11.3627	11.018
			GuassMF	11.752	11.395
		2	TriMF	11.5872	10.5447
			TrapMF	11.8556	11.7203
			GbellMF	11.2267	10.9138
			GuassMF	11.2953	10.5941
	3	3	TriMF	10.817	11.1617
			TrapMF	12.7665	11.0029
			GbellMF	10.9622	11.2086
			GuassMF	10.8476	10.982
		4	TriMF	10.8296	10.3001
			TrapMF	11.7925	11.6935
			GbellMF	10.5668	10.517
			GuassMF	10.5635	10.4175
	4	2	TriMF	10.1881	**9.2656**
			TrapMF	10.8889	10.7132
			GbellMF	10.444	10.0762
			GuassMF	10.306	9.7862
		3	TriMF	9.6049	9.8867
			TrapMF	10.9803	13.3816
			GbellMF	9.8319	9.7877
			GuassMF	9.5899	10.233
		4	TriMF	9.4163	10.7883
			TrapMF	10.6358	11.3201
			GbellMF	9.5284	10.2981
			GuassMF	9.2615	11.424
3	2	2	TriMF	12.6072	12.271
			TrapMF	11.3408	10.8497
			GbellMF	11.5463	10.7256
			GuassMF	12.0439	11.3296
		3	TriMF	10.8437	10.714
			TrapMF	11.4072	14.19
			GbellMF	10.3776	10.6676
			GuassMF	10.4805	10.2498
		4	TriMF	11.0571	10.996
			TrapMF	11.1353	11.193

			GbellMF	10.3301	10.7445
			GuassMF	10.4119	10.4194
	3	2	TriMF	11.1322	10.5672
			TrapMF	13.4138	12.757
			GbellMF	11.5373	10.4813
			GuassMF	11.1443	10.2459
		3	TriMF	10.4049	10.8124
			TrapMF	13.5947	13.0998
			GbellMF	10.8773	10.5235
			GuassMF	10.4487	10.6969
		4	TriMF	10.4021	10.2736
			TrapMF	13.5272	13.8355
			GbellMF	10.3891	11.8172
			GuassMF	10.1205	11.5497
	4	2	TriMF	9.6486	9.3244
			TrapMF	10.2131	12.3904
			GbellMF	9.4025	10.5907
			GuassMF	9.4114	10.1798
		3	TriMF	9.1395	9.9152
			TrapMF	10.9901	13.9781
			GbellMF	9.273	10.5795
			GuassMF	9.0581	10.484
		4	TriMF	9.0718	10.8926
			TrapMF	10.6337	11.9532
			GbellMF	8.8883	11.0093
			GuassMF	8.8374	12.5118
4	2	2	TriMF	11.8185	12.2359
			TrapMF	10.832	10.1841
			GbellMF	10.9275	10.4707
			GuassMF	11.3155	11.16
		3	TriMF	10.2174	10.8166
			TrapMF	10.8364	10.2974
			GbellMF	10.1346	9.895
			GuassMF	10.1801	9.7666
		4	TriMF	10.6126	11.2005
			TrapMF	10.8393	11.3007
			GbellMF	10.1676	9.6689

			GuassMF	10.1933	9.9037
	3	2	TriMF	10.3187	10.8064
			TrapMF	11.0816	10.9887
			GbellMF	10.1502	10.8989
			GuassMF	10.0601	10.9786
		3	TriMF	9.7736	11.0159
			TrapMF	11.9395	11.0393
			GbellMF	10.0271	11.2763
			GuassMF	9.7789	11.0752
		4	TriMF	9.8765	9.7057
			TrapMF	11.2589	11.9106
			GbellMF	9.7837	11.477
			GuassMF	9.6061	10.8284
	4	2	TriMF	9.3097	10.6609
			TrapMF	9.7414	10.2985
			GbellMF	9.3103	10.296
			GuassMF	9.24	10.425
		3	TriMF	8.7501	11.4424
			TrapMF	10.2617	16.4253
			GbellMF	8.9706	11.2656
			GuassMF	8.8297	11.2173
		4	TriMF	8.9023	12.1216
			TrapMF	10.2548	11.7019
			GbellMF	8.6903	11.4587
			GuassMF	8.5984	12.1113

Appendix E.

Evaluation and error analysis of various settings for Model 2A, i.e. AR(1)MO(1)MA(2) model for Retailer 2

No. of MFs for each input:				***Types of output function: Constant***	
$Q_d(t)$	***Mo(t)***	***$Ma_2(t)$***		Training error	Testing error
2	2	2	TriMF	14.3998	**11.5383**
			TrapMF	14.3036	12.3333
			GbellMF	13.0486	13.4625
			GuassMF	13.6178	12.5266

		3	TriMF	13.5026	12.3045
			TrapMF	14.1358	12.7181
			GbellMF	13.2727	12.7403
			GuassMF	13.4559	12.5297
		4	TriMF	13.3972	12.7329
			TrapMF	12.9836	13.1851
			GbellMF	12.6180	13.3165
			GuassMF	12.9117	13.3912
	3	2	TriMF	13.2475	12.5970
			TrapMF	14.4727	14.6867
			GbellMF	13.1813	13.4963
			GuassMF	12.8981	13.3583
		3	TriMF	12.6767	13.1350
			TrapMF	15.4999	13.6039
			GbellMF	12.3690	13.6204
			GuassMF	12.5274	13.1847
		4	TriMF	12.0651	14.7664
			TrapMF	14.8245	13.3447
			GbellMF	11.8832	13.8679
			GuassMF	11.7229	14.3461
	4	2	TriMF	12.5901	13.3576
			TrapMF	12.9325	14.2068
			GbellMF	12.7658	13.3438
			GuassMF	12.7060	13.4607
		3	TriMF	12.1085	13.4715
			TrapMF	13.1479	13.5536
			GbellMF	11.8904	14.1628
			GuassMF	12.1490	13.7145
		4	TriMF	11.5983	14.9337
			TrapMF	12.4438	13.8822
			GbellMF	11.2222	14.7522
			GuassMF	11.2207	14.8989
3	2	2	TriMF	13.2037	12.4580
			TrapMF	13.2560	13.0195
			GbellMF	12.8889	12.6623
			GuassMF	13.1923	12.3512
		3	TriMF	12.3122	13.6529

			TrapMF	13.8290	12.5653
			GbellMF	12.5468	13.9160
			GuassMF	12.8487	13.1497
		4	TriMF	12.5012	13.5758
			TrapMF	12.7217	12.9977
			GbellMF	12.2152	13.2103
			GuassMF	11.9340	14.2880
	3	**2**	TriMF	12.5450	13.5452
			TrapMF	14.5970	14.8624
			GbellMF	12.8847	13.1975
			GuassMF	12.8170	13.3189
		3	TriMF	11.6749	14.6799
			TrapMF	14.7079	12.9802
			GbellMF	11.9952	14.2222
			GuassMF	11.8336	14.0465
		4	TriMF	11.9125	15.0774
			TrapMF	14.5737	13.8598
			GbellMF	11.6714	14.0815
			GuassMF	11.4274	14.7838
	4	**2**	TriMF	12.0528	13.7527
			TrapMF	12.5803	13.7913
			GbellMF	12.0332	13.7940
			GuassMF	11.9971	13.8994
		3	TriMF	11.0454	15.1424
			TrapMF	13.0700	13.7050
			GbellMF	11.3965	15.3460
			GuassMF	11.7694	14.2828
		4	TriMF	11.0412	15.9151
			TrapMF	12.4423	21.6795
			GbellMF	11.1263	15.6520
			GuassMF	11.1207	15.4167
4	**2**	**2**	TriMF	13.1769	12.3653
			TrapMF	12.9478	13.2189
			GbellMF	12.5002	13.4805
			GuassMF	12.9363	12.8986
		3	TriMF	12.6113	13.3123
			TrapMF	13.6980	12.8870

		GbellMF	12.0395	14.2931
		GuassMF	12.5949	13.2343
	4	TriMF	12.3630	13.9285
		TrapMF	12.5655	13.4957
		GbellMF	11.7966	14.2921
		GuassMF	11.9148	14.5747
3	2	TriMF	12.0153	14.2681
		TrapMF	14.1344	14.1479
		GbellMF	12.3438	13.6046
		GuassMF	11.9867	13.7716
	3	TriMF	11.8232	14.2400
		TrapMF	14.3626	13.1858
		GbellMF	11.7232	14.1200
		GuassMF	11.6435	14.5794
	4	TriMF	11.4895	15.7647
		TrapMF	13.9390	12.8877
		GbellMF	11.3794	16.0987
		GuassMF	11.0414	14.9974
4	2	TriMF	11.5442	13.4632
		TrapMF	12.5642	13.9687
		GbellMF	11.5120	14.7590
		GuassMF	11.5332	14.2628
	3	TriMF	11.3274	14.4623
		TrapMF	12.7109	14.3869
		GbellMF	11.0208	15.6308
		GuassMF	10.9752	15.4478
	4	TriMF	10.7534	15.3114
		TrapMF	12.1839	15.2000
		GbellMF	10.8711	15.9224
		GuassMF	10.7702	15.5959

Appendix F.
Evaluation and error analysis of various settings for Model 2B, i.e. AR(1)MO(1)MA(3) model for Retailer 2

No. of MFs for each input:				***Types of output function: Constant***	
$Q_d(t)$	***Mo(t)***	***$Ma_3(t)$***		Training error	Testing error
2	**2**	**2**	TriMF	13.8957	**11.1557**
			TrapMF	13.6854	11.8365
			GbellMF	13.4167	11.6083
			GuassMF	13.6817	11.3256
		3	TriMF	12.7536	13.0986
			TrapMF	12.2278	13.0045
			GbellMF	12.0170	12.0439
			GuassMF	12.1224	12.1862
		4	TriMF	12.4913	12.1311
			TrapMF	12.2496	12.5470
			GbellMF	11.5497	12.6522
			GuassMF	11.7845	12.6899
	3	**2**	TriMF	12.8519	11.6571
			TrapMF	14.8673	14.6439
			GbellMF	13.1179	12.5875
			GuassMF	12.8665	12.0819
		3	TriMF	11.6920	12.8691
			TrapMF	13.1771	16.0450
			GbellMF	10.9032	14.3349
			GuassMF	10.8767	13.7197
		4	TriMF	11.4556	12.4071
			TrapMF	14.0981	15.2762
			GbellMF	10.9392	14.0651
			GuassMF	11.0124	13.5921
	4	**2**	TriMF	11.6301	13.6723
			TrapMF	12.2490	16.3646
			GbellMF	11.8939	13.7777
			GuassMF	11.6714	13.5406
		3	TriMF	10.8534	14.7281
			TrapMF	11.3818	14.6695

			GbellMF	10.5556	14.0747
			GuassMF	10.4290	14.3376
		4	TriMF	10.6804	14.5866
			TrapMF	11.3326	14.5580
			GbellMF	10.3207	14.9455
			GuassMF	10.3938	14.9628
3	2	2	TriMF	12.4250	12.1946
			TrapMF	12.7330	12.6839
			GbellMF	12.3067	12.5158
			GuassMF	12.3865	12.3973
		3	TriMF	11.6152	13.4787
			TrapMF	12.4513	12.8763
			GbellMF	11.5477	12.6061
			GuassMF	11.4613	12.8771
		4	TriMF	10.9984	13.2093
			TrapMF	11.8814	13.9555
			GbellMF	10.6989	13.3774
			GuassMF	10.3618	13.9017
	3	2	TriMF	11.8394	12.6296
			TrapMF	13.8852	14.2184
			GbellMF	12.3067	13.1732
			GuassMF	11.9035	13.1910
		3	TriMF	11.1508	12.8958
			TrapMF	12.9463	14.6022
			GbellMF	10.7671	14.3561
			GuassMF	10.6836	13.9003
		4	TriMF	10.6597	13.2210
			TrapMF	13.6482	14.0915
			GbellMF	10.1610	14.3567
			GuassMF	10.1610	14.4742
	4	2	TriMF	11.0724	14.1190
			TrapMF	11.6262	12.9497
			GbellMF	10.6606	14.2745
			GuassMF	10.6690	14.4151
		3	TriMF	10.5528	14.6133
			TrapMF	12.0409	13.6703
			GbellMF	10.0190	15.2198

