DEVELOPMENT OF A RFID-CLOUD-BASED LOCATION ASSIGNMENT AND TRACKING SYSTEM FOR THE PACKAGED FOOD INDUSTRY

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M.Phil

The Hong Kong Polytechnic University

2017

THE HONG KONG POLYTECHNIC UNIVERSITY
DEPARTMENT OF INDUSTRIAL AND SYSTEMS ENGINEERING

Development of a RFID-Cloud-based Location Assignment and Tracking System for the Packaged Food Industry

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A thesis submitted in partial fulfilment of the requirements for the degree of Master of Philosophy

November 2016

CERTIFICATE OF ORIGINALITY

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Abstract

Food safety is increasingly of concern to the public. To ensure the quality of packaged food, storage operations along the supply chain play critical roles. In addition, the trend of e-retailing has posed additional pressure on the warehouse, therefore the warehouse has to be more efficient. Among the various storage operations, storage location assignment is a complex yet important decision to make. Assigning a suitable storage location for food can prevent food deterioration caused by the reactivity between food, food packaging and the physical environment. Besides, suitably locating products can improve the operational efficiency of the facility. On the other hand, having an effective tracking system can quickly help to retrieve any problematic food lots from the supply chain, which in turn can reduce the number of potential victims of such food. Thus, a packaged food warehouse should be equipped with a system for both assigning suitable locations for various food products, and in facilitating the external and internal tracking of the products. However, the existing decision support system (DSS) for storage location assignment seldom considers the storage needs of the food products, and the existing Radio-Frequency-Identification-based tracking system has rarely been integrated with a DSS to tackle integrative storage location assignment and product tracking.

Therefore, this research proposes a comprehensive DSS called the RFID-Cloud-based Location Assignment and Tracking System (R-CLATS) for the packaged food industry. The system consists of four modules: The Data Capturing Module, Information Consolidation Module, FARM Variable Selection Module and Location Assignment Module. The Data Capturing Module applies Radio Frequency Identification (RFID) technology to collect real-time data regarding the inbound and outbound activities in the warehouse, in order to track product locations. The Information Consolidation Module uses a cloud-based database to consolidate data and information from the warehouse and external shippers in real time for further processing. The FARM Variable Selection Module applies FARM to identify the most relevant input variables regarding the storage time of products and predicts the range of storage time of products. Finally, the Location Assignment Module employs both fuzzy logic and association rule mining to assign locations for the packaged food, according to the product and package characteristics and the product's inter-relationships.

The developed system was validated through a case study of a packaged food wholesaler, who runs a packaged food warehouse in Hong Kong. The pilot run of the system in the case company was successful, which means the system design is feasible. The results of R-CLATS implementation was then used to evaluate the performance of the system. The evaluation results proved that after implementing the system, the operational efficiency of the warehouse was enhanced, the quality of products can be maintained and product traceability was enabled in the warehouse. In addition, recommendations given by this fuzzy-based approach were proven to be more precise than those provided by a rigid rule-based approach. Therefore, R-CLATS has been shown to be a feasible and effective DSS for enhancing the overall performance of a packaged food warehouse.

Publications Arising From the Thesis

(1 international journal paper has been published and 1 international journal paper is under 3rd review. 3 conference papers have been published. 1 book chapter has been published.)

List of International Journal Papers

Hui, Y. 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-Fulfilment Warehouse. *International Journal of Engineering Business Management, 2016, 8,* pp.1-15.

Hui, Y. Y. Y., Choy, K. L., Ho, G. T. S., Carman K.M. Lee, C.K.H. Lee and Lam, H.Y. (2016). A RFID-based Storage Location Assignment and Tracking System for Packaged Food Industry. *Expert Systems* (Submitted for 3rd review).

List of International Conference Papers

Hui, Y. Y. Y., Choy, K. L., Ho, G. T. S., Lam, C. H. Y., Lee, C. K. H., and Cheng, S. W. (2015). An intelligent fuzzy-based storage assignment system for packaged food warehousing. *Proceeding of the Portland International Conference on Management of Engineering and Technology (PICMET'15), Portland, Oregon, USA, 2-6 August 2015*, pp. 1869-1878.

Hui, Y. Y. Y., Choy, K. L., Ho, G. T. S. and Lam, C. H. Y. (2016). A Fuzzy Association Rule Mining Framework for Variables Selection Concerning the Storage Time of Packaged Food. *Proceeding of the 2016 IEEE International Conference on Fuzzy Systems (FUZZ), Vancouver, Canada, 24-29 July 2016,* pp. 671-677.

Leung, K. H., Choy, K. L., Tam, M. C., **Hui, Y. Y. Y.**, Lam, C. H. Y., Tsang, P. P. L. (2016). A knowledge-based decision support framework for wave put-away operations of e-commerce and O2O shipments. *Proceeding of the 6th International Workshop of Advanced Manufacturing and Automation (IWAMA 2016), University of Manchester, UK, 10-11 November 2016, 7(5),* pp. 495-507.

Other Output - Book Chapter

Leung, K. H., Cheng, S. W. Y., Choy, K. L., Wong, D. W. C., Lam, H. Y., **Hui, Y. Y. Y.**, Tsang, Y. P., Tang, V. (2016). A Process-oriented Warehouse Postponement Strategy for E-commerce Order Fulfillment in Warehouses and Distribution Centers. *Managerial Strategies and Solutions for Business Success in Asia* (pp.21-34): IGI-Global, DOI: 10.4018/978-1-5225-1886-0.ch002.

Acknowledgements

Foremost, I would like to express my sincere gratitude to my chief supervisor, Dr. K.L. Choy, for his continuous guidance, motivation and endless support throughout my study and research. His academic knowledge and life wisdom have been beneficial to me and have made me a better researcher and lifelong learner. In addition, my gratitude also goes to my co-supervisor, Dr. George T.S. Ho, for his valuable experience sharing and insightful comments that have kept me in the right direction.

Secondly, I would like to thank my industrial supervisor in the sponsored company, Mr. Ken Chu, for his support in the project related to my research. I truly appreciate the Innovation and Technology Commission and Princess Margaret China Limited for their financial support of my research studentship under the University-Industry Collaboration Programme.

Besides my supervisors, I would like to thank my research teammates and colleagues. My sincere thanks goes to Dr. Cathy Lam for her patience and encouragement throughout my study. Thanks to Mr. Eric Leung for his inspirational ideas sharing and constructive discussion. Besides, I am grateful to have Ms. Valerie Tang, Mr. Paul Tsang, Ms. Annie Lam, and Mr. Ram Wong as my teammates, who supported and encouraged me during my study. In addition, I appreciate very much the technical support offered by Mr. Peter Lau.

Last but not the least, a million thanks go to my family: my parents and sister, for fully supporting me in my study and reminding me to be a better person throughout my life. I am truly grateful to my friends, who have been encouraging and supporting me since we met.

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List of Abbreviations

1D	One-dimensional
2D	Two-dimensional
AaaS	Analytics-as-a-Service
AI	Artificial Intelligence
ARM	Association Rule Mining
CBR	Case-based Reasoning
COA	Center of Area
CPU	Central Processing Unit
C-DOT	Cloud Data Orchestration Tool
CSP	Cloud Service Provider
C-DB	Cloud SQL Database
C-DSS	Cloud-Based Decision Support System
CRRS	Cloud-based Responsive Replenishment System
COI	Cube-per-Order-Index
CRM	Customer Relationship Management
DCM	Data Capturing Module
MDM	Data Management Services
DM	Data Mining
DaaS	Data-as-a-Service
DSS	Decision Support System
DC	Distribution Centres
EP	Effectiveness of Package
ERP	Enterprise Resources Planning
VSM	Farm Variable Selection Module
FARM	Fuzzy Association Rule Mining
FL	Fuzzy Logic
GB	Gega Bytes
HF	High Frequencies
HK	Hong Kong
ICM	Information Consolidation Module
IaaS	Information-as-a-Service
I/O	Input and Output

KPIs	Key Performance Indicators
LAM	Location Assignment Module
LF	Low Frequencies
MS	Microsoft
MCT	Minimum Confidence Threshold
MST	Minimum Support Threshold
NIST	National Institute of Standards and Technology
NFC	Near Field Communication
OLAP	Online Analytical Processing
PET	Polyethylene Terephthalate
PMC	Princess Margaret China Limited
PO	Purchase Orders
RFID	Radio Frequency Identification
R-CLATS	RFID-Cloud-Based Location Assignment and Tracking System
RI	Rule Induction
RBR	Rule-based Reasoning
RBS	Rule-based System
SKU	Stock Keeping Unit
SMEs	Small and Medium Enterprises
SLAP	Storage Location Assignment Problem
SOPs	Standard Operating Procedures
UHF	Ultra-High Frequencies
WMS	Warehouse Management System

Chapter 1 Introduction

In this chapter, the research background is discussed in order to recognize the potential problems facing the packaged food industry. The problem areas are then identified to be the focus area of this research. After that, the research objectives, methodology and significance are presented.

1.1 Research background

Packaged food is now a major consumer product for the public at large. Since food is often processed in places far away from the final consumers, food packaging thus helps to contain and protect food from contamination during movement along the supply chain. In addition to containment and protection for food, the functions of food packaging include offering convenience to customers who demand different serving sizes of food, and offering communication channels for producers to release product information, such as nutritional information, to consumers (Robertson, 2013). For some companies, attractive packaging is used as a marketing means to build positive images for their products and brands. With all the important functions brought about by food packaging, the packaged food industry has long been a core part of the food industry. In recent years, the industry has been thriving, particularly the confectionery market that involves trading in packaged chocolate, candy and processed fruit and nuts. In the past five years, it had an annual growth rate of 2% and was worth around USD$200 billion in 2014 (Euromonitor International, 2014). It highlights the needs of the related logistics services, including warehousing, because consumers often look for food produced around the world.

The warehousing of packaged food, however, has been challenging. The industry often faces dynamic demand as food is affected by sell-by dates, changes in the seasons and customer preferences. During peak seasons, packaged food warehouses should operate at maximum efficiency so as to handle the large amount of product mixes that arrive at the same time. Furthermore, food safety remains a critical issue in food-related industries, including the packaged food industry. Food contamination can occur in any section of the food supply chain. Along the chain, storage in distribution centres (DC) and warehouses has high importance in food safety as it occurs in an upper stream of the chain and deals with a relatively larger amount of products. There are four main factors concerning the storage of packaged food that must not be overlooked by warehouse operators in regard to maintaining food safety. First of all, the storage requirements of different types of food have to be recognized and complied with during storage, or else the food may have a shorter shelf life or even deteriorate. Besides the food itself, the materials and sizes of the package determine how the food quality may be affected by the external environment, so the type of food packaging is another influential factor. In addition, the food expiry date is the clearest indicator of the remaining shelf life of a product, therefore suitable storage approaches should be adopted in order to avoid keeping expired food. Finally, an effective product tracing system should be available to support the identification of potentially problematic food and to reduce the number of cases of any subsequent illness (McEntire et al., 2010), in case of food contamination. Therefore, to avoid food-quality-related problems in warehouses, favourable storage conditions have to be achieved by adopting the right storage procedures and setting up a product tracking system.

In addition to food safety, the trend of e-retailing has been adding pressure to packaged food warehousing. E-retailing, or online retailing, is the delivery of products and services over the internet, which is a channel without time and geographical boundaries (Ahn et al., 2007; Jain et al., 2015). The trend of online shopping has been penetrating into the food market such that the e-retailing of food products is expanding at an unexpected rate (Xiao et al., 2015; Zhu et al., 2014). Among various food products that are sold online, packaged food is a major category of food e-retailing as it is not as perishable as fresh produce. E-fulfilment, the fulfilment of orders placed by customers via online platforms, is a key component of e-retailing operations that directly affects the customer satisfaction of e-retailing (Koufteros et al., 2014). It involves areas such as warehousing, stocking, flexible delivery time and methods and reverse logistics (Jain et al., 2015). E-fulfilment is a critical and expensive e-retailing operation (Agatz et al., 2008), especially for the e-retailing of packaged food, as the quality of food and the well-being of food packaging must be guaranteed throughout the e-fulfilment processes. The storage facility plays an important role in the e-fulfilment operation as it is responsible for the picking, packing, preparing, expediting and storage of a large amount of products for pickup at short notice (Lang & Bressolles, 2013). However, the considerable growth in the number of online transactions implies that the facilities which take care of packaged food e-orders are under greater pressure.

Comparing with fulfilling traditional orders, the operational challenges faced by the packaged food warehouse in fulfilling e-orders are shown in Figure 1.1.

Regarding the receiving operation, because the customers can access and place orders to a much larger number of online stores throughout the world via the e-retailing platform, there are more diversified types and volumes of food are need to be handled within the same timeframe T1 (Leung et al., 2016b), when compared with traditional order fulfilment. Therefore, to avoid environmental influences placed on the packaged food due to long waiting times at the unloading dock, more efficient receiving procedures are required.