			GuassMF	10.2670	15.3401
		4	TriMF	10.1257	14.5267
			TrapMF	11.1541	14.5406
			GbellMF	9.7535	14.6454
			GuassMF	9.4362	14.6915
4	2	2	TriMF	12.7015	11.6773
			TrapMF	12.5921	12.5240
			GbellMF	12.1993	12.2408
			GuassMF	12.3968	11.9992
		3	TriMF	11.3730	13.7195
			TrapMF	12.0907	12.8710
			GbellMF	11.5192	12.3486
			GuassMF	11.3161	12.5909
		4	TriMF	10.5963	14.9317
			TrapMF	11.6574	12.8615
			GbellMF	9.9075	14.1684
			GuassMF	9.9120	14.6375
	3	2	TriMF	12.0882	12.4074
			TrapMF	13.8516	13.0825
			GbellMF	12.1258	13.1219
			GuassMF	11.8987	13.1393
		3	TriMF	10.9766	13.8193
			TrapMF	11.9485	14.0001
			GbellMF	10.3375	15.3708
			GuassMF	10.3610	15.2107
		4	TriMF	10.3322	14.7420
			TrapMF	13.3602	14.5735
			GbellMF	9.9543	14.2557
			GuassMF	9.8065	14.2179
	4	2	TriMF	10.6860	14.3883
			TrapMF	11.6767	15.0930
			GbellMF	10.2138	14.5646
			GuassMF	10.3305	14.5057
		3	TriMF	10.3412	15.0589
			TrapMF	11.6968	13.9684
			GbellMF	9.9779	16.1678
			GuassMF	9.8048	16.6236

		4	TriMF	9.6418	15.8648
			TrapMF	11.0448	14.3943
			GbellMF	9.2461	14.3528
			GuassMF	9.0671	15.4470

Appendix G.
Evaluation and error analysis of various settings for Model 3A,
i.e. AR(1)MO(1)MA(2) model for Retailer 3

No. of MFs for each input:			***Types of output function: Constant***		
$Q_d(t)$	***Mo(t)***	***$Ma_2(t)$***		Training error	Testing error
2	**2**	**2**	TriMF	14.4693	11.2639
			TrapMF	13.6159	12.2938
			GbellMF	12.9924	11.7906
			GuassMF	13.3282	11.6649
		3	TriMF	13.7751	11.1240
			TrapMF	13.2900	11.8759
			GbellMF	12.8616	11.3161
			GuassMF	13.0639	11.3323
		4	TriMF	13.6759	11.1298
			TrapMF	12.9829	11.2648
			GbellMF	12.4482	10.9120
			GuassMF	12.8427	10.9284
	3	**2**	TriMF	12.6504	11.5262
			TrapMF	13.4655	16.2689
			GbellMF	12.0745	11.3669
			GuassMF	12.3100	11.6025
		3	TriMF	11.8633	11.6393
			TrapMF	15.0365	12.7538
			GbellMF	12.7072	11.2765
			GuassMF	12.3295	11.6956
		4	TriMF	11.4772	11.9664
			TrapMF	13.5416	13.1191
			GbellMF	11.8188	12.2097
			GuassMF	11.6123	12.2186
	4	**2**	TriMF	11.9767	12.0658

			TrapMF	12.6332	11.7351
			GbellMF	12.1359	11.0784
			GuassMF	12.1350	11.0909
		3	TriMF	11.0450	11.5183
			TrapMF	12.3776	12.7111
			GbellMF	11.6151	11.5350
			GuassMF	11.2194	11.4248
		4	TriMF	10.8489	11.9304
			TrapMF	11.7275	11.8352
			GbellMF	10.8269	11.9122
			GuassMF	10.7057	11.9634
3	2	2	TriMF	12.9161	11.4658
			TrapMF	12.6571	11.3554
			GbellMF	12.4395	10.9133
			GuassMF	12.6624	**10.8748**
		3	TriMF	12.3340	11.5042
			TrapMF	13.1010	11.7401
			GbellMF	12.0929	11.1906
			GuassMF	11.8543	11.1536
		4	TriMF	12.0881	11.7126
			TrapMF	12.4882	12.0443
			GbellMF	11.4583	11.5292
			GuassMF	11.2140	11.8198
	3	2	TriMF	12.0061	10.9272
			TrapMF	14.9642	12.7801
			GbellMF	13.1724	11.8778
			GuassMF	12.8211	11.5110
		3	TriMF	11.3336	11.6089
			TrapMF	15.3373	12.8447
			GbellMF	11.6485	11.7539
			GuassMF	11.1369	11.6888
		4	TriMF	10.8307	11.5176
			TrapMF	15.0043	13.0727
			GbellMF	11.0538	11.9738
			GuassMF	10.8384	11.8641
	4	2	TriMF	11.2374	11.7023
			TrapMF	12.1486	12.0751

			GbellMF	11.3225	11.5472
			GuassMF	11.0330	11.6799
		3	TriMF	10.7895	11.1888
			TrapMF	12.1488	13.0729
			GbellMF	10.7054	11.8520
			GuassMF	10.7715	11.7858
		4	TriMF	10.3908	12.1940
			TrapMF	11.5255	14.1643
			GbellMF	10.0719	12.1283
			GuassMF	10.2780	12.1134
4	2	2	TriMF	12.7220	12.0857
			TrapMF	13.0412	11.1011
			GbellMF	12.5676	10.9302
			GuassMF	12.9033	11.3178
		3	TriMF	12.0344	12.0730
			TrapMF	12.8588	11.7829
			GbellMF	11.5403	12.0304
			GuassMF	11.7214	11.2957
		4	TriMF	12.0701	12.0223
			TrapMF	11.5519	11.8350
			GbellMF	10.8022	11.4840
			GuassMF	11.0315	12.1340
	3	2	TriMF	11.3677	11.3644
			TrapMF	13.0305	12.6547
			GbellMF	11.7036	11.3706
			GuassMF	11.4467	11.1403
		3	TriMF	10.6993	12.1188
			TrapMF	14.3902	13.2734
			GbellMF	10.6700	11.0952
			GuassMF	10.9631	10.9836
		4	TriMF	10.4538	11.9354
			TrapMF	12.5627	13.6963
			GbellMF	10.7399	11.4992
			GuassMF	10.4484	11.9461
	4	2	TriMF	10.5943	12.3683
			TrapMF	11.8275	11.2176
			GbellMF	10.7330	11.2532

			GuassMF	10.7877	11.3499
		3	TriMF	10.2240	11.9714
			TrapMF	11.3989	13.1503
			GbellMF	10.3732	11.4822
			GuassMF	10.4476	11.1312
		4	TriMF	10.0536	12.7101
			TrapMF	10.6585	13.3506
			GbellMF	9.7784	11.7145
			GuassMF	10.1468	12.0611

Appendix H.
Evaluation and error analysis of various settings for Model 3B,
i.e. AR(1)MO(1)MA(3) model for Retailer 3

No. of MFs for each input:			***Types of output function: Constant***		
$Q_d(t)$	***Mo(t)***	***$Ma_3(t)$***		Training error	Testing error
2	2	2	TriMF	13.9691	11.4841
			TrapMF	13.6403	10.8385
			GbellMF	13.3863	10.8947
			GuassMF	13.7032	11.1526
		3	TriMF	12.1098	11.1257
			TrapMF	11.8903	11.2449
			GbellMF	11.2711	10.7337
			GuassMF	11.5234	10.6938
		4	TriMF	12.5911	11.5778
			TrapMF	12.5951	11.3254
			GbellMF	12.0512	10.8094
			GuassMF	12.1824	11.0090
	3	2	TriMF	11.9435	11.4655
			TrapMF	13.0168	13.2856
			GbellMF	11.6025	12.1236
			GuassMF	11.5283	11.9397
		3	TriMF	11.1093	10.7682
			TrapMF	13.3065	12.5737
			GbellMF	10.5234	11.5262
			GuassMF	10.5570	11.1690

		4	TriMF	10.5690	11.8199
			TrapMF	12.5892	13.0719
			GbellMF	10.4653	11.9181
			GuassMF	10.3479	11.8301
	4	2	TriMF	10.5023	12.3480
			TrapMF	11.4966	11.7128
			GbellMF	10.5768	11.8210
			GuassMF	10.4290	12.0165
		3	TriMF	10.0896	11.7194
			TrapMF	11.3248	11.9560
			GbellMF	10.0248	11.5356
			GuassMF	10.0353	11.6113
		4	TriMF	9.6724	11.8623
			TrapMF	11.1261	12.3379
			GbellMF	9.8756	11.6577
			GuassMF	9.7289	11.4326
3	2	2	TriMF	12.5313	10.5077
			TrapMF	12.3517	11.2067
			GbellMF	11.9553	10.7050
			GuassMF	12.2956	10.5939
		3	TriMF	10.8656	10.3123
			TrapMF	11.5582	12.0968
			GbellMF	10.3825	11.6920
			GuassMF	10.3901	11.1687
		4	TriMF	11.1511	11.2423
			TrapMF	11.7807	12.5861
			GbellMF	10.4506	11.4335
			GuassMF	10.0490	11.6926
	3	2	TriMF	10.9738	10.9507
			TrapMF	13.8155	12.1942
			GbellMF	11.3660	11.6507
			GuassMF	10.8949	11.4003
		3	TriMF	10.6273	10.5008
			TrapMF	13.7983	12.0556
			GbellMF	10.5703	11.9598
			GuassMF	10.3370	11.5696
		4	TriMF	9.7798	11.8799

		TrapMF	13.9613	12.7496
		GbellMF	10.3864	12.2207
		GuassMF	9.8761	11.4765
	2	TriMF	9.5482	11.6609
		TrapMF	11.1066	11.7216
		GbellMF	9.7940	11.5819
		GuassMF	9.7073	11.6538
4	**3**	TriMF	9.1019	11.0467
		TrapMF	10.6351	13.4041
		GbellMF	9.3824	11.8962
		GuassMF	9.1208	11.7303
	4	TriMF	8.9653	11.3867
		TrapMF	10.6470	12.7520
		GbellMF	8.8875	11.4255
		GuassMF	8.4482	11.0523

4	**2**	**2**	TriMF	12.6888	10.7319
			TrapMF	12.3458	10.6811
			GbellMF	12.0063	**10.3066**
			GuassMF	12.2852	10.5115
		3	TriMF	9.9229	10.9907
			TrapMF	11.4195	12.1262
			GbellMF	10.1691	11.6414
			GuassMF	9.9798	11.4028
		4	TriMF	10.8072	12.0473
			TrapMF	11.7405	11.5443
			GbellMF	9.9074	11.4857
			GuassMF	9.7535	11.7627
	3	**2**	TriMF	10.1939	12.1235
			TrapMF	12.0061	12.8762
			GbellMF	10.1370	11.8184
			GuassMF	9.9357	11.9419
		3	TriMF	9.6685	11.3135
			TrapMF	12.5858	13.0107
			GbellMF	9.8176	11.7620
			GuassMF	9.6221	11.4419
		4	TriMF	9.4106	12.2614
			TrapMF	12.1269	13.0490

			GbellMF	9.6144	11.7014
			GuassMF	9.1626	11.5868
		2	TriMF	9.6535	11.9265
			TrapMF	10.6003	11.2334
			GbellMF	9.3831	11.2704
			GuassMF	9.3279	11.4192
	4	3	TriMF	9.0033	11.5621
			TrapMF	10.3208	13.1245
			GbellMF	9.0663	11.9703
			GuassMF	8.7997	12.3012
		4	TriMF	8.8051	12.0326
			TrapMF	10.3659	11.5334
			GbellMF	8.2604	10.9018
			GuassMF	7.9951	11.4631

Appendix I.

Evaluation and error analysis of various settings for Model 4A, i.e. AR(1)MO(1)MA(2) model for Retailer 1+2+3 where order arrival figures for Retailer 1, 2 and 3 are aggregated

No. of MFs for each input:				***Types of output function: Constant***	
$Q_d(t)$	***$Mo(t)$***	***$Ma_2(t)$***		Training error	Testing error
2	2	2	TriMF	37.7711	29.7414
			TrapMF	35.5013	33.1329
			GbellMF	31.9491	32.0650
			GuassMF	34.2310	32.0820
		3	TriMF	35.1525	31.0028
			TrapMF	34.9126	33.7051
			GbellMF	32.2945	30.4435
			GuassMF	33.1540	31.4999
		4	TriMF	34.6093	30.1445
			TrapMF	32.8900	30.5707
			GbellMF	31.3274	**28.2246**
			GuassMF	32.5972	28.3347
	3	2	TriMF	31.1209	31.1737
			TrapMF	33.4402	36.9642

			GbellMF	30.1771	33.2900
			GuassMF	30.1497	32.0298
		3	TriMF	28.8430	30.0207
			TrapMF	37.7959	35.3432
			GbellMF	30.1269	30.6355
			GuassMF	29.7762	30.3419
		4	TriMF	25.5409	31.9664
			TrapMF	34.4029	39.6396
			GbellMF	27.0118	34.7674
			GuassMF	26.3110	33.8983
	4	2	TriMF	29.7317	32.0540
			TrapMF	30.9428	33.7764
			GbellMF	28.9683	30.6947
			GuassMF	29.4817	31.2889
		3	TriMF	26.1971	29.6256
			TrapMF	30.1612	31.7667
			GbellMF	25.9952	31.7454
			GuassMF	26.1172	29.8903
		4	TriMF	24.1102	31.2327
			TrapMF	27.2220	34.4056
			GbellMF	24.0447	30.9296
			GuassMF	23.8856	31.3405
3	2	2	TriMF	33.0971	31.9886
			TrapMF	31.9228	29.7260
			GbellMF	30.6329	28.9870
			GuassMF	31.3824	29.7189
		3	TriMF	30.2330	32.8590
			TrapMF	35.0554	33.6221
			GbellMF	29.1483	31.6450
			GuassMF	29.8347	32.7649
		4	TriMF	30.2846	29.1719
			TrapMF	30.0930	61.4093
			GbellMF	27.2389	33.7140
			GuassMF	27.0964	35.0796
	3	2	TriMF	28.2449	31.1303
			TrapMF	38.0883	38.2237
			GbellMF	31.9944	30.5122

			GuassMF	30.9546	30.6924
		3	TriMF	26.4293	31.7838
			TrapMF	41.4571	34.9674
			GbellMF	26.9842	32.3613
			GuassMF	25.9680	32.7760
		4	TriMF	24.3596	33.7753
			TrapMF	37.6801	157.9972
			GbellMF	24.5176	33.9350
			GuassMF	24.8757	33.2980
	4	**2**	TriMF	26.3239	31.5547
			TrapMF	30.2066	30.1737
			GbellMF	26.5866	30.1039
			GuassMF	25.5263	30.0557
		3	TriMF	24.8587	31.6488
			TrapMF	31.5181	37.8219
			GbellMF	24.9054	30.9590
			GuassMF	24.8044	31.7779
		4	TriMF	23.0272	32.6283
			TrapMF	27.4809	34.2971
			GbellMF	22.5372	33.4546
			GuassMF	22.3665	31.9902
4	**2**	**2**	TriMF	32.5966	32.4637
			TrapMF	31.6952	30.0141
			GbellMF	30.5046	28.7010
			GuassMF	32.1447	30.2904
		3	TriMF	29.1001	34.3140
			TrapMF	32.6340	32.3464
			GbellMF	27.0989	29.9642
			GuassMF	27.4007	32.0546
		4	TriMF	29.8484	32.1172
			TrapMF	29.1876	31.6428
			GbellMF	24.2982	33.9999
			GuassMF	26.4535	35.0576
	3	**2**	TriMF	26.6899	31.3338
			TrapMF	34.2278	33.1412
			GbellMF	28.5772	31.6075
			GuassMF	27.6552	31.2187

		3	TriMF	24.1298	35.9261
			TrapMF	37.5707	32.5203
			GbellMF	24.9437	35.6530
			GuassMF	24.9677	32.8281
		4	TriMF	23.5289	32.5790
			TrapMF	32.8850	37.9708
			GbellMF	23.5226	34.6061
			GuassMF	22.9912	33.3830
	4	**2**	TriMF	24.5383	33.3301
			TrapMF	28.6065	30.4290
			GbellMF	24.0717	30.7144
			GuassMF	24.1908	31.8722
		3	TriMF	23.2414	33.6718
			TrapMF	27.6866	33.5366
			GbellMF	22.3005	33.0594
			GuassMF	22.7798	32.1008
		4	TriMF	22.4259	35.9409
			TrapMF	25.1930	35.4917
			GbellMF	20.9080	34.2562
			GuassMF	21.4624	34.3788

Appendix J.

Evaluation and error analysis of various settings for Model 4B,
i.e. AR(1)MO(1)MA(3) model for Retailer 1+2+3 where order arrival figures for Retailer 1, 2 and 3 are aggregated

No. of MFs for each input:			***Types of output function: Constant***		
$Q_d(t)$	***$Mo(t)$***	***$Ma_3(t)$***		Training error	Testing error
2	**2**	**2**	TriMF	37.1960	37.1959
			TrapMF	34.6317	29.5271
			GbellMF	34.3474	28.2751
			GuassMF	35.9787	29.0726
		3	TriMF	31.9749	34.9142
			TrapMF	30.7342	33.2349
			GbellMF	30.3697	32.0101
			GuassMF	31.1201	32.3838

		4	TriMF	34.0805	31.3958
			TrapMF	31.5598	28.4648
			GbellMF	30.4429	29.5445
			GuassMF	31.8912	30.4602
	3	2	TriMF	31.3331	30.3906
			TrapMF	34.4711	40.5871
			GbellMF	31.1631	35.4390
			GuassMF	30.8113	33.5053
		3	TriMF	28.6660	30.1608
			TrapMF	34.2671	40.3885
			GbellMF	27.7584	34.0956
			GuassMF	27.5937	32.0043
		4	TriMF	25.9729	32.3567
			TrapMF	34.1586	38.7210
			GbellMF	27.1853	32.2610
			GuassMF	26.4207	31.9550
	4	2	TriMF	26.3621	31.5235
			TrapMF	27.2008	34.0094
			GbellMF	25.6482	32.1846
			GuassMF	25.7817	31.7652
		3	TriMF	25.0957	31.7613
			TrapMF	27.6002	35.5163
			GbellMF	24.0327	31.9221
			GuassMF	24.8142	31.3674
		4	TriMF	22.5534	28.9425
			TrapMF	25.7180	32.2791
			GbellMF	22.8647	29.1763
			GuassMF	22.5182	28.1690
3	2	2	TriMF	31.5476	29.8702
			TrapMF	30.1574	30.4156
			GbellMF	29.6256	29.1300
			GuassMF	30.8988	29.4688
		3	TriMF	26.5119	31.1857
			TrapMF	30.0801	34.9125
			GbellMF	26.7693	34.3555
			GuassMF	26.7237	32.9699
		4	TriMF	26.0289	32.0746

		TrapMF	27.8146	55.5373
		GbellMF	24.5478	31.2448
		GuassMF	24.0847	32.8908
		TriMF	28.0162	30.8895
	2	TrapMF	36.6376	34.4445
		GbellMF	30.7247	31.8831
		GuassMF	28.8704	31.4578
		TriMF	26.0655	30.0482
3	**3**	TrapMF	35.1542	34.8745
		GbellMF	27.4649	34.6092
		GuassMF	26.4827	31.7786
		TriMF	23.6312	34.6039
	4	TrapMF	37.7357	35.8491
		GbellMF	25.8721	34.7604
		GuassMF	24.8266	33.5007
		TriMF	23.7671	32.0337
	2	TrapMF	26.6314	29.7041
		GbellMF	22.8027	31.6851
		GuassMF	22.9748	31.4599
		TriMF	21.9494	31.5020
4	**3**	TrapMF	28.1056	36.4831
		GbellMF	21.6338	32.1236
		GuassMF	21.4890	31.5915
		TriMF	20.5724	30.6597
	4	TrapMF	23.9835	30.2716
		GbellMF	20.0916	31.0390
		GuassMF	19.6246	29.5022
4	**2**	TriMF	32.6374	30.4187
	2	TrapMF	30.3525	27.8652
		GbellMF	30.4547	**27.4482**
		GuassMF	31.6127	28.7692
		TriMF	25.8668	32.8113
	3	TrapMF	28.4831	35.7053
		GbellMF	25.4697	33.6931
		GuassMF	25.7193	33.1815
	4	TriMF	26.4427	33.3037
		TrapMF	28.3899	27.8913

		GbellMF	22.7918	33.9946
		GuassMF	23.0326	33.3366
3	2	TriMF	26.3585	34.0476
		TrapMF	32.8438	34.6630
		GbellMF	26.8473	33.5426
		GuassMF	26.2561	33.7289
	3	TriMF	24.7977	32.9369
		TrapMF	31.4334	41.6054
		GbellMF	24.4010	34.9026
		GuassMF	24.6243	33.1777
	4	TriMF	22.5638	35.3830
		TrapMF	32.5719	33.5196
		GbellMF	24.2033	33.5234
		GuassMF	22.6219	33.1129
4	2	TriMF	22.9799	33.1564
		TrapMF	25.2218	31.4189
		GbellMF	20.6582	31.4121
		GuassMF	21.2526	32.3138
	3	TriMF	22.0811	32.3310
		TrapMF	26.2708	37.6090
		GbellMF	19.5313	32.7109
		GuassMF	20.3082	32.9837
	4	TriMF	19.9210	30.2822
		TrapMF	23.1040	33.5519
		GbellMF	18.6889	32.5329
		GuassMF	18.6355	29.8441

References

Aamodt, A. and Plaza, E. (1994). Case-based reasoning: foundational issues, methodological variations, and system approaches. *AICom – Artificial Intelligence Communications*, 7(1), 39-59.

Abhishek, V., Jerath, K., & Zhang, Z. J. (2015). Agency selling or reselling? Channel structures in electronic retailing. *Management Science*, 62(8), 2259-2280.

Accorsi, R., Manzini, R., & Maranesi, F. (2014). A decision-support system for the design and management of warehousing systems. *Computers in Industry*, 65(1) pp. 175-186.

Admuthe, L. S., & Apte, S. (2010). Adaptive neuro-fuzzy inference system with subtractive clustering: a model to predict fiber and yarn relationship. *Textile Research Journal*, 80(9), 841-846.

Aengchuan, P., & Phruksaphanrat, B. (2018). Comparison of fuzzy inference system (FIS), FIS with artificial neural networks (FIS+ ANN) and FIS with adaptive neuro-fuzzy inference system (FIS+ ANFIS) for inventory control. *Journal of Intelligent Manufacturing*, 29(4), 905-923.

Agatz, N.A., Fleischmann, M., & Van Nunen, J.A. (2008). E-fulfillment and multi-channel distribution: a review. *European Journal of Operational Research*, 187, pp. 339–356.

Agrawal, R., Imieliński, T., Swami, A. (1993). Mining association rules between sets of items in large databases. *Proceedings of the 1993 ACM SIGMOD international conference on Management of data - SIGMOD '93*. 207.

Ahmad, M. W., Mourshed, M., & Rezgui, Y. (2017). Trees vs Neurons: Comparison between random forest and ANN for high-resolution prediction of building energy consumption. *Energy and Buildings*, 147, 77-89.

Akcayol, M. A. (2004). Application of adaptive neuro-fuzzy controller for SRM. *Advances in Engineering Software*, 35(3–4), 129–137.

Akhter, F., Hobbs, D., & Maamar, Z. (2005). A fuzzy logic-based system for assessing the level of business-to-consumer (B2C) trust in electronic commerce. *Expert Systems with Applications*, 28(4), 623-628.

Akter, S., & Wamba, S. F. (2016). Big data analytics in E-commerce: a systematic review and agenda for future research. *Electronic Markets*, 26(2), 173-194.

Al-Harbi, K. M. A. S. (2001). Application of the AHP in project management. *International Journal of Project Management*, 19(1), 19-27.

Alrashed, A. A., Gharibdousti, M. S., Goodarzi, M., de Oliveira, L. R., Safaei, M. R., & Bandarra Filho, E. P. (2018). Effects on thermophysical properties of carbon based nanofluids: Experimental data, modelling using regression, ANFIS and ANN. *International Journal of Heat and Mass Transfer*, 125, 920-932.

Altug, S., Chow, M.Y., & Trussell, H.J. (1999). Fuzzy inference systems. implemented on neural architectures for motor. *IEEE Transactions on Industrial Electronics*, 46 (6), 1069-1079.

ARC Advisory Group, 'Warehouse Management Systems ARC Advisory Group', Retrieved 29/12/14 World Wide Web, http://www.arcweb.com/market-studies/pages/warehouse-management-systems.aspx.

Areerachakul, S. (2012). Comparison of ANFIS and ANN for estimation of biochemical oxygen demand parameter in surface water. *International Journal of Chemical and Biological Engineering*, 6, 286-290.

Armbrust, M., Fox, A., Griffith, R., Joseph, A.D., Katz, R., Konwinski, A., Lee, G., Patterson, D., Rabkin, A., Stoica, I. and Zaharia, M. (2010). A view of Cloud computing. *Communications of the ACM*, 53(4), 50 – 58.

Attaran, M. (2007). RFID: an enabler of supply chain operations. *Supply Chain Management: An International Journal*, 12(4), 249-257.