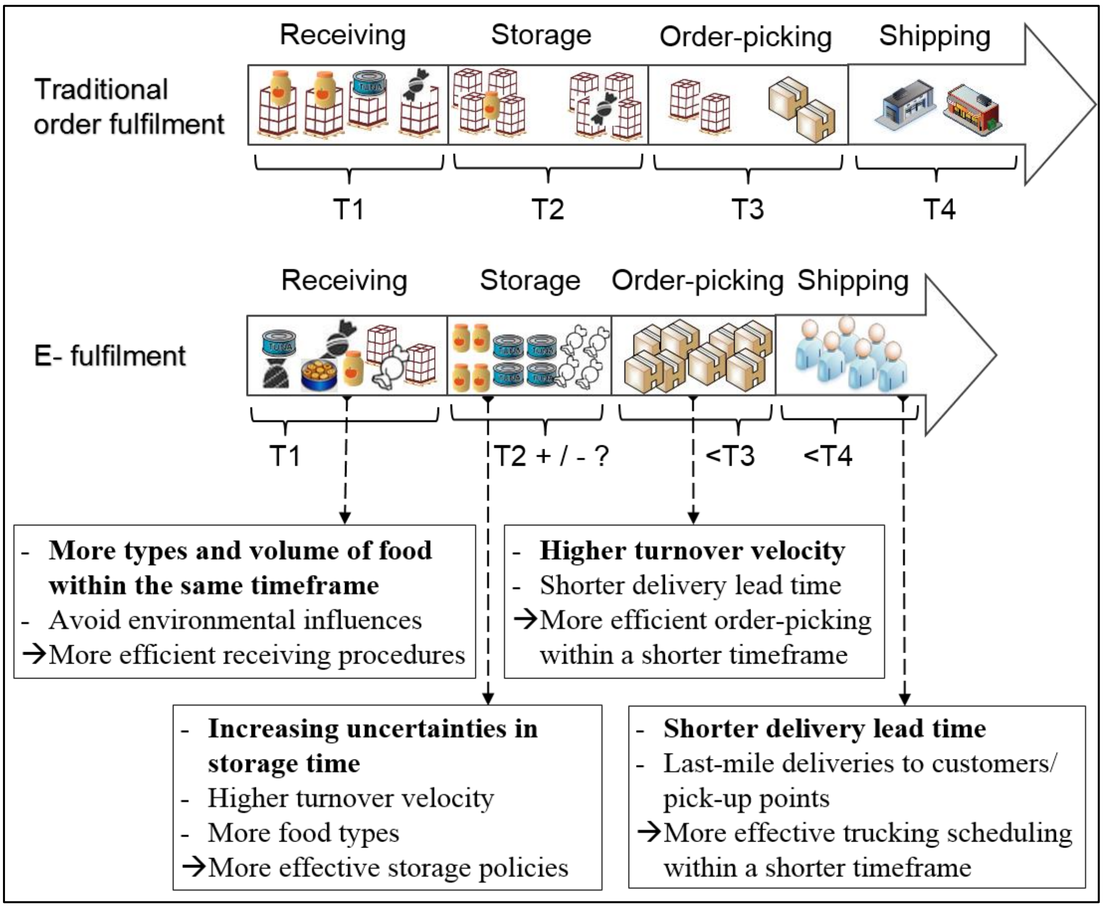


Figure 1.1 Operational challenges faced by decision makers of the e-fulfilment packaged food warehouse

Concerning the storage operation, increasing uncertainties in the storage time of the stored products are caused by the customer-oriented e-fulfilment practices, of which the end-customers are the decision makers of how and when the products are consolidated and delivered. Unlike the traditional order fulfilment practice in which the product outbound time can be scheduled in advance, the product outbound time facing the e-DC is unplanned.

In addition, a higher turnover velocity of products and more food types are observed in the e-fulfilment warehouse, due to the ease of placing orders by customers to any supplier at any time. This ordering convenience boosts smaller sized and larger numbers of orders which have to be delivered quickly. In order to cope with the more complex storage operations, more effective storage policies are thus needed.

In respect of the order-picking operation, in addition to the phenomenon of higher turnover velocity, a shorter delivery lead time is expected by customers, who perceive the logistics as a determinant factor of their online shopping experience (Vanelslander et al., 2013; Subramanian et al., 2014). Therefore, more efficient order-picking is pursued within a shorter time frame.

Finally, the shipping operation becomes more time-sensitive too. The expectation of shorter delivery lead times requires faster last-mile deliveries to customers or pick-up points, therefore a more effective trucking scheduling within a shorter timeframe is needed.

Given the aforementioned requirements in food safety, tracking ability and efficient and effective operations, the packaged food warehouse is in need of some new approaches to cope with the challenges.

1.2 Problem areas

It is seen in the last section that there are a lot of operational challenges involving the packaged food warehouse nowadays. In this research, the more fundamental problems faced by the warehouse are sought and tackled. In order to fulfil the requirements of being a packaged food warehouse, considerations of food safety, operational efficiency enhancement and tracking ability of the warehouse have to be well-handled. However, four problems related to these considerations are commonly found in ordinary warehouses that handle packaged food, as shown in Figure 1.2:

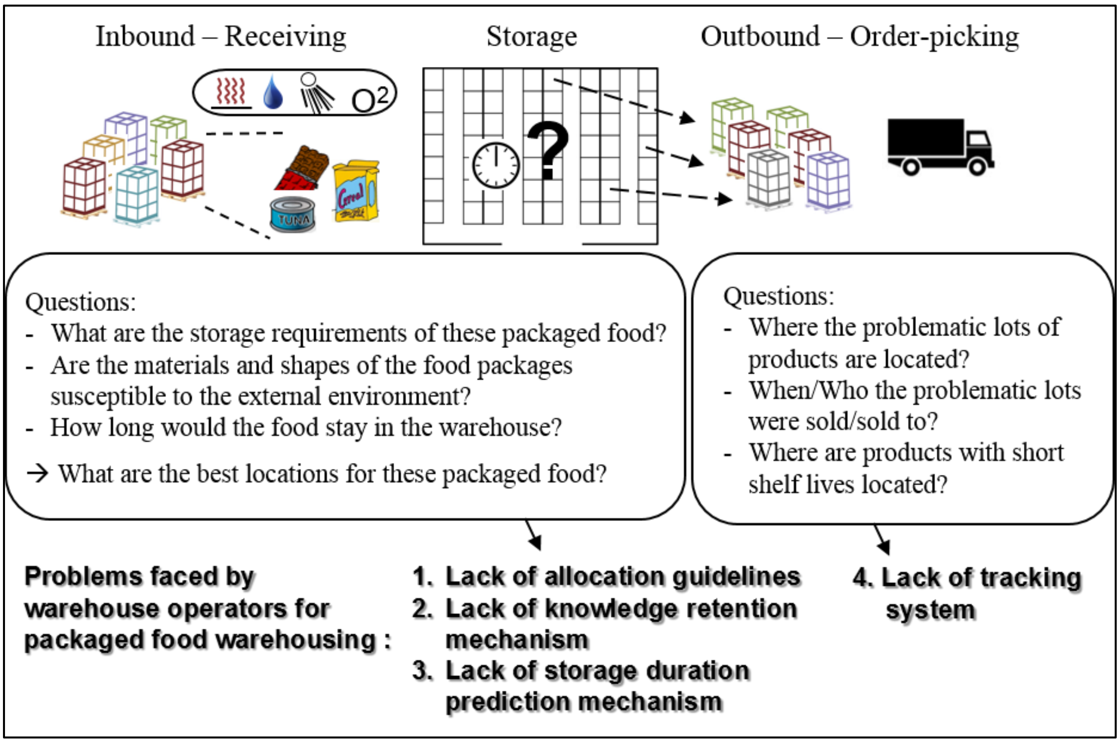


Figure 1.2 Problems of packaged food warehousing

i. A lack of allocation guidelines

Warehouse operators often do random storage location assignment without considering comprehensively the characteristics of the incoming products. However, since the storage of food has certain requirements in respect to temperature, relative humidity, light and gases, such as oxygen, random storage of food can lead to a shortening of the shelf life of food and even food deterioration. Therefore, appropriate allocation guidelines as to what are the best locations for different types of food should be available to the stock keeper.

ii. A lack of a knowledge retention mechanism

Knowledge regarding the best locations for various food and the best practices of food storage is not often not retained in the warehouse. Besides the basic food storage requirements mentioned in the last paragraph, professional knowledge of how the properties of a package determine its susceptibility to the external environment, is not cultivated, or is lost when an experienced staff leaves. This kind of knowledge is invaluable since stock keepers rely on it to handle vulnerable packaged food properly. If there is a knowledge retention mechanism, it can help new comers to prevent damage to food packaging and chemical reaction of the food content when handling the products.

iii. A lack of storage time prediction mechanism

Under the trend of e-retailing, the storage time of products becomes unpredictable, because the customer may wait for several products to be combined in the warehouse before arranging the delivery. Without knowing the storage time of products, it is difficult for the warehouse operator to assign a suitable location for a product according to its outbound time. However, the e-fulfilment warehouse seldom has a storage time prediction mechanism to predict the potential storage duration of the product, rendering a reduction in the efficiency of order-picking.

iv. A lack of an accurate real-time tracking system

Information that enables the external and internal traceability of food, such as lot number and location, is often missing in the supply chain. It occurs when the warehouse operator believes that the products would only stay in the warehouse for a short period of time, thus there is a lack of initiatives to set up an accurate real-time tracking system in the warehouse. Without knowing where the problematic lots of products are located and when and who the problematic lots were sold and sold to, slow tracking is caused when food contamination or quality-related incidents occur.

In order to avoid the consequences caused by the four problems, there is a need to develop an intelligent decision support and real-time tracking system for the packaged food warehouse, helping in forming allocation guidelines, retain food-storage-related knowledge, predict product storage time and track the products.

1.3 Research objectives

In view of the problems and needs mentioned the last section, this research aims to develop a system that can assist the packaged food warehouse in daily operations to fulfil the storage requirements for packaged food. The proposed system should be able to provide decision support for complex storage-related decisions, contain a knowledge base for retaining knowledge, predict product storage time and enable the warehouse to have product tracking ability. As a result, the warehouse will be able to handle the challenges related to food safety and e-retailing facing the industry. The specific objectives of this research are:

(i) To design a comprehensive system that considers the specific needs of packaged food storage. It will be able to offer storage location assignment recommendations according to the storage requirements and packaging characteristics of different food products. Besides, it will first predict the range of storage time for various products, and then take the prediction result as one of the considerations when generating the guidelines. In addition, the system will offer a real-time product tracking function to the packaged food warehouse operator,

(ii) To employ efficient and reliable technologies for data retrieval and consolidation. Consequently, timely and accurate decision support can be offered by the system even under the dynamic e-retailing business environment.

(iii) To predict the range of storage time of packaged food products using data mining (DM) techniques such as the fuzzy association rule mining (FARM). This storage time prediction functionality can greatly enhance the quality of the recommendations provided by the system,

(iv) To establish a decision support module that will make use of artificial intelligence (AI) techniques such as fuzzy logic (FL), to convert imprecise human reasoning into precise computer reasoning, enabling decision support and knowledge base construction.

This research seeks to achieve these four objectives by developing an intelligent prototype system called the RFID-Cloud-based Location Assignment and Tracking System (R-CLATS). The system applies Radio Frequency Identification (RFID) technology, cloud-based data and information repository, FARM, FL and Association Rule Mining (ARM) to actualize real-time tracking and storage location decision support. While the RFID helps to retrieve data reflecting the real-time situation in the warehouse, the cloud-based repository collects such internal data and external data provided by the shippers and consolidates these data. After that, FARM makes use of the consolidated data to select the most relevant variables for predicting the product storage time. FL is then applied to transfer the storage time and other input variables into the recommended storage locations for different products. Finally, ARM is used to further enhance the location recommendation by considering the relationships between products.

R-CLATS will then be verified through a case study. If it can fulfil the objectives, the aims of the research about maintaining food safety in upstream of the supply chain and enhancing operation efficiency in the packaged food warehouse, can be achieved.

1.4 Significance of the research

While the packaged food industry has been thriving recently, the food safety and e-retailing issues impose many challenges to the packaged food warehouse. This research has the following significance and value in contributing to the industry:

(i) The intelligent system applies both FL and ARM techniques to tackle the storage location assignment problem (SLAP) in the packaged food industry. This combination of AI and DM techniques considers the physical environment of the warehouse, the storage requirements and packaging characteristics of the packaged food, and the relationship between SKUs, in order to provide a comprehensive storage location assignment solution to warehouse operators who need to deal with food products. With the guidelines provided by the system, warehouse operators can handle packaged food in the right way, establish suitable storage policies in a faster manner and in turn achieve efficient and effective warehousing of packaged food.

(ii) The FARM Variable Selection Module of the system uses FARM to predict the range of product storage time. This is a novel yet useful approach to deal with the uncertainties in storage time brought about by the customer-oriented e-fulfilment operation.

(iii) The proposed system can retain knowledge for a warehouse. The if-then relationships between the input variables and the range of storage time are stored in the system in terms of fuzzy association rules. In addition, in the fuzzy decision support module, the attributes of various products are identified after data analysis, and then are stored in the proposed system, helping to preserve explicit knowledge regarding the storage requirements of products. Furthermore, a set of association rules regarding the relationships between different SKUs are created for allocating SKUs in particular locations. This set of rules, which can facilitate order picking, will be preserved in the system. Finally, the tacit knowledge generated from experienced staff about how to handle products that are vulnerable, is retained in the proposed system in the form of if-then rules.