Autry, C.W., Grawe, S.J., Daugherty, P. and Richey, R.G. Jr (2010). The effects of technological turbulence and breadth on supply chain technology acceptance and adoption. *Journal of Operations Management*, 28(6), 522-36.

Avci, E. (2008). Comparison of wavelet families for texture classification by using wavelet packet entropy adaptive network based fuzzy inference system. *Applied Soft Computing*, 8(1), 225–231.

Avci, E., Hanbay, D., & Varol, A. (2007). An expert discrete wavelet adaptive network based fuzzy inference system for digital modulation recognition. *Expert Systems with Applications*, 33(3), 582–589.

Azadeh, A., Asadzadeh, S. M., Saberi, M., Nadimi, V., Tajvidi, A., & Sheikalishahi, M. (2011). A neuro-fuzzy-stochastic frontier analysis approach for long-term natural gas consumption forecasting and behavior analysis: the cases of Bahrain, Saudi Arabia, Syria, and UAE. *Applied Energy*, 88(11), 3850-3859.

Badger, L., Grance, T., Patt-Corner, P. and Voas, J. (2011). *Draft-Cloud Computing Synopsis and Recommendations*. National Institute of Standards and Technology, Gaithersburg, MD, May.

Ballou, R.H. (1999). *Business Logistics Management*. Prentice-Hall, Englewood Cliffs, NJ.

Barbosa, Hisano D. and Musetti, Andreotti M. (2010). Logistics information systems adoption: an empirical investigation in Brazil. *Industrial Management & Data Systems*, 110(6), 787-804.

Battini, D., Calzavara, M., Persona, A., & Sgarbossa, F. (2015). Order picking system design: the storage assignment and travel distance estimation (SA&TDE) joint method. *International Journal of Production Research*, 53(4), 1077-1093.

Berg, J., and Zijm, W. (1999). Models for warehouse management: Classification and examples. *International Journal of Production Economics*, 59(1-3), 519-528.

Billah, B., King, M.L., Snyder, R.D.& Koehler, A.B. (2006). Exponential smoothing model. selection for forecasting. *International Journal of Forecasting*, 22, 239-247.

Bindi, F., Manzini, R., Pareschi, A., & Regattieri, A. (2009). Similarity-based storage allocation rules in an order picking system: an application to the food service industry. *International Journal of Logistics Research and Applications*, 12(4), pp.233-247.

Bloom, J. Z. (2005). Market segmentation: A neural network application. *Annals of Tourism Research*, 32(1), 93-111.

Boone, C., Craighead, C., & Hanna, J. (2007). Postponement: an evolving supply chain concept. *International Journal of Physical Distribution & Logistics Management*, 37(8), 594-611.

Bowersox, D.J., Closs, D.J. and Stank, T.P. (1999). *21st Century Logistics: Making Supply Chain Integration a Reality*. Council of Logistics Management, Oak Brook, IL.

Box, G.& Jenkins, G. (1976). *Time Series Analysis: Forecasting and Control*. Holden-Day.

Boyacioglu, M. A., & Avci, D. (2010). An adaptive network-based fuzzy inference system (ANFIS) for the prediction of stock market return: the case of the Istanbul stock exchange. *Expert Systems with Applications*, 37(12), 7908-7912.

Boyer, K.K. and Hult, G.T.M. (2005). Extending the supply chain: integrating operations and marketing in the online grocery industry. *Journal of Operations Management*, 23(6), 642-61.

Brézillon, P. et al. (2000), SART: An Intelligent Assistant System for Subway Control. *Pesquisa Operacional*. 20(2), 247-268.

Bridgman, P. W. (1922). *Dimensional analysis*. Yale University Press.

Brown, R.G. (1959). *Statistical Forecasting for Inventory Control*. McGraw-Hill, New York

Brown, R.G. (1963). *Smoothing, Forecasting and prediction of Discrete Time Series*. Prentice-Hall, Englewood Cliffs.

Buyya, R., Vecchiola, C. and Selvi, S. (2013). *Mastering cloud computing*. Waltham, MA: Morgan Kaufmann.

Cabeza, M., & Moilanen, A. (2001). Design of reserve networks and the persistence of biodiversity. *Trends in ecology & evolution*, 16(5), 242-248.

Can, F., Altingövde, I. S., & Demir, E. (2004). Efficiency and effectiveness of query processing in cluster-based retrieval. *Information Systems*, 29(8), 697-717.

Cao, M., Luo, X., Luo, X. R., & Dai, X. (2015). Automated negotiation for e-commerce decision making: a goal deliberated agent architecture for multi-strategy selection. *Decision Support Systems*, 73, 1-14.

Cardona, L. F., Soto, D. F., Rivera, L., & Martínez, H. J. (2015). Detailed design of fishbone warehouse layouts with vertical travel. *International Journal of Production Economics*, 170, 825-837.

Carlson, J., O'Cass, A., & Ahrholdt, D. (2015). Assessing customers' perceived value of the online channel of multichannel retailers: A two country examination. *Journal of Retailing and Consumer Services*, 27, 90-102.

Caron, F., Marchet, G., & Perego, A. (2000). Optimal Layout in Low-Level Picker-to-Part Systems. *International Journal of Production Research*, 38, 101-117.

Castro-Schez, J., Miguel, R., Vallejo, D., & López-López, L. (2011). A highly adaptive recommender system based on fuzzy logic for B2C e-commerce portals. *Expert Systems with Applications*, 38(3), 2441-2454.

Census and Statistics Department. (2003), *Hong Kong Monthly Digest of Statistics*. December 2013. Hong Kong, pp. 1-16.

Chan, F., & Kumar, V. (2009). Hybrid TSSA algorithm-based approach to solve warehouse-scheduling problems. *International Journal of Production Research*, 47(4), 919-940.

Chan, H., He, H., & Wang, W. (2012). Green marketing and its impact on supply chain management in industrial markets. Industrial Marketing Management, 41(4), 557-562.

Chang, J. R., Wei, L. Y., & Cheng, C. H. (2011). A hybrid ANFIS model based on AR and volatility for TAIEX forecasting. *Applied Soft Computing*, 11(1), 1388-1395.

Chen, B., & Lee, C. (2008). Logistics scheduling with batching and transportation. *European Journal of Operational Research*, 189(3), 871-876.

Chen, J., & Shen, X. L. (2015). Consumers' decisions in social commerce context: An empirical investigation. *Decision Support Systems*, 79, 55-64.

Chen, M., Zhang, D. and Zhou, L. (2007). Empowering collaborative commerce with web services enabled business process management systems, D*ecision Support Systems*, 43(2), 530-546.

Chen, X., & Lin, H. (2013). Research on e-commerce logistics system informationization in chain. *Procedia-social and behavioral sciences*, 96, 838-843.

Chew, E. P., & Tang, L.C. (1999). Travel time analysis for general item location assignment in a rectangular warehouse. *European Journal of Operational Research*, 112, 582–597.

Chi, R.T., Chen, M. and Kiang, M.Y. (1993). Generalized case-based reasoning system for portfolio management. *Expert Systems with Applications*, 6, 67-76.

Chia Jane, C. (2000), Storage location assignment in a distribution center, *International Journal of Physical Distribution & Logistics Management*, 30 (1), pp. 55-71.

Chiu, S. L. (1994). Fuzzy model identification based on cluster estimation. *Journal of Intelligent and Fuzzy Systems*, 2, 267–278.

Cho, Jay Joong-Kun, Ozment, J., & Sink, H. (2008). Logistics capability, logistics outsourcing and firm performance in an e-commerce market. *International Journal of Physical Distribution & Logistics Management*, 38(5), 336 – 359.

Cho, V. (2003). A comparison of three different approaches to tourist arrival forecasting. *Tourism management*, 24(3), 323-330.

Choi, K., Narasimhan, R., & Kim, S. (2012). Postponement strategy for international transfer of products in a global supply chain: A system dynamics examination. *Journal of Operations Management*, 30(3), 167-179.

Chow, Harry K.H., Choy, K.L., Lee, W.B., & Lau, K.C. (2006). Design of a RFID case-based resource management system for warehouse operations. *Expert Systems with Applications*, 30(4), 561-576, 2006.

Chow, H.K.H., Choy, K.L., Lee, W.B. and Chan, F.T.S. (2007). Integration of web-based and RFID technology in visualizing logistics operations – a case study. *Supply Chain Management: An International Journal*, 12(3), 221-234.

Choy, K. L., Lee, W. B., Lau, H. C., & Choy, L. C. (2005). A knowledge-based supplier intelligence retrieval system for outsource manufacturing. *Knowledge-based systems*, 18(1), 1-17.

Christopher, M. (2016). *Logistics & supply chain management*. Pearson UK.

CLM (2004). *Definition of logistics. Council of Logistics Management*, available at: www.cscmp.org/

Craw, S., Wiratunga, N. and Rowe, R. (2006). Learning adaptation knowledge to improve case-based reasoning. *Artificial Intelligence*, 170(16-17), 1175-1192.

Crum, M.R., Premkumar, G. and Ramamurthy, K. (1996). An assessment of motor carrier adoption, use and satisfaction with EDI. *Transportation Journal*, 35(4), 44-57.

Cunnane, Chris. (2015). *E-Commerce Growth Brings Last Mile Headaches*. Logistics Viewpoints, ARC Advisory Group. [Online]. Available: http://www. http://logisticsviewpoints.com/ [Accessed: 15 July, 2015]

Cybenko, G. (1989). Approximation by superpositions of a sigmoidal function. *Mathematics of control, signals and systems*, 2(4), 303-314.

Davenport, T.H., and Brooks, J.D. (2004). Enterprise systems and the supply chain. *Journal of Enterprise Information Management*, 17(1), pp. 8-19.

Davidsson, Paul et al. (2005). An Analysis of Agent-Based Approaches to Transport Logistics. *Transportation Research Part C: Emerging Technologies*, 13(4), pp. 255-271.

De Koster, M., Van der Poort, E., & Wolters, M. (1999). Efficient order batching methods in warehouses. *International Journal of Production Research*, 37(7), pp. 1479-1504.

De Koster, R.B.M. (2003). Distribution strategies for online retailers. *IEEE Transactions on Engineering Management*, 50, 448–457.

De Koster, R., Le-Duc, T., & Roodbergen, K. J. (2006). Design and control of warehouse order picking: a literature review, *ERIM Report Series Research in Management*.

De Koster, R., Le-Duc, T., & Roodbergen, K. (2007). Design and control of warehouse order picking: A literature review. *European Journal of Operational Research*, 182(2), 481-501.

Didehkhani, H., Jassbi, J., & Pilevari, N. (2009). Assessing flexibility in supply chain using adaptive neuro fuzzy inference system. In *Industrial Engineering and Engineering Management*. IEEM 2009, 513-517.

Dolnicar, S., & Fluker, M. (2003). Behavioural market segments among surf tourists: investigating past destination choice. *Journal of Sport Tourism*, 8(3), 186-196.

Dombi, J., Jónás, T., & Tóth, Z. E. (2018). M2odeling and long-term forecasting demand in spare parts logistics businesses. *International Journal of Production Economics*, 201, 1-17.

Drury, J. (1988). *Towards more efficient order picking*. IMM Monograph No. 1, The Institute of Materials Management, Cranfield, U.K.

Duclos, L.K., Vokurka, R.J. and Lummus, R.R. (2003). A conceptual model of supply chain flexibility. *Industrial Management and Data Systems*, 103 (6), 446-63.

Efendigil, T., Önüt, S., & Kahraman, C. (2009). A decision support system for demand forecasting with artificial neural networks and neuro-fuzzy models: A comparative analysis. *Expert Systems with Applications*, 36(3), 6697-6707.

Egrioglu, E., Aladag, C. H., Basaran, M. A., Yolcu, U., & Uslu, V. R. (2011). A new approach based on the optimization of the length of intervals in fuzzy time series. *Journal of Intelligent & Fuzzy System*s, 22(1), 15-19.

El-Shafie, A., Jaafer, O., & Akrami, S. A. (2011). Adaptive neuro-fuzzy inference system based model for rainfall forecasting in Klang River, Malaysia. *International Journal of Physical Sciences*, 6(12), 2875-2888.

Esfahanipour, A., & Aghamiri, W. (2010). Adapted neuro-fuzzy inference system on indirect approach TSK fuzzy rule base for stock market analysis. *Expert Systems with Applications*, 37(7), 4742-4748.

Esper, T. L., Jensen, T. D., Turnipseed, F. L., & Burton, S. (2003). The last mile: an examination of effects of online retail delivery strategies on consumers. *Journal of Business Logistics*, 24(2), 177-203.

Evangelista, P., McKinnon, A., Sweeney, E. (2013). Technology adoption in small and medium-sized logistics providers. *Industrial Management & Data Systems*, 113 (7), pp. 967-989

Evangelista, P. and Sweeney, E. (2006). Technology usage in the supply chain: the case of small 3PLs. *International Journal of Logistics Management*, 17(1), 55-74.

European Commission, (2012). *Report of the High Level Group on the Development of the EU Road Haulage Market*. Brussels.

Faber, N., de Koster, R. and van de Velde, S. (2002). Linking warehouse complexity to warehouse planning and control structure. *International Journal of Physical Distribution & Logistics Management*, 32(5), 381-395.

Falk, M., & Hagsten, E. (2015). E-commerce trends and impacts across Europe. *International Journal of Production Economics*, 170, 357-369.

Fernie, J., & McKinnon, A. (2009). *The development of e-tail logistics*. In Fernie, J. and Sparks, L. (eds), Logistics and Retail Management, Emerging Issues and New Challenges in the Retail Supply Chain. London: Kogan Page, 207–232.

Findler, Nicholas V., and Lo, Ron. (1986). An Examination Of Distributed Planning In The World Of Air Traffic Control. *Journal of Parallel and Distributed Computing 3.3*, 411-431.

Flores, J.J., Graff, M.& Rodriguez, H. (2012). Evolutive design of ARMA and ANN. models for time series forecasting. *Renewable Energy*, 44, 225-230.

Food Dive. (2018). *8 major challenges facing the food and beverage industry in 2016*. [online] Available at: https://www.fooddive.com/news/8-major-challenges-facing-the-food-and-beverage-industry-in-2016/411408/ [Accessed 23 Feb. 2018].

Forrester Research, (2016a). *eCommerce Trends and Outlook In Australia, China, India, Japan, And South Korea*.

Forrester Research, (2016b). *Forrester Research Online Cross-Border Retail Forecast, 2016 To 2021 (Global)*.

Fredericks, E. (2005). Infusing flexibility into business-to-business firms: a contingency theory and resource-based view perspective and practical implications. *Industrial Marketing Management*, 34(6), 555-65.

Funahashi, K. I. (1989). On the approximate realization of continuous mappings by neural networks. *Neural networks*, 2(3), 183-192.

Galindo, J., Urrutia, A., & Piattini, M. (2006). *Introduction to Fuzzy Logic*. In J. Galindo, A. Urrutia , & M. Piattini (Eds.), Fuzzy Databases: Modeling, Design and Implementation (pp. 1-44). Hershey, PA: IGI Global.

García-Crespo, Á., Ruiz-Mezcua, B., López-Cuadrado, J., and González-Carrasco, I. (2009). A review of conventional and knowledge based systems for machining price quotation. *Journal of Intelligent Manufacturing*, 22(6), 823-841.

Gartner, Inc. (2013). *Trends and Directions of SaaS in Asia/Pacific*. [Online]. Available: http://www.mscmalaysia.my/ [Accessed: 16 November, 2015]

Gartner, Inc. (2014). *Information Technology (IT) Spending Forecast*. [Online]. Available: http://www.gartner.com/technology/research/it-spending-forecast/ [Accessed: 20 November, 2015]

Gavade, R. K. (2014). Multi-Criteria Decision Making: An overview of different selection problems and methods. *International Journal of Computer Science and Information Technologies*, 5(4), 5643-5646.

Geismar, H., Laporte, G., Lei, L., & Sriskandarajah, C. (2008). The Integrated Production and Transportation Scheduling Problem for a Product with a Short Lifespan. *INFORMS Journal on Computing*, 20(1), 21-33.

Gen, M., Cheng, R. (2000). *Genetic Algorithms and Engineering Optimization*, Wiley, New York.

Gibson, D. R., & Sharp, G. P. (1992). Order batching procedures. *European Journal of Operational Research*, 58(1), 57-67.

Giordano, F., La Rocca, M., & Perna, C. (2007). Forecasting nonlinear time series with neural network sieve bootstrap. *Computational Statistics & Data Analysis*, 51(8), 3871-3884.

Global Logistics Research Team at Michigan State University (1995). *World Class Logistics: The Challenge of Managing Continuous Change*, Council of Logistics Management, Oak Brook, IL.

Global Web-Index (2017). *GWI Market Report 2017*. London: Trendstream Limited.

Goetschalckx, M., & Ashayeri, J. (1989). Classification and design of order picking. *Logistics World*, 2(2), 99-106.

Goguen, J. A. (1969). *The logic of inexact concepts*. Synthese, 19(3-4), 325-373.

Goldberg, D.E. (1989). *Genetic algorithm in search*. In: Optimization and Machine Learning, Addison-Wesley, New York.

Graudina, V., Grundspenkis, J. (2005). Technologies and Multi-Agent System Architectures for Transportation and Logistics Support: An Overview. In: Rachev, *International Conference on Computer Systems and Technologies - CompSysTech' 2005*, IIIA.6-1 – IIIA.6-6.

Grosse, E. H., & Glock, C. H. (2015). The effect of worker learning on manual order picking processes. *International Journal of Production Economics*, 170, 882-890.

Grosse, E. H., Glock, C. H., Jaber, M. Y., & Neumann, W. P. (2015). Incorporating human factors in order picking planning models: framework and research opportunities. *International Journal of Production Research*, 53(3), 695-717.

Gu, J., Goetschalckx, M. and McGinnis, L. (2007). Research on warehouse operation: A comprehensive review. *European Journal of Operational Research*, 177(1), 1-21.

Gu, W., Foster, K., & Shang, J. (2016). Enhancing market service and enterprise operations through a large-scale GIS-based distribution system. *Expert Systems with Applications*, 55, 157-171.

Gubbi, J., Buyya, R., Marusic, S. and Palaniswami, M. (2013). Internet of Things (IoT): A vision, architectural elements, and future directions. *Future Generation Computer Systems*, 29(7), 1645-1660.

Gunasekaran, A., & Ngai, E. W. (2004). Information systems in supply chain integration and management. *European Journal of Operational Research*, 159(2), 269-295.

Gunasekaran, A., Patel, C., & McGaughey, R. E. (2004). A framework for supply chain performance measurement. *International Journal of Production Economics*, 87(3), 333-347.

Güneri, A. F., Ertay, T., & Yücel, A. (2011). An approach based on ANFIS input selection and modeling for supplier selection problem. *Expert Systems with Applications*, 38(12), 14907-14917.

Gupta, N., Mangal, N., Tiwari, K., & Mitra, P. (2006). Mining quantitative association rules in protein sequences. In *Data Mining*. Springer Berlin/Heidelberg, 273-281.

Guresen, E., Kayakutlu, G., & Daim, T. U. (2011). Using artificial neural network models in stock market index prediction. *Expert Systems with Applications*, 38(8), 10389-10397.

Habazin, J., Glasnović, A., & Bajor, I. (2017). Order picking process in warehouse: Case study of dairy industry in Croatia. *Promet-Traffic & Transportation*, 29(1), 57-65.

Hall, D.J., Skipper, J.B., Hazen, B.T. and Hanna, J.B. (2012). Inter-organizational IT use, cooperative attitude, and inter-organizational collaboration as antecedents to contingency planning effectiveness. *International Journal of Logistics Management*, 23(1), 50-76.

Han, S.G., Lee, S.G. and Jo, G.S. (2005). Case-based tutoring systems for procedural problem solving on www. *Expert Systems with Applications*, 29, 573-82.

Hansen, J.V., McDonald, J.B., & Nelson, R.D. (1999). Time series prediction with genetic-algorithm designed neural networks: An empirical comparison with modern statistical models. *Computational Intelligence*, 15 (3), 171-184.

Harmon, R.L. (1993). *Reinventing the warehouse, world-class distribution logistic*. New York: The Free Press p. 89.

Hassan, M.M.D. (2002). A framework for the design of warehouse layout. *Facilities*, 20(13/14), 432-440.

Hassanien, A., El-Bendary, N., Sweidan, A., Mohamed, A. and Hegazy, O. (2015). Hybrid-Biomarker Case-Based Reasoning System for Water Pollution Assessment in Abou Hammad Sharkia, Egypt, *Applied Soft Computing*, In Press.

Helo, P., and Szekely, B. (2005). Logistics information systems: An analysis of software solutions for supply chain coordination. *Industrial Management & Data Systems*, 105(1), 5-18.

HKTDC Research. (2015). *Sea Transport Industry In Hong Kong*. Hong Kong: Hong Kong Trade Development Council (HKTDC) Research.

HKTDC Research. (2016). *China Launches E-commerce Logistics Plan*. Hong Kong: Hong Kong Trade Development Council (HKTDC) Research.

Ho, G.T.S., Lau, H.C.W., Chung, S.H., Fung, R.Y.K., Chan, T.M., & Lee, C.K.M. (2008). Fuzzy rule sets for enhancing performance in a supply chain network. *Industrial Management & Data Systems*, 108(7), 947-972.

Holland, J. (1975). *Adaptation In Natural and Artificial System*s. University of Michigan Press, Ann Arbor.

Holt, C.C. (1957). *Forecasting seasonals and trends by exponentially weighted moving*. averages. Off. Nav. Res. Res. Memo. 52.

Huang, C., Liang, W., Lai, Y., & Lin, Y. (2010). The agent-based negotiation process for B2C e-commerce. *Expert Systems with Applications*, 37(1), 348-359.

Huang, G., Zhang, Y. and Jiang, P. (2007). RFID-based wireless manufacturing for walking-worker assembly islands with fixed-position layouts. *Robotics and Computer-Integrated Manufacturing*, 23(4), 469-477.

Huang, S., Kwan, I. and Hung, Y. (2001). Planning enterprise resources by use of a reengineering approach to build a global logistics management system. *Industrial Management & Data Systems*, 101(9), 483-491.

Hultkrantz, O., & Lumsden, K. (2001). E-commerce and consequences for the logistics industry. In Proceedings for Seminar on "*The Impact of E-Commerce on Transport.*" Paris.

Hvam, L., Pape, S., and Nielsen, M. (2006). Improving the quotation process with product configuration. *Computers in Industry*, 57(7), 607-621.

Jahromi, M. Z., Parvinnia, E., & John, R. (2009). A method of learning weighted similarity function to improve the performance of nearest neighbor. *Information sciences*, 179(17), 2964-2973.

Jain, S.K., Bhargava, A., & Pal, R.K. (2015). Three area power system load frequency control using fuzzy logic controller. In: *IEEE Conference Indore*, 10–12.

Jain, A., & Kumar, A. M. (2007). Hybrid neural network models for hydrologic time series forecasting. *Applied Soft Computing*, 7(2), 585-592.

Jaipuria, S., & Mahapatra, S. S. (2014). An improved demand forecasting method to reduce bullwhip effect in supply chains. *Expert Systems with Applications*, 41(5), 2395-2408.

Jane, C.C. (2000). Storage location assignment in a distribution center. *International Journal of Physical Distribution & Logistics Management*, 30(1), 55-71.

Jang, J. S. R. (1993). ANFIS: Adaptive network-based fuzzy inference systems. *IEEE Transactions on Systems, Man, and Cybernetics*, 23, 665–685.

Jang, J.S.R., Sun, C.T., & Mizutani, E. (1997). *Neuro-fuzzy soft computing*. Englewood Cliffs, NJ: Prentice-Hall.

Johnson, M. E., & Whang, S. (2002). E-business and supply chain management: an overview and framework. *Production and Operations management*, 11(4), 413-423.

Kaastra, I., & Boyd, M. (1996). Designing a neural network for forecasting financial and economic time series. *Neurocomputing*, 10(3), 215-236.

Kang, I. S., Na, S. H., Kim, J., & Lee, J. H. (2007). Cluster-based patent retrieval. *Information processing & management*, 43(5), 1173-1182.

Kar, S., Das, S., & Ghosh, P. K. (2014). Applications of neuro fuzzy systems: A brief review and future outline. *Applied Soft Computing*, 15, 243-259.

Karageorgos, A., Mehandjiev, N., Weichhart, G., Hämmerle, A. (2003). Agent-based optimisation of logistics and production planning. *Engineering Applications of Artificial Intelligence, Intelligent Manufacturing*, 16(4), 335-348.

Kaytez, F., Taplamacioglu, M. C., Cam, E., & Hardalac, F. (2015). Forecasting electricity consumption: A comparison of regression analysis, neural networks and least squares support vector machines. *International Journal of Electrical Power & Energy Systems*, 67, 431-438.