(iv) Since the attributes and requirements of different types of product vary, by changing the input and criteria of the system, the proposed system can be extended and used in determining storage location assignments for products in other industries.

1.5 Chapters layout

This thesis is comprised of six chapters. In Chapter 1, the research background, problem areas, research objective, methodology and significance of this research are introduced. Chapter 2 is a literature review section that firstly studies the problems faced by the packaged food industry, then examines the automatic data retrieval technologies, cloud-based decision support system (DSS), variable selection and decision support techniques that could be used in this research. Chapter 3 illustrates the details of the design and operational mechanism of R-CLATS, which contains four modules to retrieve and consolidate data, predict storage time and finally to recommend storage locations and handling methods to the warehouse operator. The system is then tested through implementing a case study for a packaged food wholesaler. The details of the case study are presented in chapter 4, which includes the company background and current situation, and the implementation roadmap and details. Chapter 5 presents the results and discussion where the R-CLATS is evaluated and the findings of the research are assessed. Finally, conclusions are given in chapter 6, which summarizes the contribution and limitations of the research and suggests directions for future work.

Chapter 2 Literature Review

With the advancement in global logistic services, shipment of food overseas has become more feasible and has grown rapidly, especially during the holiday periods. This reveals a need to improve the operational efficiency of warehouses that handle packaged food in order to support the demanded growth. Warehousing of packaged food is challenging because of the specific storage requirements and packaging characteristics of the products themselves and the characteristics of the industry: (i) the demand for packaged food fluctuates with respect to the holiday periods, (ii) a large variety of products is involved, and (iii) the expiry date and food safety are of great concern. Packaged food warehouses thus have to operate at top efficiency, be able to store products according to their different storage requirements, and take the food expiry date into account when establishing storage policies. In addition, since food packaging offers protective and aesthetic functions to food products (Robertson, 2013), the movement of products by any means within the storage area has to be avoided. Having effective storage operations and decision making ability thus play important roles in packaged food warehouses.

In this chapter, through examining previous literature, specific needs concerning packaged food warehousing are identified and the possible approaches for fulfilling those needs are studied. The approach is inspired in developing a novel and effective approach that can solve the storage-related problems faced by the packaged food warehouse. There are five focus areas in this chapter. Firstly, current issues in packaged food warehousing are reviewed. The issues include food safety, storage operations and e-retailing of packaged food. Secondly, the automatic data retrieval technologies, i.e., Bar-code, RFID and Near Field Communication (NFC) technology, and their applications in warehouse operations are reviewed and compared in order to apply the most suitable one in this research. Thirdly, the applications of cloud-based DSS are studied to assess the potential for enhancing the research methodology. Finally, DM and AI techniques that are commonly used in variable selection and decision support in the DSS are reviewed. These techniques are clustering, rule induction (RI), ARM, FARM, rule-based reasoning (RBR), case-based reasoning (CBR) and FL . After the review, the core analytical techniques for predicting the range of product storage time and recommending the most suitable locations for various products are then selected. At the end of this chapter, implications of the literature review are summarized for designing the proposed DSS.

2.1 Current issues in packaged food warehousing

This section reviews the recent major issues that involve packaged food warehousing. Firstly, the food safety issues related to the packaged food warehousing are studied. The issues include the reactivity between food packaging and storage environment, and food contamination. Secondly, the storage operations in the packaged food warehouse are studied to reveal the main operational problems that the warehouse should tackle. Thirdly, how the trend of e-retailing affects the packaged food warehouse is discussed. Finally, based on the study in this section, the problems that a packaged food warehouse should focus on are presented.

2.1.1 Food safety issues

Packaged food is a major part of the modern food industry because food packaging offers irreplaceable functions in protecting the food during shipment and in offering different serving sizes to consumers (Robertson, 2013). In terms of the protection function, according to Marsh and Bugusu (2007), food packaging provides three types of protection in maintaining food quality, namely chemical, biological and physical protection. While chemical protection prevents damage that is caused by environmental influences such as temperature, moisture, gases and light, biological protection prevents food from being contaminated by microorganisms. Physical protection keeps the impacts of shock and vibration on the food at small or insignificant levels. The protection ability of the package varies according to the materials and format/type of the package, as there is interaction between the package environment and the food (Biji et al., 2015).The properties of the food package thus become one of three controlling factors of the shelf life of food, where the shelf life refers to the time during which the food product will remain fresh, healthy and maintain a good taste (Goyal & Goyal, 2012). The other two controlling factors of the shelf life of food are the intrinsic food characteristics such as the water and nutrient content of the food, and extrinsic environmental components such as storage temperature and relative humidity that the food is exposed to during distribution and storage (Pereira de Abreu et al., 2012). All three factors highly depend on the suitability of the storage environment, therefore the storage sector of a supply chain plays a crucial role in achieving food safety in the packaged food industry.

In addition, food contamination is another food safety issue that affects the packaged food warehouse. A larger number of more serious food contamination outbreaks are reflected by the increasing number of food commodity recalls in the United States (Chebolu-Subramanian & Gaukler, 2015). The food borne illness outbreaks bring destructive effects to public health, as well as to the entire supply chain network, which cannot operate normally until the source of pollution is found (Chebolu-Subramanian & Gaukler, 2015). The outbreaks can happen not only in a supply chain of fresh food, but also in that of packaged food. For instance, there was more than one outbreak related to peanut butter, which happened in 2006 and 2008, and an outbreak linked to chili sauce in 2007 in the US (McEntire et al., 2010). The seriousness of a food contamination outbreak is based on the time needed to recognize a problematic product and the smoothness of the recall process (Hora et al., 2011; Roth et al., 2008), where the smoothness of a recall process greatly depends on the tracing and retrieval processes of the problematic product lot (Rose & Fernandes, 2013). Hence, the implementation of traceability systems is a hot topic for food contamination handling, where RFID has been applied in these system. The implication of the above studies is that a tracking system is required when running a packaged food warehouse, because it can dampen the possible harm brought on by a food contamination outbreak.

2.1.2 Storage operations in the packaged food warehouse

Since the food safety issues reviewed indicate that the storage sector is of great importance in maintaining food safety along the packaged food supply chain, the operations of storage facility are studied to identify the focus of this research. The four general operations in storage facilities, including warehouses, are receiving, storage, order picking and shipping (Ballestín et al., 2013). According to Gu et al. (2007), receiving and shipping are the incoming and outgoing flows of material in warehouses respectively. Storage is about the organization of products kept in the warehouse for achieving optimal space utilization and material handling. Order picking includes the processes of gathering products from the inventory and sorting them according to orders for shipment (Guo et al., 2014). Among the four operations, packaged food is involved in storage operations for the longest hours. Besides, a suitable storage environment affect the shelf life of food directly, therefore, storage operations in packaged food warehouse should be emphasized.

Storage operations consist of three major decisions: (i) the amount of inventory to be stored, (ii) the replenishment time, and (iii) the storage location assignment among different storage areas (Gu et al., 2007). The third decision, which is also referred as SLAP in the rest this research, should be the focus area of this research. The reasons are that the first two decisions are related to inventory control but irrelevant to food safety of packaged food storage. Furthermore, storage location assignment is an upstream operation in which its effectiveness has direct influence on the efficiency of order-picking (Accorsi et al., 2012; Ene & Öztürk, 2012), as assigning reasonable locations for SKUs can reduce the travelling distance for the order-pickers (Accorsi et al., 2012; Bottani et al., 2012). For the packaged food industry, it faces dynamic demand fluctuation whenever a special occasion such as Christmas approaches, therefore handling SLAP in the right way to enhance order picking efficiency is also important in the warehouse.

SLAP is regarded as the placement of a batch of items in a warehouse seeking optimal performance for the designated performance indicators (Fontana & Cavalcante, 2014). While assigning storage locations for common products is generally a trade-off between operational efficiency and warehouse space utilization (Chan & Chan, 2011), for packaged food it is fundamentally about maintaining the quality of food, since the storage environment can trigger different levels of chemical and biological reactions in food (Brunazzi et al., 2014). Therefore, it is worthwhile to additional attention to the SLAP in the packaged food warehouse.

2.1.3 The e-retailing of packaged food

Apart from food safety and storage operations, E-tailing is another recent issue that has been affecting packaged food warehousing. E-retailing has been thriving in recent years, as reflected by the annual growth rate of online shopping sales of 17% from 2007 to 2012, equivalent to $521 billion in 2012, and the estimated sales amount of $1248.7 billion in 2017 (Verma et al., 2016). The e-commerce sales in China increased by 40% from 2013 to 2014, where the growth was mainly contributed by the food sector (Barnes, 2016). Among various food products that are sold online, packaged food is a major category of food e-retailing due to the consumer trust problem in fresh food products. Unlike buying packaged food in which sensory touching of the products is not necessary, consumers often prefer to sniff and touch fresh food products before making the buying decision (Barnes, 2016; Sharma et al., 2014). On the contrary, consumers have prior experience regarding the food content inside the packaged food, therefore, the perceived risk of buying packaged food is lower (Nepomuceno et al., 2014). In addition, the food packaging serves as a protection of the food content, a communication channel to the customer regarding the product information, and sometimes a beautiful-looking food wrapper that makes the product look like a gift (Robertson, 2013). Therefore, the trust issue and the functions of the food packaging have made packaged food a common option for online food purchase, especially when it involves food that is produced overseas. In order to move the food products around the world, they are required to have proper food packaging (Barnes, 2016), therefore gradually, packaged food will become a dominant sector of the e-retailing of food.

The warehousing of e-orders, however, are more complex and time-sensitive than that of traditional orders. Since an e-order can be placed at any time through the internet, e-fulfilment often involves more fragmented orders and smaller and more frequent deliveries (Barnes, 2016). Moreover, the orders have to be delivered within tighter delivery windows (Mkansi et al., 2011). The challenges related to the delivery of e-orders create great pressures to the order-picking operations in the warehouse.

Besides, customers are now becoming indifferent in choosing their buying channels, rendering difficulties in demand forecast. The customer behaviours "Showrooming" and "Webrooming" that are derived from e-commerce are more commonly seen. The two concepts were suggested by Chatterjee (2010) and Zhang and Oh (2013) to describe customer behaviour that involves both online and offline retail channels: "Showrooming" is denoted as the customer behaviour in which customers search for product information in physical stores and through mobile devices, but finally complete the transactions online. Contrarily, "Webrooming" means customers research the products of interest on the net but eventually shop in a physical store. These new behaviours render difficulties in predicting sales patterns, and thus affect the product arrival and turnover patterns in the e-fulfilment warehouse. In such cases, operational decisions and planning, such as SLAP and batching, have to be made within a smaller amount of time.

In addition, most e-retailing platforms, such as Taobao, seeks to offer impressive service to their customers in that they allow customers to track the product locations online (Lu et al., 2016). The product tracking service, however, cannot be implemented if the e-fulfilment storage facility does not contain product tracking devices and systems. Hence, the e-fulfilment packaged food warehouse should equip the tracking system with real-time data retrieval ability.

Apart from the challenges faced by most e-fulfilment warehouses, the warehouses that needs to deal with packaged food have to pay extra attention in securing the quality of their products. A suitable storage location of food has a lot of effect on the quality of food (Hui et al., 2015). Warehouse operators have to handle SLAP within a short period of time to prevent deterioration of the food after unloading, because slow decision making causes tardy receiving operations, in turn exposing the food in the open areas. Moreover, inappropriate allocation of storage locations, such as assigning fast-moving products to areas with low accessibility, results in longer travelling distances and frequencies. These lead to lengthen the order picking time, and thus increased human resources usage and lower turnover rate of the warehouse. Furthermore, lengthened transportation yields a higher chance of having food package damage as careless employment of fork lifters sometimes damages the food packets (Teo, 2011). Therefore, the packaged food warehouses that handle e-orders should be able to make quality decisions in SLAP.

2.1.4 Problems faced by packaged food warehouse

In view of the discussed issues of food safety, storage operations and e-retailing that concerns the packaged food industry, the specific problem at which the proposed system is targeted is the SLAP and development of tracking ability.

The study in food safety issues indicates that since the shelf life of food and food packages are prone to environmental changes, offering suitable locations for various food according to their requirements has become an important consideration for warehouse operators. At the same time, the recalling processes for recovering contaminated food products in previous outbreaks bring up the value of having a reliable food tracking system in the warehouse.

Meanwhile, it can be concluded from the study in storage operations that (i) the efficiency of order-picking greatly depends on the quality of storage location assignment, and (ii) existing methodologies related to SLAP are seldom concerned with the quality of the products. Hence, a SLAP solving approach that takes food quality into account should be developed.

Finally, it is revealed from the study of packaged food e-retailing that a packaged food warehouse has to equip itself for fulfilling a larger number of the more time sensitive and unpredictable e-orders. Since the arrival time and volume of products become uncertain and the order-picking operations have to be more efficient, there is an urged need for a SLAP DSS that can assist warehouse operators in making more timely and complex decisions. The system should be able to maintain food quality, enhance operational efficiency and track food locations at the same time.