Ketikidis, P., Koh, S., Dimitriadis, N., Gunasekaran, A. and Kehajova, M. (2008). The use of information systems for logistics and supply chain management in South East Europe: Current status and future direction. *Omega*, 36(4), 592-599.

Khashei, M., & Bijari, M. (2010). An artificial neural network (p, d, q) model for timeseries forecasting. *Expert Systems with applications*, 37(1), 479-489.

Khoshnevisan, B., Rafiee, S., Omid, M., Mousazadeh, H., & Clark, S. (2014). Environmental impact assessment of tomato and cucumber cultivation in greenhouses using life cycle assessment and adaptive neuro-fuzzy inference system. *Journal of Cleaner Production*, 73, 183-192.

Kia, R., Khaksar-Haghani, F., Javadian, N. and Tavakkoli-Moghaddam, R. (2014). Solving a multi-floor layout design model of a dynamic cellular manufacturing system by an efficient genetic algorithm. *Journal of Manufacturing Systems*, 33(1), 218-232.

Kilpala, H., Solvang, W.D., Widmark, J., Bagaeva, A. and Tuohinto, P. (2005). Analysis of ICT use in the Barents region: research findings from logistics service providers and forest industry. *Sustainable Transport in the Barents Region (STBR)*, Publications No. 11.

Kochak, A., & Sharma, S. (2015). Demand forecasting using neural network for supply chain management. *International journal of mechanical engineering and robotics research*, 4(1), 96.

Koploy, M. (2011). *2011 Market Trend Report: Warehouse Management Systems*. Software Advice. [Online]. Available: http://www.warehousemanagementsystemsguide.com/. [Accessed: July 13, 2014]

Korpela, J., & Tuominen, M. (1996). A decision aid in warehouse site selection. *International Journal of Production Economics*, 45(1-3), 169-180.

Kosko, B. (1994). Fuzzy systems as universal approximators. *IEEE Transactions on Computers*, 43(11), 1329-1333.

Krauth, E., Moonen, H., Popova, V., & Schut, M. C. (2005, May). Performance Measurement and Control in Logistics Service Providing. In *ICEIS* (2), 239-247.

Kristiansen, T., (2012). Forecasting Nord Pool day-ahead prices with an autoregressive model. *Energy Policy*, 49, 328-332.

Kucukaltan, B., Irani, Z., & Aktas, E. (2016). A decision support model for identification and prioritization of key performance indicators in the logistics industry. *Computers in Human Behavior*, 65, 346-358.

Kumar, D., Singh, J., & Singh, O. P. (2013). A fuzzy logic based decision support system for evaluation of suppliers in supply chain management practices. *Mathematical and Computer Modelling*, 57(11), 2945-2960.

Lai, F., Zhao, X. and Wang, Q. (2006). The impact of information technology on the competitive advantage of logistics firms in China. *Industrial Management & Data Systems*, 106(9), 1249-1271.

Lai, F., Zhao, X. and Wang, Q. (2007). Taxonomy of information technology strategy and its impact on the performance of third-party logistics (3PL) in China. *International Journal of Production Research*, 45(10), 2195-2218.

Lai, V. S., Wong, B. K., & Cheung, W. (2002). Group decision making in a multiple criteria environment: A case using the AHP in software selection. *European Journal of Operational Research*, 137(1), 134-144.

Lam, Cathy H.Y., Choy K.L., & Chung, S.H. (2011). A decision support system to facilitate warehouse order fulfillment in cross-border supply chain. *Journal of Manufacturing Technology Management*, 22(8), 972 – 983.

Lam, C. H., Choy, K. L., Ho, G. T., & Lee, C. K. M. (2014). An order-picking operations system for managing the batching activities in a warehouse. *International Journal of Systems Science*, 45(6), 1283-1295.

Lam, H.Y., Choy, K.L., Ho, G.T.S., Cheng, S.W.Y. and Lee, C.K.M. (2015). A knowledge-based logistics operations planning system for mitigating risk in warehouse order fulfillment. *International Journal of Production Economics*, 170, 763-779.

Lang, G., & Bressolles, G. (2013). Economic Performance and Customer Expectation in e-fulfillment Systems: a Multi-Channel Retailer Perspective. *Supply Chain Forum: an International Journal*, 14(1), 16-26.

Lao, S.I., Choy, K.L., Ho, G.T.S., Tsim, Y.C., Poon, T.C. and Cheng, C.K. (2012). A real-time food safety management system for receiving operations in distribution centers. *Expert Systems with Applications*, 39(3), pp. 2532-2548.

Lauren, S., Harlili, S. (2014). Stock trend prediction using simple moving average. supported by news classification. *2014 International Conference of Advanced Informatics: Concept, Theory and Application*, 135-139.

Lee, C.K.H., Choy, K.L. Ho, G.T.S., & Lam, C.H.Y. (2016). A Slippery Genetic Algorithm-Based Process Mining System for Achieving Better Quality Assurance in The Garment Industry. *Expert Systems with Applications*, 46, 236-248.

Lee, H., and Tang, C. (1997). Modelling the Costs and Benefits of Delayed Product Differentiation. *Management Science*, 43(1), 40-53.

Lee, K. Y., Cha, Y. T., & Park, J. H. (1992). Short-term load forecasting using an artificial neural network. *IEEE Transactions on Power Systems*, 7(1), 124-132.

Lee, T. L. (2008). Back-propagation neural network for the prediction of the short-term storm surge in Taichung harbor, Taiwan. *Engineering Applications of Artificial Intelligence*, 21(1), 63-72.

Lekovic, S., & Milicevic, N. (2013). *The importance and characteristics of logistics in electronic commerce*.

Leung, K.H., Cheng, W.Y., Choy, K.L., Wong, W.C., Lam, H.Y., Hui, Y.Y., Tsang, Y.P., & Tang, Valerie (2016). A Process-Oriented Warehouse Postponement Strategy for E-Commerce Order Fulfillment in Warehouses and Distribution Centers in Asia. In Patricia Ordóñez de Pablos (Eds.), *Managerial Strategies and Solutions for Business Success in Asia*. Hershey, PA: IGI Global, 21-34.

Leung, K.H., Choy, K.L., Siu, P.K.Y., Ho, G.T.S., Lam, H.Y. and Lee, C.K.M. (2018). A B2C e-commerce intelligent system for re-engineering the e-order fulfilment process. *Expert Systems with Applications*, 91, 386-401.

Leung, K.H., Choy, K.L., Tam, M.C., Cheng, Stephen W.Y., Lam, H.Y., Lee, Jason C.H., & Pang, G.K.H. (2016). Design of a case-based multi-agent wave picking decision support system for handling e-commerce shipments. In: *Technology Management for Social Innovation*. United States of America, Portland: Portland International Conference on Management of Engineering and Technology (PICMET), 2248 – 2256.

Li, Gang et al. (2009). The Impact of IT Implementation On Supply Chain Integration and Performance. *International Journal of Production Economics*, 120(1), pp. 125-138.

Liljana, F.T., Blaž, M., & Aleš, T. (2016) Demand forecasting with four-parameter exponential smoothing. *International Journal of Production Economics*, 181, 162-173.

Lin, C., Choy, K.L., Ho, G.T.S., & Ng, T.W. (2014). A Genetic Algorithm-based optimization model for supporting green transportation operations. *Expert Systems with Applications*, 41(7), 3284-3296.

Lin, C. and Ho, Y. (2009). RFID technology adoption and supply chain performance: an empirical study in China's logistics industry. *Supply Chain Management: an International Journal*, 14(5), 369-378.

Lin, C.Y. (2007). Factors affecting innovation in logistics technologies for logistics service providers in China. *Journal of Technology Management in China*, 2(1), 22-37.

Lin, C.Y. (2008). Determinants of the adoption of technological innovations by logistics service providers in China. *International Journal of Technology Management and Sustainable Development*, 7(1), 19-38.

Lin, C.Y. and Jung, C. (2006). Influencing factors on the innovation in logistics technologies for logistics service providers in Taiwan. *Journal of American Academy of Business*, 9(2), 257-264.

Liu, H., Ke, W., Wei, K.K., Gu, J. and Chen, H. (2010). The role of institutional pressures and organizational culture in the firm's intention to adopt internet-enabled supply chain management systems. *Journal of Operations Management*, 28(5), 372-84.

Liu, H. and Orban, D. (2008). Gridbatch: cloud computing for large-scale data-intensive batch applications. In: *8th IEEE International Symposium on Cluster Computing and the Grid*, Lyon, 295-305.

Lopez De Mantaras, R., Mcsherry, D., Bridge, D., Leake, D., Smyth, B., Craw, S., Faltings, B., Maher, M.L., Cox, M.T., Forbus, K., Keane, M., Aamodt, A., Watson, I. (2006). Retrieval, reuse, revision and retention in case-based reasoning. *The Knowledge Engineering Review*, 20(3), 215-240.

Lu, W., McFarlane, D., Giannikas, V., & Zhang, Q. (2016). An algorithm for dynamic order-picking in warehouse operations. *European Journal of Operational Research*, 248(1), 107-122.

Lu, W., Pedrycz, W., Liu, X., Yang, J., & Li, P. (2014). The modeling of time series based on fuzzy information granules. *Expert Systems with Applications*, 41(8), 3799-3808.

Macharis, C., Springael, J., De Brucker, K., & Verbeke, A. (2004). PROMETHEE and AHP: The design of operational synergies in multicriteria analysis.: Strengthening PROMETHEE with ideas of AHP. *European Journal of Operational Research*, 153(2), 307-317.

Maity, M., & Dass, M. (2014). Consumer decision-making across modern and traditional channels: E-commerce, m-commerce, in-store. *Decision Support Systems*, 61, 34-46.

Makridakis S. & Hibon M. (2000). The M3-Competition: results, conclusions and. implications. *International Journal of Forecasting*, 16, 451-476.

Makridakis, S., Wheelwright, S.C. & Hyndman, R.J. (1998). *Forecasting: Methods. and Applications* (Third ed.).

Maltz, A.B., Rabinovich, E., & Sinha, R. (2004). Logistics: the key to e-retail success. *Supply Chain Management Review*, 8, 48–54.

Mangiaracina, R., Marchet, G., Perotti, S., & Tumino, A. (2015). A review of the environmental implications of B2C e-commerce: a logistics perspective.

International Journal of Physical Distribution & Logistics Management, 45(6), 565-591.

Mangold, W. G., & Faulds, D. J. (2009). Social media: The new hybrid element of the promotion mix. *Business horizons*, 52(4), 357-365.

Mason-Jones, R., & Towill, D. R. (1997). Information enrichment: designing the supply chain for competitive advantage. *Supply Chain Management: an International Journal*, 2(4), 137-148.

Mason, S., Cole, M., Ulrey, B. and Yan, L. (2002). Improving electronics manufacturing supply chain agility through outsourcing. *International Journal of Physical Distribution & Logistics Management*, 32(7), 610-620.

Mason, Scott J., Mauricio Ribera, P., Farris, Jennifer A., Kirk, Randall G. (2003). Integrating the warehousing and transportation functions of the supply chain. *Transportation Research Part E*, 39(2), 141-159.

Masoudi, S., Sima, M., & Tolouei-Rad, M. (2018). Comparative study of ann and anfis models for predicting temperature in machining. *Journal of Engineering Science and Technology*, 13(1), 211-225.

McCrea, B. (2013). 11th Annual Software Users Survey: Caution remains. *Logistics Management*, 52(6), 36-40.

McCrea, B. (2014). State of Cloud Computing: Defining itself in SCM. *Logistics Management*. 53(10), pp.34-36.

McKinnon, A.C., (2009). Innovation in road freight transport: achievements and opportunities. Report prepared from the International Transport Forum workshop on '*Innovation in Road Transport*', Lisbon, 2nd October. Available at: http://www.internationaltransportforum.org/Proceedings/Lisbon2009/1-McKinnon.pdf [Accessed 07 Jan. 2015].

Mellat-Parast, M., & Spillan, E. J. (2014). Logistics and supply chain process integration as a source of competitive advantage. *International Journal of Logistics Management*, 25(2), 289-314.

Mendes, J. J. M., Gonalves, J. F., & Resende, M. G. C. (2009). A random key based genetic algorithm for the resource constrained project scheduling problem. *Computers and Operations Research*, 36, 92–109.

Miller D. W., Starr M. K. (1969). *Executive decisions and operations research*. 2nd ed. Englewood Cliffs, N. J.: Prentice-Hall.

Moradi, F., Bonakdari, H., Kisi, O., Ebtehaj, I., Shiri, J., & Gharabaghi, B. (2018). Abutment scour depth modeling using neuro-fuzzy-embedded techniques. *Marine Georesources & Geotechnology*, 1-11.

Moreno, M. N., Segrera, S., & López, V. F. (2005). Association Rules: Problems, solutions and new applications. *Actas del III Taller Nacional de Minería de Datos y Aprendizaje*, Tamida, 317-323.

Moreno, S. R & Leandro, D. S. C. (2018). Wind speed forecasting approach based on. Singular Spectrum Analysis and Adaptive Neuro Fuzzy Inference System. *Renewable Energy*, 126, 736-754.

Morganti, E., Seidel, S., Blanquart, C., Dablanc, L., & Lenz, B. (2014). The Impact of E-commerce on Final Deliveries: Alternative Parcel Delivery Services in France and Germany. *Transportation Research Procedia*, 4, 178-190.

Mueller, S. (2005). *Market basket analysis with Data Mining*. Economie et sociologie rurales.

Muppani Muppant, V., & Adil, G. (2008). Efficient formation of storage classes for warehouse storage location assignment: A simulated annealing approach. *Omega*, 36(4), 609-618.

Narang, B., & Arora, J.B. (2018). Present and Future of Mobile Commerce: Introduction, Comparative Analysis of M Commerce and E Commerce, Advantages, Present and Future. In *I. Management Association (Ed.), Mobile Commerce: Concepts, Methodologies, Tools, and Applications*. Hershey, PA: IGI Global, 1431-1447.

Neto, A. H., & Fiorelli, F. A. S. (2008). Comparison between detailed model simulation and artificial neural network for forecasting building energy consumption. *Energy and buildings*, 40(12), 2169-2176.

Ngai, E., Lai, K. and Cheng, T. (2008). Logistics information systems: The Hong Kong experience. *International Journal of Production Economics*, 113(1), 223-234.

Nguyen, D. H., de Leeuw, S., & Dullaert, W. E. (2018). Consumer behaviour and order fulfilment in online retailing: a systematic review. *International Journal of Management Reviews*, 20(2), 255-276.

Nhita, Fhira, N., Deni, S., Untari Novia, A., & Untari Novia, W. (2015). Comparative Study of Moving Average on Rainfall Time Series Data for Rainfall Forecasting Based on Evolving Neural Network Classifier. *3rd International Symposium on Computational and Business Intelligence*, 112-116.

Nilashi, M., Fathian, M., Gholamian, M. R., & Ibrahim, O. B. (2011). Propose a model for customer purchase decision in B2C websites using adaptive neuro-fuzzy inference system. International Journal of Business Research and Management (IJBRM), 2(1), 1-18.

Novák, V., Perfilieva, I., & Mockor, J. (2012). *Mathematical principles of fuzzy logic.* Springer Science & Business Media, 517.

Oliveira, R., Cardoso, I., Barbosa, J., da Costa, C., & Prado, M. (2015). An intelligent model for logistics management based on geofencing algorithms and RFID technology. *Expert Systems with Applications*, 42(15-16), 6082-6097.

Oliveira, T., Alhinho, M., Rita, P., & Dhillon, G. (2017). Modelling and testing consumer trust dimensions in e-commerce. *Computers in Human Behavior*, 71, 153-164.

Omero, M., D'Ambrosio, L., Pesenti, R. and Ukovich, W. (2005), Multiple-attribute decision support system based on fuzzy logic for performance assessment. *European Journal of Operational Research*, 160, 710–725.

Önüt, S., Tuzkaya, U. & Doğaç, B. (2008). A particle swarm optimization algorithm for the multiple-level warehouse layout design problem. *Computers & Industrial Engineering*, 54(4), 783-799.

Osório, G. J., Matias, J. C. O., & Catalão, J. P. S. (2015). Short-term wind power forecasting using adaptive neuro-fuzzy inference system combined with evolutionary particle swarm optimization, wavelet transform and mutual information. *Renewable Energy*, 75, 301-307.

Othman, A.M., Ajit, A., Kerop, J. &Pier, M. (2015). Recursive wind speed forecasting. based on Hammerstein Auto-Regressive model. *Applied Energy*, 145, 191-197.

Pagh, J.D., Cooper, M.C. (1998). Supply chain postponement and speculation strategies: how to choose the right strategy. *Journal of Business Logistics*, 19(2), 13–33.

Palmer, A., Montano, J. J., & Sesé, A. (2006). Designing an artificial neural network for forecasting tourism time series. *Tourism Management*, 27(5), 781-790.

Pan, J., Shih, P., Wu, M., & Lin, J. (2015). A storage assignment heuristic method based on genetic algorithm for a pick-and-pass warehousing system. *Computers & Industrial Engineering*, 81, 1-13.

Pappas, I. O., Kourouthanassis, P. E., Giannakos, M. N., & Chrissikopoulos, V. (2016). Explaining online shopping behavior with fsQCA: The role of cognitive and affective perceptions. *Journal of Business Research*, 69(2), 794-803.

Park, H. S., & Jun, C. H. (2009). A simple and fast algorithm for K-medoids clustering. *Expert systems with applications*, 36(2), 3336-3341.

Park, J., Kang, M., & Lee, K. (1996). An intelligent operations scheduling system in a job shop. *International Journal of Advanced Manufacturing Technology*, 11(2), 111-119.

Parunak, H.V.D. (1999). *Industrial and practical applications of DAI*. In: Weiss, G. (Ed.), Multiagent Systems. MIT Press, Cambridge, MA.

Patriarca, R., Costantino, F., & Di Gravio, G. (2016). Inventory model for a multi-echelon system with unidirectional lateral transshipment. *Expert Systems with Applications*, 65, 372-382.

Patterson, K., Grimm, C. and Corsi, T. (2003). Adopting new technologies for supply chain management. *Transportation Research Part E: Logistics and Transportation Review*, 39(2), pp. 95-121.

Petersen, C.G. (2000). An evaluation of order picking policies for mail order companies. *Production and Operations Management*, 2000, 9(4), 319-335.

Petry, F. E. (2013). Data Discovery Approaches for Vague Spatial Data. In I. Management Association (Ed.), *Data Mining: Concepts, Methodologies, Tools, and Applications*. Hershey, PA: IGI Global, 50-65.

Pokharel, S. (2005). Perception on information and communication technology perspectives in logistics – a study or transportation and warehouse sectors in Singapore. *Journal of Enterprise Information Management*, 18(2), 136-149.

Polat, K., & Güneş, S. (2007). An expert system approach based on principal component analysis and adaptive neuro-fuzzy inference system to diagnosis of diabetes disease. *Digital Signal Processing*, 17(4), 702-710.

Poon, T. C., Choy, K. L., Chow, H. K., Lau, H. C., Chan, F. T., & Ho, K. C. (2009). A RFID case-based logistics resource management system for managing order-picking operations in warehouses. *Expert Systems with Applications*, 36(4), 8277-8301.

Poon, T.C., Choy, K.L., Chan, F.T.S., Ho G.T.S., Gunasekaran, A., Lau, H.C.W., & Chow, H.K.H. (2011). A real-time warehouse operations planning system for small batch replenishment problems in production environment. *Expert Systems with Applications*, 38(7), 8524-8537.

Prasad, K., Gorai, A. K. & Goyal, P. (2016). Development of ANFIS models for air. quality forecasting and input optimization for reducing the computational cost and time. *Atmospheric Environment*, 128, 246-262.

Prater, E. (2005). A framework for understanding the interaction of uncertainty and information systems on supply chains", *International Journal of Physical Distribution and Logistics Management*, 35(7), 524-39.

Pressey, R. L., Possingham, H. P., & Day, J. R. (1997). Effectiveness of alternative heuristic algorithms for identifying indicative minimum requirements for conservation reserves. *Biological Conservation*, 80(2), 207-219.

Rajak, A., & Gupta, M. K. (2008). Association rule mining: applications in various areas. In Proceedings of *International Conference on Data Management*, Ghaziabad, India, 3-7.

Renner, G., & Ekárt, A. (2003). Genetic algorithms in computer aided design. *Computer-Aided Design*, 35(8), 709-726.

Rodrigue, Jean-Paul, Comtois, C., Slack, B., (2009). The "Last Mile" in Freight Distribution. *The Geography of Transport Systems* (2nd ed.). Routledge. 212.

Roodbergen, K. J., Vis, I. F. A., & Taylor, G. D. (2014). Simultaneous determination of warehouse layout and control policies. *International Journal of Production Research*, 53(11), 3306-3326.

Ross, D. F. (2016). *Introduction to e-supply chain management: engaging technology to build market-winning business partnerships*. CRC Press.

Saaty, T. L. (1980). *The analytic hierarchy process: planning, priority setting, resources allocation*. New York: McGraw, 281.

Sahin, F. and Robinson, E. (2002). Flow coordination and information sharing in supply chains: Review, implications, and directions for future research. *Decision Sciences*, 33(4), 55-536.

Salo, A. A., & Hämäläinen, R. P. (1997). On the measurement of preferences in the analytic hierarchy process. *Journal of Multi-Criteria Decision Analysis*, 6(6), 309-319.

Sánchez, J. M. B., Lugilde, D. N., de Linares Fernández, C., de la Guardia, C. D., & Sánchez, F. A. (2007). Forecasting airborne pollen concentration time series with neural and neuro-fuzzy models. *Expert Systems with Applications*, 32(4), 1218-1225.

Sarac, A., Absi, N. and Dauzère-Pérès, S. (2010). A literature review on the impact of RFID technologies on supply chain management. *International Journal of Production Economics*, 128(1), 77-95.

Sasikala, P. (2011). Cloud computing: present status and future implications. *International Journal of Cloud Computing*, 1(1), p.23.

Sene, A., Kamsu-Foguem, B., and Rumeau, P. (2015). Telemedicine framework using case-based reasoning with evidences. *Computer Methods and Programs in Biomedicine*, 121(1), 21-35.

Serban, G., Czibula, I.G., & Campan, A. (2006). A programming interface for medical diagnosis prediction. Studia Universitatis" Babes-Bolyai", *Informatica*, LI(1), 21-30.

Shaikh, Aijaz A., and Heikki Karjaluoto (2015). Making the most of information technology & systems usage: a literature review, frameworks and future research agenda. *Computers in Human Behavior*, 49, 541-566.

Shao, X. F., & Ji, J. H. (2008). Evaluation of postponement strategies in mass customization with service guarantees. *International Journal of Production Research*, 46(1), 153-171.

Shin, K. S., & Han, I. (2001). A case-based approach using inductive indexing for corporate bond rating. *Decision Support Systems*, 32(1), 41-52.

Shiri, J., Dierickx, W., Pour-Ali Baba, A., Neamati, S., & Ghorbani, M. A. (2011). Estimating daily pan evaporation from climatic data of the State of Illinois, USA using adaptive neuro-fuzzy inference system (ANFIS) and artificial neural network (ANN). *Hydrology Research*, 42(6), 491-502.

Shojaiemehr, B., & Rafsanjani, M. K. (2018). A supplier offer modification approach based on fuzzy systems for automated negotiation in e-commerce. *Information Systems Frontiers*, 20(1), 143-160.

Siddique, N. and Adeli, H. (2013). Introduction to Fuzzy Logic. In Siddique, N. and Adeli, H. (Eds.), *Computational Intelligence: Synergies of Fuzzy Logic, Neural Networks and Evolutionary Computing*, John Wiley & Sons, Ltd., 19-63.

Singh, H., Gupta, M., Meitzler, T., Hou, Z., Garg, K., Solo, A. and Zadeh, L. (2013). Real-Life Applications of Fuzzy Logic. *Advances in Fuzzy Systems*, 2013, 1-3.

Smykay, E. W. and Bowersox, D. J. et al. (1961). *Physical Distribution Management: Logistics Problems of the Firm*. Macmillan, New York, NY.

So, Gregory, (2012). *SCED's speech at GS1 Hong Kong Supply Chain Management Excellence Summit 2012*. [online] Available at: http://www.info.gov.hk/gia/general/201211/09/P201211090275.htm [Accessed 14 Dec. 2015].

Statista Inc. (2015). *Digital buyer penetration worldwide from 2011 to 2018. Key Figures of E-Commerce*. [Online]. Available: http://www.statista.com/statistics/261676/digital-buyer-penetration-worldwide/ [Accessed: 17 January, 2016]

Statista (2017). Statista Digital Market Outlook - Trend Report. *Statista Report 2017 - B2B e-Commerce*. New York: United States. Statista, 7.