2.2 Automatic data retrieval technologies

Most of the current logistics operations involve the usage of computers, with data retrieval methods. Though manual data entry still exists, more and more automatic entry methods have been developed to remove the constraints of manual input, such as non-real-time data capturing capability. By automatic data entry, it means "a single entry event can result in the capture of a stream of data" (Palmer, 2001). There is a wide range of automatic data retrieval technologies, such as voice recognition, magnetic stripe, barcodes, RFID and NFC. Among these technologies, barcodes, RFID and more recently, NFC, have been commonly applied in warehouse operations. This section therefore looks into these three technologies and compares them in order to select the most suitable one for this research.

2.2.1 Bar-code technology

According to Palmer (2001), a one-dimensional (1D) barcode is comprised of bars and spaces that are parallel to each other but with different widths. Information including numerical, alphabetical and special characters is encoded and represented by the width of the bars and spaces. There are many types of barcode that are distinguished by their symbologies, where symbology is denoted as the sets of rules for describing how information is encoded into the bars and spaces. In 1991, a breakthrough regarding the type of barcode occurred and afterwards, two-dimensional (2D) barcode emerged (Drobnik, 2015). Compared with the 1D barcode which can only store 20-25 characters, 2D can read and write a larger amount of alphanumeric characters, i.e. thousands of characters (Kim et al., 2013). Moreover, a

2D barcode is more durable than a 1D barcode (Rathod & Ladhake, 2012). According to Kim et al. (2013), there are two types of 2D barcode, the matrix (e.g. QR code) and the stacked (e.g. PDF417) barcodes, which are shown in Figure 2.1. In general, an increase in code size raises the information capacity of a 2D barcode and an increase in error correction level dampens that of a 2D barcode. Besides the barcode, a barcode system also requires the availability of a barcode reader, which can convert the encoded information into digital data that is compatible with the computer. Since it is much more complex for a reading system to decode a 2D than a 1D barcode (Palmer, 2001), the 1D barcode is still more popular than the 2D barcode in industrial applications.

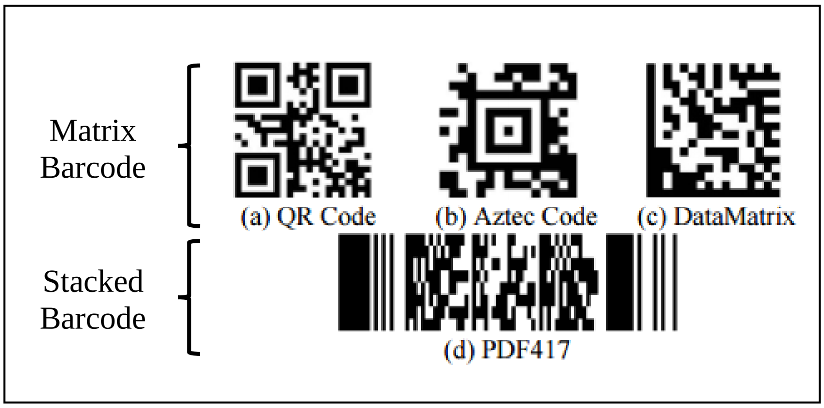


Figure 2.1 Types of 2D barcode (Kim et al., 2013)

The barcode has been widely applied in the logistics field. The application areas include manufacturing, warehouse management, transportation, distribution, and e-commerce (Bose & Pal, 2005; Palmer, 2001; Lin & Wadhwa, 2008). In respect to warehouse management, barcoding has long been used to speed up the stock taking process to enhance the inventory control operation. Besides recording the product numbers and quantities, location and time information can be gathered through the barcode. The receiving operation in the warehouse can be smoothened if barcodes are placed on the arriving products by the vendor. In such cases, product names, quantities and purchase order numbers of the arriving products can be easily updated in the computer through barcode scanning. Regarding the storage operation, when barcodes are attached to the products, the stock keeper can use a portable scanner to scan a product, and then the barcode fixes the storage location. Consequently, the locations of products are recorded and usable in the order-picking process. During order-picking, a list of items with their locations would be available to the stock keepers, which assists them to find and pick the right products. Therefore, barcoding is one of the mature automatic data retrieval technologies that can facilitate location tracking in a warehouse.

2.2.2 Radio frequency identification technology

RFID is a technology that can improve data transmission time and information accuracy by identifying objects and transmitting related data in a wireless network through radio waves (Lao et al., 2012). RFID is different from the barcode because the means of data retrieval are different. According to Chabanne et al. (2011), while a barcode is passively read by an optical laser, an RFID tag actively emits radio frequency signals that can be captured by the RFID reader. A general RFID system, as shown in Figure 2.2, consists of: (i) an RFID tag that is composed of a chip with an integrated circuit for storing data and an antenna for transmitting signals between the tag and the RFID reader, and (ii) an RFID reader which emits an electromagnetic signal to and receives the reply signal from the RFID tag. The returned wave is then converted into data for further processing (Shah, 2010).

The RFID system complies with four categories of radio frequency emission standards, which composed of the radio frequencies available, power levels and associated bandwidths (Chabanne et al., 2011). The four categories are Low Frequencies (LF), High Frequencies (HF), Ultra-high Frequencies (UHF) and Microwave Frequencies, which work at frequencies below 135, around 13.56 MHz, 860-960MHz and around 2.45 GHz respectively (Ghiotto et al., 2008; Chabanne et al., 2011). A RFID system with a higher frequency implies that it has faster reading speed and larger coverage area due to longer reading distance (Shah, 2010).

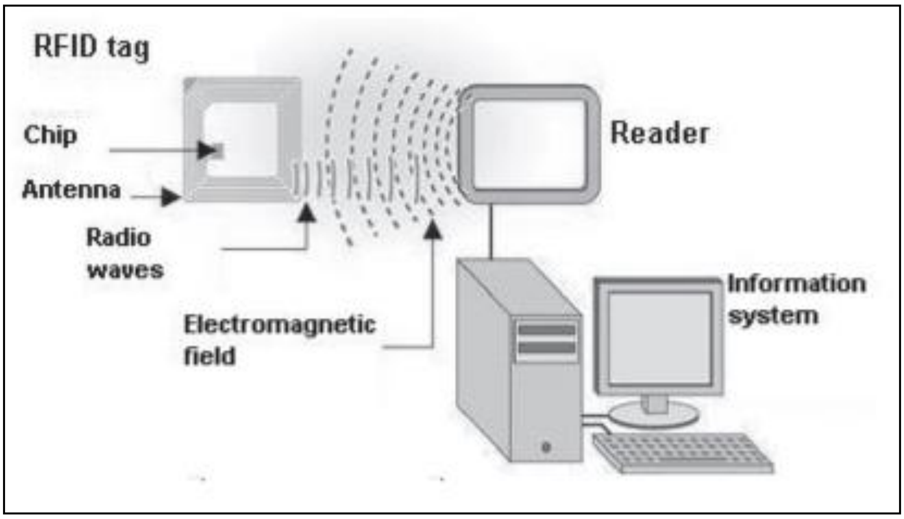


Figure 2.2 Elements of a RFID system (Chabanne et al., 2011)

According to the tags' electric power requirements, there are three types of RFID tag: passive, semi-passive and active. The characteristics of these types of tag are provided by Ghosh and Kundu (2015) and Deshmukh (2014), and are summarized in Table 2.1:

Table 2.1 Characteristics of different types of RFID tag

Types of RFID Tags	Source of Power	Read Range	Cost (USD)
Passive	RFID reader	Short (10 cm to 4.6 m)	Cheapest (25cents - a few dollars)
Semi-passive	- Internal battery for the tag's internal operations - RFID reader for communication	Long (up to 90 m)	-
Active	Internal battery	Long (up to 100 m)	Most expensive (50 - 250 dollar)

Apart from power requirements, RFID tags can be categorized into five classes with regard to the tags' features (Chabanne et al., 2011), as shown in Table 2.2. Industrial practitioners can choose an appropriate RFID tag according to their requirements in the coverage area, budget and functions needed.

Table 2.2 The five classes of RFID tag

Classes of RFID Tags	Main Function	Main Feature	Types of Tag
0	Binary detection	-	Simple passive
1	Identification	Read-only (Write once, read many)	Generally passive
2	Traceability	Contain memory, able to read and write	All three types
3	Sensor data recording	Contain sensors and memories	Semi-passive or active
4	Establish wireless network between the tags for communication	Contain sensors and memories	Active

RFID has been widely used throughout the supply chain in fields such as production scheduling, inventory, warehouse, and transportation management (Chen et al., 2013). One of the major advantages of RFID is that it can identify products at the item level, which enables traceability of a product along the supply chain (Vlachos, 2014). Therefore, RFID was applied in studies that concern both food safety and storage at the same time. The focus of these studies include the traceability of food products, cold chain monitoring, shelf life prediction and quality monitoring (Costa et al., 2013; Trebar et al., 2011; Kumari et al., 2015).

Regarding the traceability of food products, McEntire et al. (2010) suggested that product traceability is important to food safety because a rapid and precise product tracing system can prevent additional cases of illness during an outbreak of food contamination. Different versions of RFID-based tracing systems were therefore proposed by various scholars. For example, Papetti et al. (2012) inserted RFID tags into eight cheese samples, where the tags contain information such as quality information, sources of milk, cheese producer and animal source. The wholesaler and consumer can use RFID readers to check the information and add feedback to the system through personal computer or smart phone applications. Trebar et al. (2011) attached RFID tags to fish cages, well boats and fish tanks and identified the cages with handheld RFID readers. The readers and antennae were installed at the entry points to warehouses and next to the conveyor belts in the processing plants. In such cases, the information needed can be transmitted throughout the supply chain. The previous studies showed that the usage of RFID in food tracking is promising.

2.2.3 Near field communication technology

As stated by McHugh and Yarmey (2012), NFC is developed from RFID, therefore it also involves the usage of radio frequency fields for communication. The information is exchanged between readers, or initiators, and targets, as illustrated in Figure 2.3. It operates when the initiator generates the 16.56MHz magnetic field while the target (NFC tag) is close enough (a few centimeters) to the initiator. The circuit of the target is then powered and activated to response to the request of the initiator (Desai & Shajan, 2012).

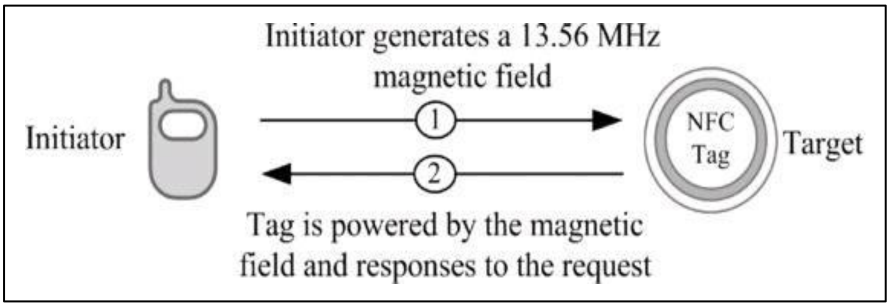


Figure 2.3 Generic reader/writer mode of communication of NFC (Coskun et al., 2012)

There are two types of communications in NFC: active and passive communication (McHugh and Yarmey, 2012). Active communication means both the reader and the target can generate radio frequency fields. Therefore, each of them can carry out the functions of an initiator and of a target. Consequently, both devices can undergo two-way and peer-to -peer information exchange. On the other hand, passive communication implies that the initiator is the only device that emit a radio frequency field to provide a power source for the communication.

NFC is treated as a new automatic data retrieval technology because of its features on top of the RFID technology. As indicated by Desai and Shajan (2012), NFC has three operating modes: reader/writer, peer-to-peer and card emulation mode. The reader/writer mode enables the NFC embedded device to read data from or write data to the NFC tag. If the tag contains previously written data, the new writing process will overwrite and update the data. In the peer-to-peer mode, two NFC embedded devices are defined as the initiator or the target according to the protocol. After that, both devices can exchange information if they are within several centimetres apart from each other. In the card emulation mode, the NFC embedded device is treated as a contactless smart card. The device is the target in this mode, therefore, it does not emit an RF field but relies on the NFC reader for starting a communication. The three modes have made NFC a technology that is distinguishable from RFID.

Currently, the most common areas of NFC application include mobile payments, access and authentication, mobile marketing, social networking, gaming, public transport and health care (McHugh and Yarmey, 2012), which mostly involve mobile devices. However, it recently has started to be applied in the logistics field as well. Ravinchandra et al. (2016) proposed a prototype Smart Stock Management Control system which uses NFC in managing stock. The system uses an NFC enabled mobile device to read the tag placed on the incoming or outgoing products. A mobile application “NFC Tools” is installed to read, write and erase the data stored in the tag. The system testing results state that the system is able to accurately record the incoming and outgoing products. Iqbal et al. (2014) developed a NFC-based inventory control system. To operate the system, passive NFC tags containing product information are attached to each product. At the same time, a computer connected to the network is attached with an active NFC reader. When a customer carries a NFC-embedded product to the cashier, the system can check and update the inventory record after scanning the NFC tag. This NFC system is claimed to be preferable to the traditional barcode system because NFC has better readability, storage capacity and security level than the barcode.

Although the application of NFC in stock management is still sparse, the above studies show that there is a great potential of using NFC in the logistics related fields.

2.2.4 Comparison of automatic data retrieval technologies

In order to select the most suitable automatic data retrieval technology for this research, a comparison of different aspects of the three mentioned technologies, i.e. barcode, RFID and NFC, is done. A table showing the results of the comparison is shown in Table 2.3, which is formed after reviewing the related studies of Arendarenko (2009), Nava-Díaz et al. (2009), Coskun et al. (2012) and Andriulo et al. (2015).

After acknowledging the relative strengths and weaknesses of the three technologies listed in Table 2.3, matching between the proposed system’s requirements and the comparisons of the three automatic data retrieval technologies is conducted. First of all, the proposed system will be used in a warehouse instead of a retailing environment. It indicates that the technology should be able to identify different levels of product categories, i.e., pallets, cases. For the same reason, as it may involve cases and pallets, simultaneous identification should be available. Secondly, since the system seeks to improve the efficiency of the receiving operations and storage location assignment, the easier and quicker the signal reading process takes place, the greater the improvement that can be brought to the operational efficiency. Therefore, the technology that can retrieve data most conveniently, i.e., has less constraints in line of sight and item orientation to the reader, and has a wider reading range, is preferred. Thirdly, as the information stored

Table 2.3 Comparison of Barcode, RFID and NFC (Arendarenko, 2009; Nava-Díaz et al., 2009; Coskun et al., 2012; Andriulo et al., 2015)

	Barcode (2D)	**RFID**	**NFC**
Line of sight	Require	Not require	Not require
Reading range	Up to 4 m	Up to 300 m	Approximately 10 cm
ID capabilities	Identify item category	Uniquely identify items, cases, pallets	Identify item category
Item orientation to reader	Need proper orientation	Relatively not important	Less important than barcode
Simultaneous identification	An item at a time	Thousands tags per second (anti-collision dependent)	An item at a time
Security, counterfeiting	Easy to be copied	High security (Unique identifier number, can be encrypted)	More secured than barcode (can be encrypted and perform other security functions)
Rewrite, reusability	No write capability	Specific class of tag supports read and write capability	Support read and write capability
Data storage capability	Limited capacity (3Kb for binary barcode and 7 Kb for QR code)	Capacity larger than barcode (up to 128 Kb)	Greater capacity (up to 760 Kb)
Cost per tag	Cheaper ($0.001 USD)	More expensive (0.1 - a few USD)	More expensive (1 EUR)

in the tag would be certain product information such as product name, lot number and quantity, for facilitating product tracking, the security issue and data storage capability are not of high importance. Finally, rewriting and reusability of the tag is not necessary. It only depends on whether the company applying this system would need to keep dynamic rather than only static information in the tag, according to their own consideration.

Referring to the above analysis regarding the matching between the system requirements and the comparisons of Barcode, RFID and NFC, it is concluded that RFID is the most suitable data retrieval technology to be applied in the proposed system. Though RFID tags may involve a higher cost than other types of tag, the potential benefits that RFID would bring to the company would justify the extra cost.

In addition, a cost analysis is conducted on system implementation in Chapter 5, in order to provide a budgeting reference to the potential user.

2.3 Cloud-based decision support system

DSS is a class of system that assists decision makers during the problem solving process by retrieving data and testing alternatives (Amin & Alrub, 2014). It has been adopted in various warehouse operations, such as storage allocation, storage assignment, order planning and storage condition monitoring and controlling, rendering improvements in the efficiency and effectiveness of the storage location assignment, order-picking and risk control (Choy et al. 2013; Lam et al., 2011; Lam et al., 2013; Accorsi et al., 2014). It is becoming popular for industrial practitioners to host part or all of their DSS in a cloud environment, in order to enjoy the low-cost scalability and flexibility offered by the cloud (Obeidat et al., 2015). In this section, the rationale and applications of cloud-based DSS (C-DSS) are reviewed in order to determine if C-DSS can be applied in this research to improve the proposed system.

2.3.1 Rationale of C-DSS

In order to understand the features, thus the applicability of C-DSS, the characteristics of cloud computing are reviewed. Cloud computing is defined by The National Institute of Standards and Technology (NIST) in the US as “a model for enabling ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources (e.g., networks, servers, storage, applications, and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction” (Mell & Grance, 2010). The definition reveals five characteristics of cloud computing. The first one is that it allows *on-demand self-service*, i.e., a consumer can obtain computing capabilities such as network storage capacity according to his needs, without interaction with the service provider. Secondly, the *broad network access* allows online computing capabilities to be accessed via different platforms, such as mobile phone, desktop, etc. Thirdly, *resource pooling* indicates that the computing resources such as storage and processing capabilities, are assigned by the service provider to different consumers. The exact location of the resources are unknown to the consumers. Fourthly, *rapid elasticity* describes that the capabilities as seemingly unlimited to the consumer and available at any time, because those capabilities released to the consumers can be scaled up or down rapidly according their needs. Finally, cloud computing is a m*easured service*. It means that there is a metering approach to measure the level of utilization of the computing capabilities. Consumer thus can pay a minimum amount according to what and how much they need to use. The five characteristics have made an information system a service instead of goods to the consumer, therefore the service-oriented DSS emerged.

A service-oriented DSS, which is also referred as C-DSS, has the following characteristics. It is a component-based system that is reusable, substitutable, scalable, and customizable (Demirkan & Delen, 2013). These characteristics indicate that the services used in the system are reusable in different workflows. Besides, alternative services can be applied to substitute the service in use when developing the same system. Furthermore, the services used in the system can be extended, and the capabilities of those services can be scaled. Finally, the generic features of the system can be customized.

The generic architecture of a C-DSS was described by Demirkan and Delen (2013) and illustrated in Figure 2.4. A C-DSS contain three service models: data-as-a-service (DaaS), information-as-a-service (IaaS) and analytics-as-a-service (AaaS). DaaS is about a concept where the actual storage location of the data is of no importance, for example in a computer

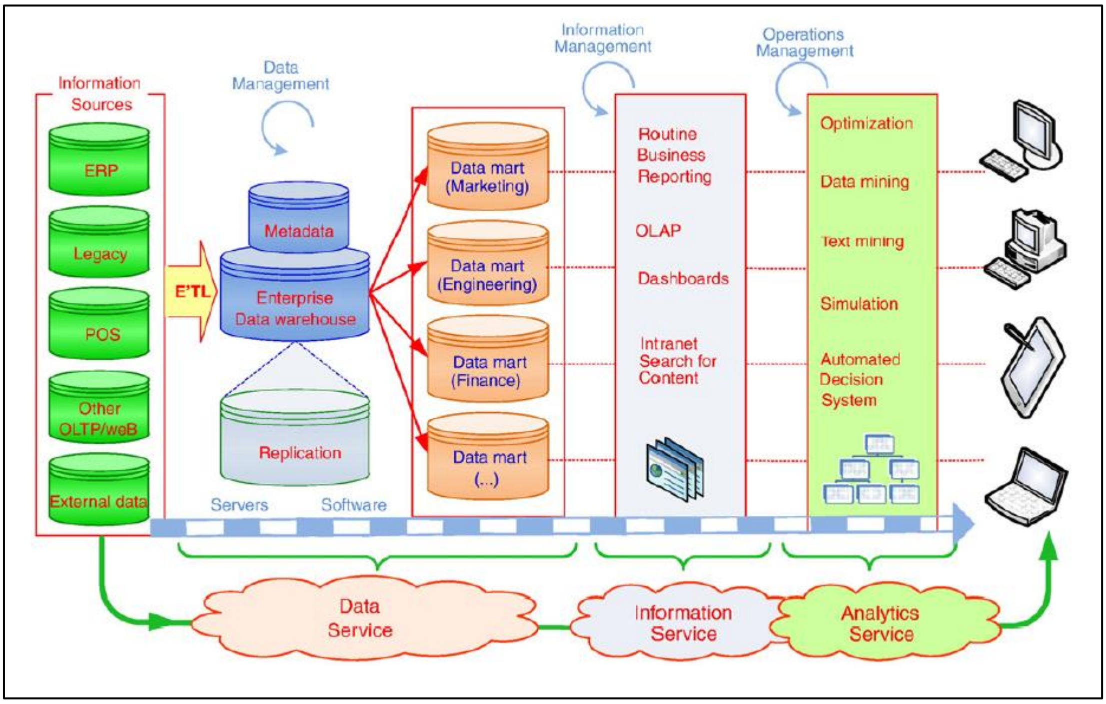


Figure 2.4 Conceptual architecture of cloud-based DSS (Demirkan & Delen, 2013)

or in a server, as long as the system can access it whenever needed. Consumers can direct various information sources into the cloud database, and then enjoy the single point of updates and data access. IaaS aims to offer information to different users, processes and applications over the enterprise at short notice. Since IaaS provides a flexible data integration platform, through master data management services (MDM) and techniques such as online analytical processing (OLAP), valuable information can be cultivated from the data. Finally, AaaS is a infrastructure that can quickly generate useful and accurate results from a large amount of structured and unstructured data. More importantly, this analytical platform has become a shared utility for the entire enterprise under AaaS. Employees can thus gain access to the analytical applications and initiate analysis easily. The common analytical techniques involved in AaaS include DM, Text Mining, Simulation, etc.

The characteristics and architecture of C-DSS have brought several advantages to C-DSS applications. According to Marston et al. (2011), the entry cost of initiating computer-intensive business analytics has been dramatically lowered, especially in the view point of small and medium enterprises (SMEs). In the past, it took a vast amount of computer resources to implement business analytics. With C-DSS, SMEs can access online analytical resources easily, and only when needed, through AaaS. Besides, businesses can scale their services flexibly according to their development and customer demand. Moreover, it enables the usage of mobile interactive applications that respond in real time to sensors, such as those for monitoring humidity and temperature in a container. Given the advantages of C-DSS, its application in different industries has become a popular research topic.

2.3.2 Applications of C-DSS

C-DSS has been applied in different industries, such as the energy industry for energy resource allocation, the medical industry for clinical decision support and the logistics industry for order planning and put-away (Dixon et al., 2013; Rajabi et al., 2013; Guo et al., 2014; Oh et al., 2015; Lee et al., 2016; Leung et al., 2016a). Recent examples of cloud-based system application demonstrate the reliability and value of adopting cloud infrastructure in DSS. Mann & Kaur (2015) designed a cloud-based data mining framework in a clinical decision support system that supports the security in cloud application. The system makes use of access control and information encryption functions of the cloud infrastructure to secure the sensitive personal information of patients. Dong et al. (2014) proposed a multicloud-based evacuation system which shows that the stability of cloud infrastructure can be secured by using the snapshot function of the cloud infrastructure. Demirkan & Delen (2013) also stated that data availability in cloud environment can be maintained by data replication. These applications imply that cloud infrastructure is reliable to be applied in the proposed DSS.

Regarding the value of adopting C-DSS, Guo et al. (2014) illustrated how to make use of the information sharing function of a cloud-based decision making system in in the apparel manufacturing industry. Cloud computing technology has been used together with RFID technology to capture real-time production data and track orders remotely. Consequently, abundant data is available for decision making and better supply chain coordination is achieved. Lee et al. (2016) proposed a Cloud-based Responsive Replenishment System (CRRS) for businesses adopting franchise business strategies. The system offers a collaborative information exchange platform for consolidating data from various parties in nearly real-time, where the consolidated data can enhance the replenishment decision support function of the system. It demonstrates a successful combination of cloud computing and AI techniques for providing quality replenishment suggestions. These studies indicate that combining RFID and cloud-computing can further enhance the efficiency in information capturing and sharing.

Since the system proposed in this research aims to serve warehouses that need to fulfil e-orders, cloud computing can facilitate data collection from a large number of parties involved in the e-transactions. Cloud infrastructure can also offer a platform for sharing information among these parties when needed. Furthermore, as the demand derived from e-retailing can be fluctuating and unpredictable, the scalability of the cloud infrastructure offers flexibility to the warehouse operator to scale the computing services up or down according to actual needs. In view of the aforementioned benefits, the proposed system should adopt cloud computing.

2.4 Variable selection techniques for decision support system

Variable selection is also referred to as feature selection, attribute selection or feature reduction, which is a technique for selecting the relevant variables to develop a learning model (Huang et al., 2010). It discards irrelevant variables to simplify the models in order for the model to have better performance (Cortez et al., 2009). This technique is particularly useful in developing a DSS, because it can avoid over-fitting of variables into the system, where over-fitting would unnecessarily slow down the computing speed of the system. Besides, with more relevant input variables, the prediction performance, thus the recommendations offered by the DSS, can be enhanced (Liu et al., 2009). For example, Ząbkowski & Szczesny (2012) reduced the number of variables from 205 to 26 after going through the variable selection procedure, rendering a more accurate and simpler prediction model in customer insolvency. Elwakil & Zayed (2014) applied VS methods to find relation between quantitative and qualitative variables from the project data in order to predict the work task durations. These applications of VS demonstrate the value and function of VS that are usable in this study.

In order to facilitate decision support in SLAP handling, different methodologies which apply mathematical algorithms and/ or artificial intelligence techniques have been proposed in previous studies (Kim & Smith, 2012; Manzini et al., 2012; Fontana & Cavalcante, 2014). Among the input variables that are considered in these methodologies, the storage time, which denotes the time that SKUs spend in the warehouse, is the most important. It reveals which SKUs are the fast-moving items that should be placed at more accessible locations, i.e. the Input and Output (I/O) Points of the warehouse (Burkard et al., 1995). However, the actual storage time of SKUs is difficult to know in advance, therefore some indices related to the demand variability of products are traditionally used to predict the storage time. For example, Turn Index, Popularity and Cube-per-Order-Index (COI) which study the turnover and pick-up rate of SKUs (Kim & Smith, 2012; Manzini et al., 2012; Fontana & Cavalcante, 2014; Kofler et al., 2015; Wutthisirisart et al., 2015). In spite of the evident relationship between demand variability and the SKU storage time, there are other potential factors related to the storage time that have not been studied in existing approaches. Therefore, the proposed DSS should execute VS to identify the most relevant factors and in turn predict the range of storage time more accurately and efficiently.