Stefansson, G. (2006). Collaborative logistics management and the role of third-party service providers. *International Journal of Physical Distribution & Logistics Management*, 36(2), 76-92.

Subramanian, N., & Ramanathan, R. (2012). A review of applications of Analytic Hierarchy Process in operations management. *International Journal of Production Economics*, 138(2), 215-241.

Sudworth, J. (2013). *Shanghai free-trade zone launched*. BBC News. [online] Available at: http://www.bbc.com/news/business-24322313 [Accessed 14 Mar. 2015].

Sugeno, M., & Yasukawa, T. (1993). A fuzzy-logic-based approach to qualitative modeling. *IEEE Transactions on Fuzzy System*, 1(1), 7–31.

Sulandari, W., Yudhanto, Y. (2015). Forecasting trend data using a hybrid simple. moving average-weighted fuzzy time series model. *International Conference on Science in Information Technology*, 303-308.

Su, C. H, Cheng, C.H. (2016). A hybrid fuzzy time series model based on ANFIS and integrated nonlinear feature selection method for forecasting stock. *Neurocomputing*, 205, 264-273.

Su, Y., Gao, W. J., Guan, D.J.& Su, W.C. (2018). Dynamic assessment and forecast of. urban water ecological footprint based on exponential smoothing analysis. *Journal of Cleaner Production*, 195, 354-364.

Svalina, I., Galzina, V., Lujić, R., & ŠImunović, G. (2013). An adaptive network-based fuzzy inference system (ANFIS) for the forecasting: The case of close price indices. *Expert systems with applications*, 40(15), 6055-6063.

Swafford, P., Ghosh, S. and Murthy, N. (2006). The antecedents of supply chain agility of a firm: scale development and model testing. *Journal of Operations Management*, 24(2), 170-188.

Tabrizi, S. S., & Sancar, N. (2017). Prediction of Body Mass Index: A comparative study of multiple linear regression, ANN and ANFIS models. *Procedia Computer Science*, 120, 394-401.

Takagi, T., & Sugeno, M. (1983). Derivation of fuzzy control rules from human operator's control actions. Proceedings of the *IFAC symposium on fuzzy information, knowledge representation and decision analysis*, 55-60.

Tana, K.H., Limb, C.P., Plattsc, K. and Koay, H.S. (2006). An intelligent decision support system for manufacturing technology investments. *International Journal of Production Economics*, 104, 179-90.

Tanaka-Yamawaki, M., & Tokuoka, S. (2007). Adaptive use of technical indicators for the prediction of intra-day stock prices. *Physica A: Statistical Mechanics and its Applications*, 383(1), 125-133.

Taniguchi, E., & Shimamoto, H. (2004). Intelligent transportation system based dynamic vehicle routing and scheduling with variable travel times. *Transportation Research Part C: Emerging Technologies*, 12(3-4), 235-250.

Taniguchi, E., & Shimamoto, H. (2004). Intelligent transportation system based dynamic vehicle routing and scheduling with variable travel times. *Transportation Research Part C: Emerging Technologies*, 12(3-4), 235-250.

Taylor, G. (2009). *Introduction to logistics engineering*. Boca Raton: CRC Press. 7-18.

Taylor, J. (2012). Density Forecasting of Intraday Call Center Arrivals Using Models Based on Exponential Smoothing. *Management Science*, 58(3), 534-549.

Thiesing, F. M., & Vornberger, O. (1997). Sales forecasting using neural networks. *International Conference on Neural Networks*, 4, 2125-2128.

Thomassey, S., Happiette, M., & Castelain, J. M. (2005). A short and mean-term automatic forecasting system – application to textile logistics. *European Journal of Operational Research*, 161, 275-284.

Triantaphyllou, E. (2000). *Multi-criteria decision making methods. In Multi-criteria decision making methods: A comparative study*. Springer, Boston, MA, 5-21.

Tse, Y. K., Tan, K. H., Ting, S. L., Choy, K. L., Ho, G. T. S., & Chung, S. H. (2012). Improving postponement operation in warehouse: an intelligent pick-and-pack decision-support system. *International Journal of Production Research*, 50(24), 7181–7197.

Turban E., Outland J., King D., Lee J.K., Liang TP., Turban D.C. (2018) Marketing and Advertising in E-Commerce. In: *Electronic Commerce 2018*. Springer Texts in Business and Economics. Springer, Cham.

Turskis, Z., Daniūnas, A., Zavadskas, E. K., & Medzvieckas, J. (2016). Multicriteria evaluation of building foundation alternatives. *Computer-Aided Civil and Infrastructure Engineering*, 31(9), 717-729.

Twede, D., Clarke, R., & Tait, J. (2000). Packaging postponement: a global packaging strategy. *Packaging Technology & Science*, 13(3), 105-115.

Übeyli, E. D., & Güler, İ. (2006). Adaptive neuro-fuzzy inference system to compute quasi-TEM characteristic parameters of microshield lines with practical cavity sidewall profiles. *Neurocomputing*, 70(1-3), 296-304.

van den Berg, J. P., & Zijm, W. H. (1999). Models for warehouse management: Classification and examples. *International journal of production economics*, 59(1-3), 519-528.

Vargas, L. G. (1990). An overview of the analytic hierarchy process and its applications. *European journal of operational research*, 48(1), 2-8.

Wang, F. K., Chang, K. K., & Tzeng, C. W. (2011). Using adaptive network-based fuzzy inference system to forecast automobile sales. *Expert Systems with Applications*, 38(8), 10587-10593.

Wang, Q., Lai, F. and Zhao, X. (2008aUIT126). The impact of information technology in the financial performance of third-party logistics firms in China. *Supply Chain Management: an International Journal*, 13(2), 138-150.

Wang, W. P., & Chen, Z. (2008b). A neuro-fuzzy based forecasting approach for rush order control applications. *Expert Systems with Applications*, 35(1-2), 223-234.

Wang, X., Zhan, L., Ruan, J., & Zhang, J. (2014). How to Choose "Last Mile" Delivery Modes for E-Fulfillment. *Mathematical Problems in Engineering*, 2014, 1-11.

Wang, Y., & Yu, C. (2017). Social interaction-based consumer decision-making model in social commerce: The role of word of mouth and observational learning. *International Journal of Information Management*, 37(3), 179-189.

Wei, L. Y., Cheng, C. H., & Wu, H. H. (2014). A hybrid ANFIS based on n-period moving average model to forecast TAIEX stock. *Applied Soft Computing*, 19, 86-92.

Weinhardt, C., Anandasivam, A., Blau, B., Borissov, N., Meinl, T., Michalk, W. and Sto ̈ßer, J. (2009). Cloud computing – a classification, business models, and research directions. *Business & Information Systems Engineering*, 1(5), 391-399.

Weiss, G. (1995). Adaptation and Learning in Multi-Agent Systems: Some Remarks and a Bibliography. In Proceedings of *IJCAI'95 Workshop on Adaptation and Learning in Multi Agent Systems*. Springer, LNAI 1042, 1-22.

Woodbridge, J., Mortazavi, B., Bui, A., and Sarrafzadeh, M. (2015). Improving biomedical signal search results in big data case-based reasoning environments. Pervasive and Mobile Computing. In *Press*.

Wooldridge, Michael (2002). *An Introduction to MultiAgent Systems*. John Wiley & Sons. p. 366.

Xiao, Y., Liu, J. J., Hu, Y., Wang, Y., Lai, K. K., & Wang, S. (2014). A neuro-fuzzy combination model based on singular spectrum analysis for air transport demand forecasting. *Journal of Air Transport Management*, 39, 1-11.

Xing, Y., Grant, D., McKinnon, A., & Fernie, J. (2011). The interface between retailers and logistics service providers in the online market. *European Journal of Marketing*, 45(3), 334-357.

Yager, R. R., & Filev, D. P. (1994). Generation of fuzzy rules by mountain clustering. *Journal of Intelligent & Fuzzy Systems*, 2(3), 209-219.

Yang, B., Burns, N., & Backhouse, C. (2004). Postponement: a review and an integrated framework. *International Journal of Operations & Production Management*, 24(5), 468-487.

Yang, B. & Yang, Y. (2010). Postponement in supply chain risk management: a complexity perspective. *International Journal of Production Research*, 48(7), 1901-1912.

Yang, P., Miao, L., Xue, Z., & Qin, L. (2015a). An integrated optimization of location assignment and storage/retrieval scheduling in multi-shuttle automated storage/retrieval systems. *Journal of Intelligent Manufacturing*, 26(6), 1145-1159.

Yang, P., Miao, L., Xue, Z., & Ye, B. (2015b). Variable neighborhood search heuristic for storage location assignment and storage/retrieval scheduling under shared storage in multi-shuttle automated storage/retrieval systems. *Transportation Research Part E: Logistics and Transportation Review*, 79, 164-177.

Yao, A., Paik, S., & Wedel, T. (2010). Developing an Efficient Warehousing Operation System: An Expert System Approach. *Journal of Management Information and Decision Sciences*, 13(1), 19-30.

Ying, L. C., & Pan, M. C. (2008). Using adaptive network based fuzzy inference system to forecast regional electricity loads. *Energy Conversation and Management*, 49, 205–211.

Yu, L.J., Zhou, L.L., Tan, L., Jiang, H.B., Wang, Y., Sheng, W.& Nie, S.F., (2014). Application of a New Hybrid Model with Seasonal Auto-Regressive Integrated Moving Average (ARIMA) and Nonlinear Auto-Regressive Neural Network (NARNN) in Forecasting Incidence Cases of HFMD in Shenzhen, China. *PLoS One*, 9(6).

Yu, X., Guo, S., Guo, J., & Huang, X. (2011). Rank B2C e-commerce websites in e-alliance based on AHP and fuzzy TOPSIS. *Expert Systems with Applications*, 38(4), 3550-3557.

Yu, Y., Wang, X., Zhong, R. Y., & Huang, G. Q. (2016). E-commerce logistics in supply chain management: Practice perspective. *Procedia Cirp*, 52, 179-185.

Yusuf, Y.Y., Gunasekaran, A., Adeleye, E.O., & Sivayoganathan, K. (2004). Agile supply chain capabilities: Determinants of competitive objectives. *European Journal of Operational Research*, 159(2), 379-392.

Zacharia, P., & Nearchou, A. (2016). A population-based algorithm for the bi-objective assembly line worker assignment and balancing problem. *Engineering Applications of Artificial Intelligence*, 49, 1-9.

Zadeh, L. A. (1965). Information and control. *Fuzzy sets*, 8(3), 338-353.

Zadeh, L.A. (1978). Fuzzy sets as a basis for theory of possibility. *Fuzzy Sets System*, 1, 3–28.

Zahedi, G., Azizi, S., Bahadori, A., Elkamel, A., & Alwi, S. R. W. (2013). Electricity demand estimation using an adaptive neuro-fuzzy network: a case study from the Ontario province–Canada. *Energy*, 49, 323-328.

Zahir, S. (1999). Clusters in a group: Decision making in the vector space formulation of the analytic hierarchy process. *European Journal of Operational Research*, 112(3), 620-634.

Zegordi, S., Abadi, I., & Nia, M. (2010). A novel genetic algorithm for solving production and transportation scheduling in a two-stage supply chain. *Computers & Industrial Engineering*, 58(3), 373-381.

Zhang, B., Li, X. and Wang, S. (2015). A novel case adaptation method based on an improved integrated genetic algorithm for power grid wind disaster emergencies. *Expert Systems with Applications*, 42(21), 7812-7824.

Zhang, G., Patuwo, B. E., & Hu, M. Y. (1998). Forecasting with artificial neural networks: The state of the art. *International journal of forecasting*, 14(1), 35-62.

Zhang, G. P. (2003). Time series forecasting using a hybrid ARIMA and neural network model. *Neurocomputing*, 50, 159-175.

Zhang, K. Z., & Benyoucef, M. (2016). Consumer behavior in social commerce: A literature review. *Decision Support Systems*, 86, 95-108.

Zhang, M., Pratap, S., Huang, G. Q., & Zhao, Z. (2017). Optimal collaborative transportation service trading in B2B e-commerce logistics. *International Journal of Production Research*, 55(18), 5485-5501.

Zhang, Q., Cheng, L. and Boutaba, R. (2010). Cloud computing: state-of-the-art and research challenges. *Journal of Internet Services and Applications*, 1(1), 7-18.

Zimmerman, J. L., & Yahya-Zadeh, M. (2011). Accounting for decision making and control. *Issues in Accounting Education*, 26(1), 258-259.

Zinn W., Bowersox, D.J. (1988). Planning physical distribution with the principle of postponement. *Journal of Business Logistics*, 19(2), 117-136.