Regarding the approaches of variable selection, they can be implemented by two types of techniques, the statistical and DM techniques. As defined by Jain and Srivastava (2013), "Data mining is the process of exploration and analysis, by automatic or semiautomatic means, of large quantities of data in order to discover meaningful patterns and rules". According to Nettleton (2014), statistical approaches such as factor analysis, Pearson correlation and data fusion, are generally used to find the relationships among the variables and look for linear relationships between them. After implementing these approaches, variables that are greatly related to each other are combined to form representative subsets of variables, in turn reducing the number of final input variables. In order to use statistical models such as logistic regression, strict assumptions on normality and linearity, and requirements in sample size have to be complied with. These restrictive prerequisites made statistical models difficult to be applied (Olson et al., 2012). On the other hand, DM approaches are applicable in unveiling non-linear relationships among variables, and are effective in analysing the relationship between input variables and the specific output variables that are determined by the analyst beforehand (Ma & Wang, 2009; Nettleton, 2014). In this research, since input variables do not necessarily have linear relationships among themselves, and the output variable, i.e. storage time, is set, DM approaches are preferable. The DM techniques that have been commonly used in variables selection include clustering and rule induction (Nettleton, 2014). These two techniques and FARM are reviewed in the following sections in order to determine the appropriate variable selection technique for predicting the storage time of SKUs in the proposed system.

2.4.1 Clustering

Verma et al. (2012) defined clustering as a data mining technique that divides dissimilar data into different clusters and group similar data into the same cluster. Though there are various clustering approaches, the common goal is to locate the cluster centers that can represent each cluster. After locating the cluster centers, new inputs to the clustering system can be compared with the cluster centers for determining the groups that the new inputs belong to. In such cases, variables can be represented by clusters, which form a smaller number of new variables for further analysis. For example, Sotoca and Pla (2010) and Fujiwara et al. (2012) illustrated how to apply clustering in variable selection. Sotoca and Pla (2010) used a feature clustering strategy to search for the most relevant variables from the original set of variables derived from the data set, where the relevancy depends on the minimal relevant redundancy criterion between the original variables and the relevant variable classes. Consequently, variables having small dissimilarity values with respect to the representative variable are grouped around that representative.

Fujiwara et al. (2012) worked on another criteria to determine the cluster. The Nearest Correlation Spectral Clustering is applied to group original variables that are grouped into variable classes according to the correlation between variables. In addition, the variable classes are validated by examining the contribution ratio of the original variables to the variable class. The number of input variables are reduced and the estimation performance is improved in both examples. It proves that clustering can be useful in reducing the input variables by forming variable classes.

2.4.2 Rule induction

Rule induction was defined by Rajola (2013) as a technique that spots and expresses data relationships in rules. It derives variables that belong to different classes from a set of historical data set through subsequent inferences, such as Quinlan's C5 rule induction algorithm. As stated by Nettleton (2014), through the algorithm, the input variables and their values are compared with the values of the output variables. The input variables and values that have the weakest linkage with the values of the output variables would be pruned from the decision tree, which is a graphic representation of data relationships in a tree shape that makes the analysis results evident. While the nodes of the tree indicate the name of the variables, the branches state the possible values that the variables can have, i.e., the conditions that lead to the subdivisions, and the leaves represent the classes, i.e., data set partitions (Rajola, 2013). Each set of node, branch and leaf represents a set of if-then rule, where "IF" represents the *condition* (branch) and "THEN" represents the *conclusion* (node/leave). An if-then rule means that when the *condition* of the rule is met, the *conclusion* can be deduced (Li & Liu, 2014).

Regarding variable selection, Cho et al. (2010), demonstrated how to apply decision tree induction in variable selection. The chi-square algorithm and entropy reduction algorithm were used to implement decision tree induction. The chi-square value shows the differences between the observed frequencies and expected frequencies for divided samples due to randomness. The nodes in the lower levels that involve larger chi-square values would be kept. The entropy value indicates that a group consists of diverse records. The nodes with lower entropy would be kept in the tree. After implementing the algorithms, 5 variables instead of the original set of

15 variables are selected as the input variables in Cho et al.'s (2010) prediction model. The performance of the prediction model is claimed to be improved with variable selection through decision tree induction.

Studies related to rule induction imply that rule induction is able to reduce the number of irrelevant variables. However, the major drawback of typical rule induction algorithms is that a large number of rules are produced, leading to hard interpretation and management of rules (Rajola, 2013). Therefore, other kinds of rule mining methods are reviewed in the next paragraphs for comparison.

2.4.3 Association rule mining and fuzzy association rule mining

ARM is a data mining technique that aims to unveil the co-occurrence relationships among data sets in an efficient way (Li & Liu, 2014). It is typically used to discover how items purchased in a store are associated with each other, but its applications are spreading into other fields, such as texting mining and web usage patterns discovery. The Apriori algorithm is a common algorithm for implementing ARM and the results are expressed in if-then rules. Association rules are said to be useful if they meet the *support* and *confidence* threshold that is set by the investigator. Besides *support* and *confidence*, *expected confidence* and *lift* are another two parameters that describe the attributes of the rules. The meaning and formula of the four parameters were summarized by Shi (2011) and are shown in Table 2.4.

Table 2.4 Meaning and Formula of the four parameters related to association rule (Shi, 2011)

Name	**Meaning**	**Formula**
Confidence	The probability of the occurrence of itemset B when itemset A is occurred	P(B|A)
Support	The probability of the occurrence of both itemset A and itemset B	P(B∪A)
Expected Confidence	The probability of the occurrence itemset B	P(B)
Lift	The ratio of confidence to the expected confidence	P(B|A) / P(B)

ARM is capable of selecting variables as it can discover and establish relationships between variables which appear in the same given records. Besides, it considers the occurrence frequency of the relationships and contains thresholds for filtering uncommon rules (Ngai et al., 2009). Therefore, the quality of rules describing the relationships among variables is assured.

Classical ARM, however, is based on Boolean logic which measures attributes solely in yes or no terms, and results in limited solutions (Roy & Chatterjee, 2013).To overcome this limitation, FARM was introduced because “fuzzy sets are an optimal tool to model imprecise terms and relations” which commonly exist in real world decision making processes (Delgado et al., 2003). For example, FARM was applied to identify the criteria that would affect the overall rating of the suppliers for supplier selection. Three criteria were found to be related to the final performance of the suppliers (Jain et al., 2014). The study of Jain et al. (2014) implies that FARM can be a promising tool for identifying vague yet important factors that affect the storage time of packaged food in a warehouse.

Considering the techniques that have been mentioned in this section, all of them have shown their capabilities in filtering out the irrelevant variables from the original sets of variables. Recalling that the main objective of undertaking variable selection by the proposed system is to predict the range of SKU storage time in order to formulate a suitable location assignment solution, storage time prediction is thus a key function requirement. However, except FARM, other techniques are based on Boolean logic, which means they can only tell which input variables are the most relevant ones among each other or with respect to the output variables. Besides, they tend to marginalize the solutions (Roy & Chatterjee, 2013). In contrast, FARM is able to cultivate relationships between ranges of the parameters, instead of only the relationships between Boolean attributes (Ho et al., 2012). This additional functionality of FARM enables the description the specific happening conditions of the if-then relationships between the input and output parameters (Ho et al., 2012; Lee et al., 2015). For example, while the other techniques only suggest that “Sales Turnover Rate is greatly positively related to the SKU storage time”, FARM can further describe the situation such as “IF Sales Turnover Rate is high, THEN the SKU storage time is Short”. The range of storage duration, which is a crucial input variable SLAP handling, can thus be accurately predicted by FARM (Hui et al., 2016a; Hui et al., 2016c). Therefore, this research will apply the FARM framework for identifying the factors and patterns concerning the storage time of SKUs, in turn assisting decision support in SKU allocation in the packaged food industry.

2.5 Decision support techniques

Apart from variable selection, the main function of the proposed system is to recommend the most suitable locations for various products in a packaged food warehouse. A vast number of approaches have been proposed in previous studies to solve SLAP in warehouses, which include optimization models and heuristic approaches.

The optimization models seek to find the optimized solution by ranking the products with certain indices before allocating and formulating mathematical models. For example, indices that are related to the demand volatility of products, such as Popularity, COI and Turn Index (Kim & Smith, 2012; Manzini et al., 2012; Fontana & Cavalcante, 2014; Kofler et al., 2015; Da Silva et al., 2015; Wutthisirisart et al., 2015), examine the relationships bewteen stolarge location and turnover, inventory level and picked-up rate of SKUs. For example, Da Silva (2015) proposed to use the multicriteria method SMARTER for ranking the importance of products, in turn assigning storage locations according to their corresponding importance with a lexicographic method. In addition, Yang et al. (2013) combined integer programming and dynamic programming in their models for solving SLAP and the storage/ retrieval scheduling problem at the same time. These models require crisp values to measure the variables in order to obtain a correct outcome. However, SLAP concerning packaged food involves variables that are difficult to be measured by crisp values, such as the effectiveness of the food packaging and the resistance level to temperature change, therefore optimization models are less preferred in this situation.

In contrast, heuristic approaches that make use of AI and DM techniques have been applied in SLAP, where AI is a promising problem-solving tool that is particularly applicable in knowledge-based operations that involve mechanisms of analogical and logical reasoning (Glover & Greenberg, 1989). Therefore, in this section, the applications of the AI and DM techniques that are used in SLAP handling are studied. The techniques include CBR, FL and ARM. The technique that can best fulfil the requirements of packagd food storage in the context of food safety assurance and operational efficiency enhancement, would be chosen as the core analytical tool of the proposed system.

2.5.1 *Case-based reasoning*

CBR is an AI technique that can be applied in SLAP handling. CBR was defined by Leeland (2011) as an approach to problem solving and learning for computers and people, based on the solutions of similar past problems. A case in CBR means a problem situation, therefore, expertise in a CBR is expressed as a collection of previous cases instead of typical rules. Each case is comprised of the description, solution and/ or outcomes of a problem. The mechanism of CBR problem-solving is illustrated in Figure 2.5.

According to López (2013), the four problem-solving processes involved in CRB are *retrieve, reuse, revise* and *retain*. *Retrieve* denotes the retrieval of past cases similar to the query problem. Cases are compared with each other in their common attributes by inductive methods in order to acknowledge their similarity. After retrieving similar cases, the ones most similar to the query are applied in the *reuse* process to develop a solution for the query problem. However, the selected case would be evaluated in the *revise* process to decide if the original case can best yield the desired outcome. If not, the original case would be revised to form a new case. The newly developed case would then be stored in the knowledge repository of the CBR engine in the *retain* process for future reference.

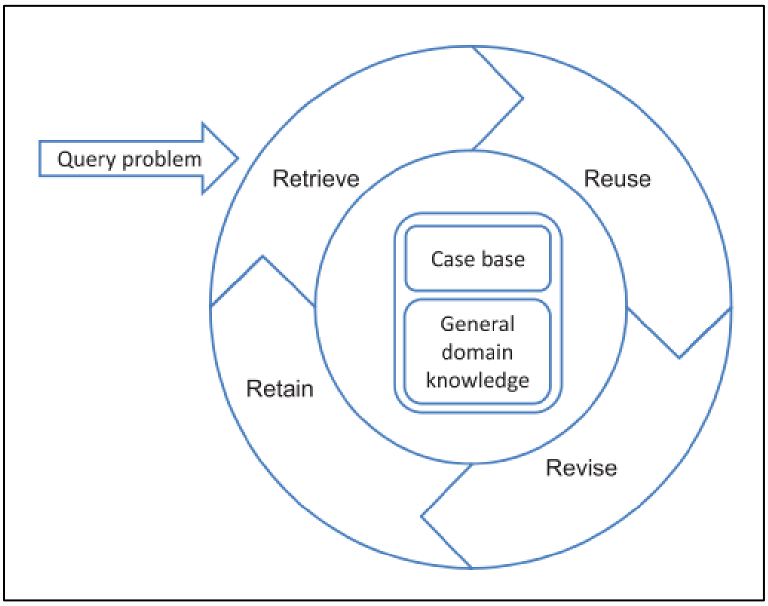


Figure 2.5 Mechanism of CBR problem-solving (López, 2013)

CBR has started to be applied in SLAP. Leung et al. (2015) defined the common attributes of electronics and high-tech products to assign each SKU into classes in a decision tree. For example, the total gross weight of the tablet computer can be categorized into 100-300 kg, 301-500 kg, etc. SKUs with different attributes which are then linked with different cases that suggest storage locations for the SKUs. When a SKU arrives at the warehouse, the case-based location assignment system selects the most similar case according the attributes of the SKU, and then provides a storage location suggestion. In such a case, the case-based system offers decision support to the warehouse operator in SLAP handling. The example shows that if the attributes of the SKU can be accurately categorized with clear boundaries between the categories, CBR could be a suitable AI tool for SLAP.

However, the most important requirement of the packaged food storage is maintaining the quality of the food content, instead of solely achieving operational efficiency. The warehouse operator thus emphases attributes such as the suitability of the storage environment, the level of protection offered to the food by the food package, the susceptibility to environmental changes of the food, and the disposal rates of the SKUs, when handling SLAP. These attributes are difficult to be measured and judged by standard measurements, and the measurements themselves are difficult to set. Therefore, it is observed that warehouse operators rely on linguistic terms to describe the decision variables. However, if the decision variables are inaccurately evaluated, the resulting solutions for SLAP can be misleading. Therefore, another technique rather than CBR, is needed to handle the specific variables concerning packaged food storage.

2.5.2 Fuzzy logic

Since the attributes describing a packaged food product are difficult to be measured by standard measurements, FL can be a suitable technique for building the proposed intelligent system. Unlike classic Boolean reasoning, where the membership of elements must be either 0 or 1, FL codifies imprecise information into crisp values that fall into membership levels expressed between 0 and 1 (Nofal & Fouad, 2015). It is an approach that can transform vague and subjective knowledge into rules that can be further analysed and used in DSS (Fouad et al., 2012). In order to acquire the implicit knowledge from the warehouse operator for solving the SLAP, FL can be applied as a bridge to fill the gaps between human reasoning, that is often imprecise, and computers that require precise definitions (Gill, 2014). Therefore it is necessary to build the knowledge repository regarding packaged food storage by expressing knowledge in terms of fuzzy if-then statements.

FL has been applied to DSS for SLAP solving in ordinary storage facilities. Vishkaei (2011) combined COI, FL and dynamic programming as a methodology applied in warehouse zoning. The first two techniques were implemented to measure the demand rates and efficiency of storing each product in one class only. The measured results were inputs to dynamic programming that sought to minimize the sum of the storage and handling costs. Another output of this fuzzy dynamic approach was the recommendation as to which product should be placed in which class in the warehouse. Gill (2014) introduced an approach of applying FL in warehouse zoning in detail. He turned the attributes of “shipment due date”, “inventory level in primary storage area” and “inventory level in reserve area” into input fuzzy sets while storage areas of “primary storage”, “reserve” and “cross-docking” were the output variables. After defining decision rules that explained the relationships between the input and output variables, demonstrations on how to allocate products with different attributes into various zones were given. Choy et al. (2014) fuzzified specific attributes, such as the length, cost and fragility, of the components of machinery, and then used those attributes as input variables to the fuzzy location assignment system. After defuzzification, allocation plans about which level of which shelf should each SKU be allocated to, are given by the system. Total order picking time and travelling distance were found to be shortened. In addition, Lam et al.(2009) and Chirici and Wang (2013) turned SKUs’ dimensions, turnover rate, expected storage days, etc. into fuzzified input variables and turned warehouse zones with varying accessibility into the output variables of their fuzzy-based DSS. Afterwards, the best locations for different SKUs in terms of accessibility are recommended by the DSS.

These studies prove that FL is able to turn imprecise information such as preference and personal knowledge into usable inputs to the DSS. Since attributes concerning packaged food, such as the vulnerability of food package and storage conditions, are vague, FL can be useful for codifying these attributes. However, the same as found in other literature in the field of SLAP solving, the aim of these study is operational efficiency enhancement. A DSS that takes the attributes concerning packaged food into account and aims at maintaining food quality when handling SLAP is still rarely found (Hui et al., 2016b). This research can therefore contribute by proposing a fuzzy-based DSS for SLAP solving for the packaged food industry.

2.5.3 Association rule mining

ARM is another AI technique that is commonly used by researchers in improving warehouse operations. It seeks to reveal valuable information in a database by identifying relationships between data (Chen & Wu, 2005). Since its operational mechanism has been explained in section 2.4.3, only the applications of ARM in warehousing are illustrated in the following paragraphs.

Chen and Wu (2005) suggested adopting the Apriori algorithm in discovering connections between customer orders in order to understand the demand patterns, and this facilitated the order batching process significantly. The numbers of batches as well as the travelling distance were cut, and better workload balance was also achieved. Other scholars made further use of the connection between orders in solving SLAP. A DM-based Storage Assignment Approach was initiated by Chiang et al. (2011). It examined connections between newly arrived products and storage location availability as well as the relationships between products. Order picking time was proven to be reduced as products with linkages were placed close to each other. The other paper of Chiang et al. (2014) made use of ARM to identify the intensity and nature, i.e. supplementary, substitutive or independent, of the relationships between products. By referring to both the relationships between products and the turnover rate of products, products are assigned to the most suitable aisle. Order picking time and travelling distance are shortened. In addition, Li et al. (2015) applied the ARM to obtain the frequency of pairs of products that were ordered together, then encoded the warehouse configuration into chromosomes for applying GA. Combining the two techniques, the travelling distance for order picking was proven to be improved. Chuang et al. (2012) applied a similar concept in handling SLAP for the retailing sector and the picking distance was decreased by over 40%.

Though ARM is not as capable as FL for codifying the attributes of the SKUs, the studies concerning ARM prove that ARM can cultivate the relationships between customer orders and make use of those relationships in SLAP effectively. Since customer orders in the packaged food industry often involve multiple products, ARM can be a suitable tool to reveal the hidden ordering patterns. Therefore, it can be embedded into the proposed DSS where deemed appropriate, in order to further enhance the quality of the storage location recommendation.

2.6 Summary

The implications of the literature review are summarized in this section. First of all, food safety, storage operations and e-retailing issues that are facing the packaged food industry emphasize the importance of having a SLAP DSS in the packaged food warehouse. The proposed SLAP DSS has to consider the storage requirements of food and enhance operational efficiency in the warehouse at the same time. Moreover, the system should be equipped with a tracking ability to enable the traceability of the warehouse.

After reviewing previous literature, the tools that seem promising in developing an intelligent system are shown in Figure 2.6.

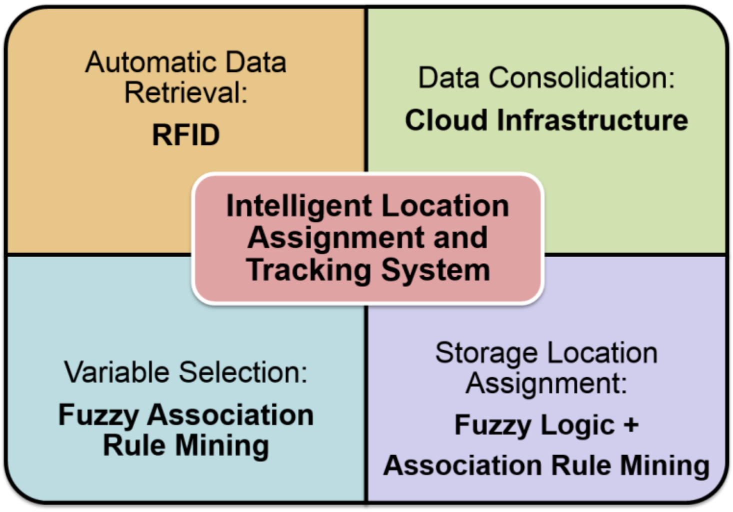


Figure 2.6 Promising tools for the intelligent system development

Among the automatic data retrieval technology, RFID is selected since it is able to identify a large number of products simultaneously, and different levels of product categories. Besides, it contains few constraints in terms of line of sight, item orientation and reading range. These features are particularly important to packaged food warehouse operations, which deal with time sensitive processes and large number of products.

Regarding data consolidation, cloud infrastructure is preferred as it can facilitate data collection and sharing online. The features of cloud computing such as the scalability of computing services, are particularly useful for the packaged food warehouse which needs to deal with unpredictable number of e-orders and partners.

Concerning the techniques applied in the DSS, FARM is suitable to be the DM tool for variable selection. To be specific, the variables contributing to the range of storage time of SKUs can be identified by FARM, where the range of storage time is a crucial input variable to the SLAP DSS. FARM is chosen because it provides more indicative information than the techniques using Boolean logic. It can predict the specific conditions happening by the if-then relationships between the variables and the range of storage time of SKUs.

In respect to the core analytical tools for SLAP analysis, FL and ARM are promising in carrying out SLAP analysis in the proposed DSS. Among the AI techniques that are applied in SLAP, FL is especially suitable as it can analyse the ambiguous storage requirements of food. Besides, it can gather explicit knowledge about how to handle food in terms of keeping food under the correct storage conditions and maintaining the integrating of the food packaging. Meanwhile, ARM is suggested in the literature as a promising technique in dealing with SLAP when there are ordering patterns hidden in customer orders containing two or more items. The two techniques would therefore be combined in the proposed system in order to offer SLAP recommendations that consider both food quality maintenance and operational efficiency enhancement.

Combining the inspirations provided by previous study, the architecture and details of the proposed system are presented in Chapter 3.

Chapter 3 Design of RFID-Cloud-based Location Assignment and Tracking System

The literature review section reveals that warehouse operations of a packaged food warehouse have to take food safety and operational efficiency into consideration when dealing with SLAP. Since SLAP involves decisions that bring great impact to food quality assurance and to the efficiency of product receiving and order-picking, a DSS is thus needed to support decision making in the complicated SLAP. Suitable components that constitute the proposed DSS are acknowledged from the previous literature. Therefore, the design of a SLAP DSS is formulated and explained in this chapter. The generic idea of the proposed system, namely R-CLATS, is introduced. After the introduction, the architecture and details of each module of R-CLATS are presented.

The generic idea of R-CLATS is shown in Figure 3.1. As its name suggests, R-CLATS is incorporated with RFID and cloud computing technology for enhancing the recommendations in storage location assignment and for enabling product traceability in a packaged food warehouse. The expected sources of input of R-CLATS include (i) real-time data retrieved from RFID, (ii) static data stored in the company's internal system such as Enterprise Resources Planning (ERP) and Warehouse Management System (WMS), and (iii) data provided by external partners, such as shippers from various regions that deliver their products to the warehouse for preparing the e-orders.

The data obtained from the three sources are then stored in a cloud-based repository which can store both data and information. Data pre-processing and processing are implemented in the cloud infrastructure in order to produce usable data and information for further analysis.

The usable data and information are then analysed with different DM and AI techniques in order to provide different decision support functionalities. The decision support functions

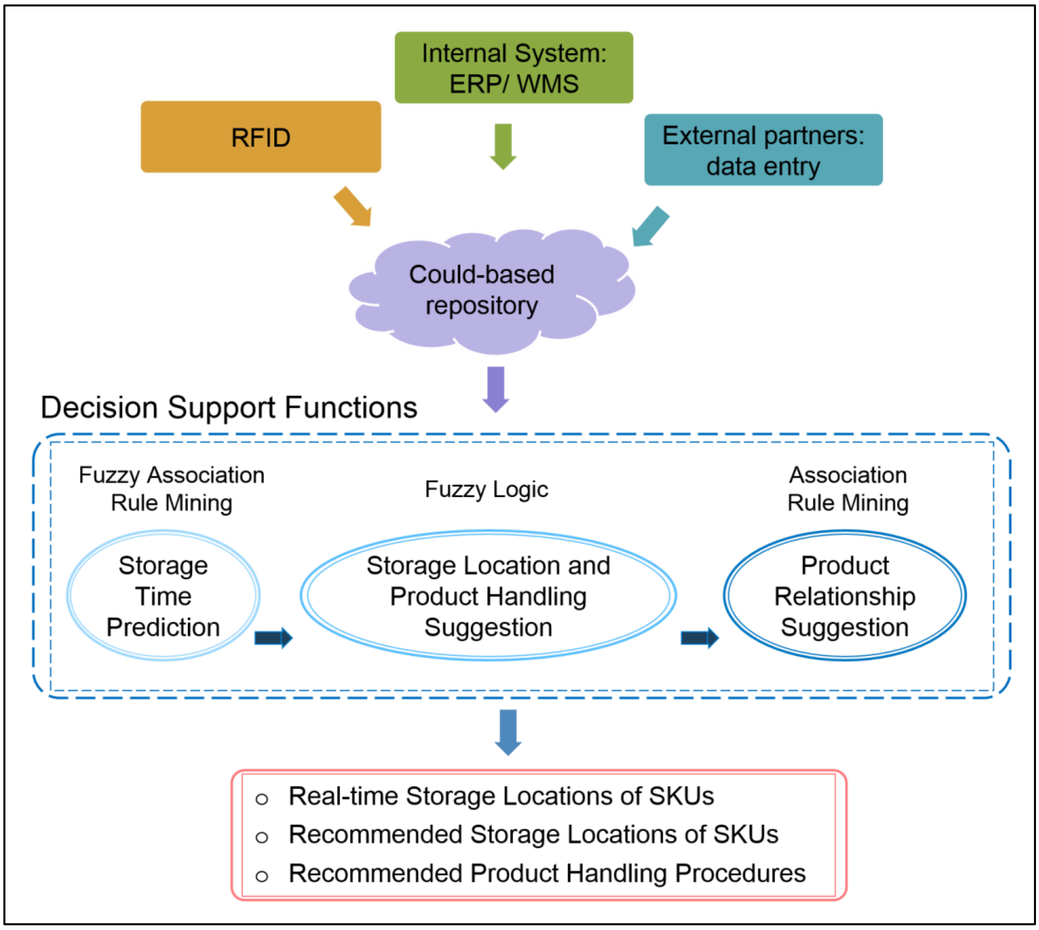


Figure 3.1 Generic idea of R-CLATS

are implemented when there are incoming products. The first decision support function provided by R-CLATS is variable selection of the ranges of SKU storage time. With FARM, besides selecting the most relevant variables of SKU storage time, this function is also able to predict the range of SKU storage time. The range of SKU storage time can be a useful piece of information for the next function, i.e., storage location and product handling suggestion. The storage location and product handling procedures are recommended after applying FL to convert the attributes of SKUs into fuzzy sets. The fuzzy if-then rules can tell the warehouse operator, that if the incoming SKUs contain particular attributes, where those SKUs should then be located and how those SKUs should be handled. With these recommendations, product deterioration and damage can be prevented. The final decision support function offered by R-CLATS is the suggestion of product relationships after applying ARM. This serves as a complementary function to the second function. It tries to unveil the ordering pattern of SKUs in order to find out which SKUs are often ordered together. The revealed pattern can provide implications to the warehouse operator about which SKUs should be placed closer to each other. Therefore, it is a function to further enhance the storage location assignment decision, and in turn to further improve the order-picking efficiency.

After carrying out various decision support analyses, three pieces of useful information are generated as the output of the system. They are real-time storage locations of SKUs, recommended storage locations of SKUs and recommended product handling procedures. With these pieces of information, warehouse operators are expected to be capable of a tracking product that is needed, making quality decisions in SLAP and handling SKUs in the right way. Consequently, SLAP solutions considering both food safety and operational efficiency can be formulated. The details of the architecture and operational details of R-CLATS are illustrated in the following sections.

3.1 Architecture of the system

The system architecture of R-CLATS is shown in Figure 3.2. R-CLATS is composed of four modules: Data Capturing Module (DCM), Information Consolidation Module (ICM), FARM Variable Selection Module (VSM) and Location Assignment Module (LAM). A brief introduction of the four modules is given in the following paragraphs.

DCM is responsible for capturing data from the internal data sources, which include the RFID and internal system. Therefore the setting up of RFID and the related data flows are included in this module.

The major functions of ICM are to take care of data from DCM, and that from the external data sources. It carries out the aforementioned functions of the cloud repository which includes features of DaaS and IaaS. Data collected in DCM are consolidated and then processed into usable information through OLAP.

VSM is responsible to realize the first decision support function of R-CLATS mentioned before. It applies FARM to select relevant variables for the feature “range of SKU storage time”, and at the same time predicts the range of SKU storage time. The output generated in this module would become a crucial input to the next module, the LAM.

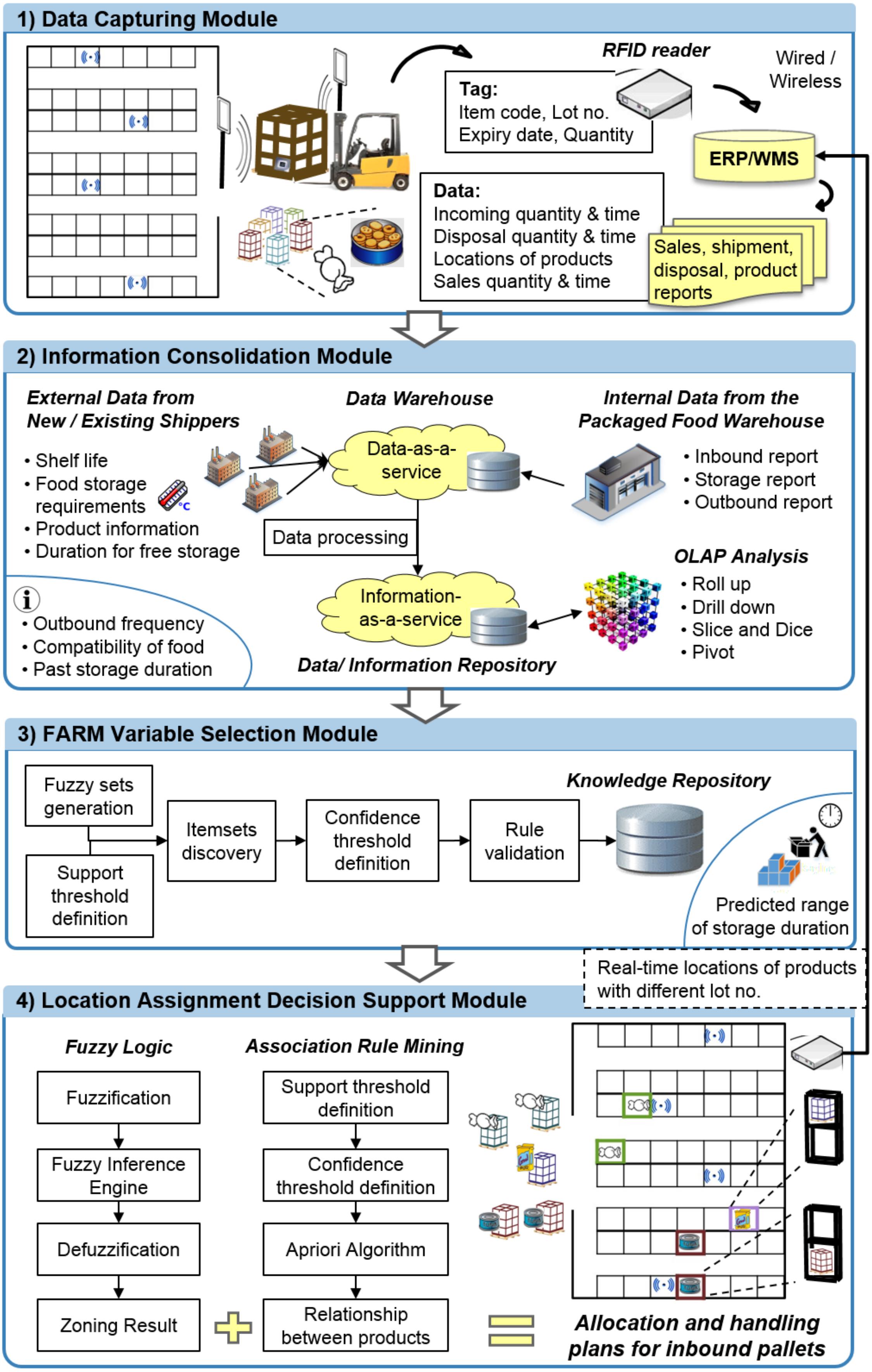


Figure 3.2 System architecture of R-CLATS

LAM is implemented to administer the second and third decision support function of R-CLATS. It goes through the standard steps for fuzzifying the attributes of SKUs and defuzzifying the output variables to recommend storage locations and product handling procedures. LAM also follows the standard steps of the Apriori algorithm to execute ARM for finding product relationships.

By developing and implementing the four modules, the desired pieces of information regarding the real-time storage locations of SKUs, recommended storage locations of SKUs and recommended product handling procedures can be obtained. The development details of each module are explained as follows.

3.2 Module 1: Data capturing module

The DCM involves the usage of RFID tags, RFID antennas, RFID readers with middleware, and internal systems such as WMS and ERP, as shown in Figure 3.3. The main function of this module is to capture real-time data reflecting the warehouse situation for further processing in the next modules.

To apply RFID technology, RFID antennas are placed at the I/O of the storage area and across the warehouse to ensure complete electromagnetic signal coverage of the area. Before pallets of food arrive at the warehouse, RFID tags containing data for each incoming pallet are prepared according to the shipment schedule and packing list. The data should include, but not be limited to, the item code, lot number, expiry date and quantity. After the pallets arrive, they are verified and attached with tags containing the most accurate data about the pallets. When these pallets pass through the I/O of the storage area, the RFID antennas generate electromagnetic signals to the surroundings to activate the passing RFID tags. After receiving responses from the tags, the arrival time and product data are transmitted to the antennas, thus the reader is connected to the antennas. The data received are then processed by the middleware in the reader. The reader is connected to an information system, e.g. a computer connected to ERP or WMS. After decoding, the data are registered into the internal systems via wireless or wired connections at the user’s choice.

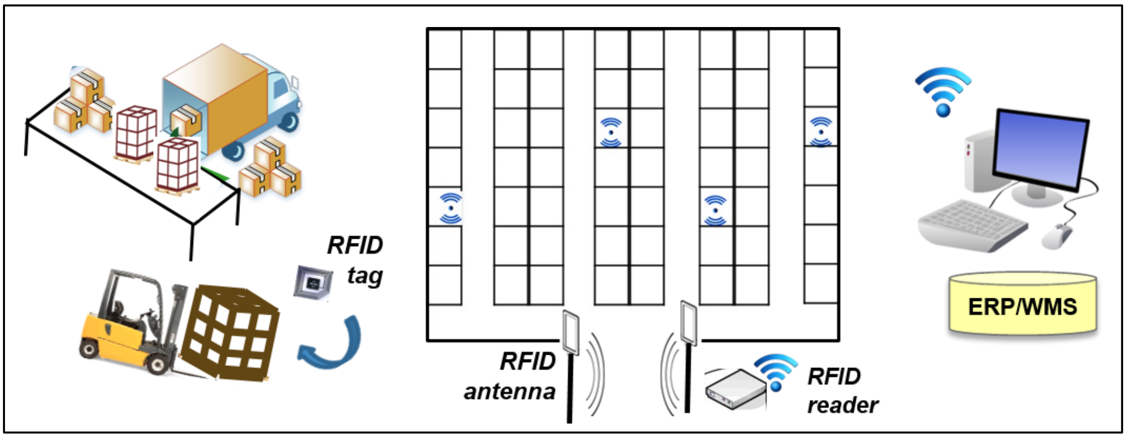


Figure 3.3 Components and operational flows concerning RFID application

Besides product receiving, movement of products inside the warehouse is triggered when other sales and disposal activities occur. All movements detected by the RFID antennas are reflected in the internal systems in real-time. The related data, such as the number of pallets sold and the changes in storage location of pallets, are recorded, and can be generated as various reports for further analysis. The application of RFID in data collection can reduce the data entry time and any errors caused by human input, and in turn facilitate quicker and better decision making in SLAP and other operations. In addition, accurate locations of each pallet, and thus the corresponding lot numbers, become available so as to achieve reliable internal tracking.

However, before introducing RFID technology into the warehouse, an evaluation of the RFID infrastructure requirements of the warehouse should be administered. The steps of evaluation are explained in detail by Hansen et al. (2008). In summary, the evaluation includes, but is not limited to: (i) process analysis concerning the requirements in reading locations and distances, application of fixed or portable devices, application of sensors, etc. , (ii) environment analysis regarding the study of the external influences to the RFID system in the target area, e.g. if there are materials, such as water, that absorb the electromagnetic energy and if the thermal and weather factors exist to affect the operation of the system, (iii) object analysis involving the potential load units and packaging of the product, and (iv) IT infrastructure analysis reviewing the data involved in the system, i.e., how much data would be stored in the tag, whether the data would be rewritten and if the data need to be encrypted. These kinds of evaluations are necessary for setting up the desired RFID system. They can be performed by the selected RFID system service provider.

3.3 Module 2: Information consolidation module

The ultimate purpose of ICM is to form a data and information repository which contains inputs required by the decision support modules. The data sources of ICM include RFID, internal systems of the enterprise and data provided by external partners. As seen in the literature review, cloud computing tends to be beneficial to the development of this type of system, so cloud infrastructure is applied to form the database and information repository in the ICM. However, it is not suggested that decision support analysing components of the system, including the implementation of FARM, FL and ARM, and the formation of knowledge base, be moved to a cloud environment. The reasons for partially applying the cloud infrastructure are explained as follows.

According to Juan-Verdejo and Baars (2013), the major advantages brought by cloud computing are the agility and scalability of computing resources at lower cost and the easy employment of computing resources. These advantages are particularly valuable for computing resources applications in an unpredictable and dynamic environment. However, the security and privacy issues have long been a concern to potential users of cloud infrastructure, because some data could be too sensitive to be placed online, even if they are stored in a private cloud. Therefore, which system components should be moved to the cloud needs to be evaluated based on the requirements of the system components, where system components refer to the database, information repository and the decision support analyses constituting R-CLATS. An evaluation is done in terms of sources of input, update frequency, users of output and data sensitivity against the features of the system components. The evaluation features are summarized in Table 3.1.

Table 3.1 Evaluation of the features of system components involving R-CLATS

System component	Source of input	Update frequency	Users of output	Data sensitivity
Database	RFID, internal systems, external partners	Close to real-time	Across the enterprise	Low
Information repository	Database	Close to real-time	Across the enterprise	Middle
Decision support analyses	Database and Information repository	Upon product arrival	Decision maker of SLAP	Low

Regarding the database of R-CLATS, its input sources are RFID, internal systems such as ERP and WMS of the enterprise, and external partners such as the shippers of products. The diversified input sources imply that the size of the database should be scalable to cope with unpredictable and dynamic amounts of data storage. Besides, since the value of RFID is to acquire nearly real-time data from the floor to facilitate timely decision making by users across the enterprise, updates should be reflected in the database, close to real-time. In addition, compared with data that contain personal or sensitive market information, data handled by a packaged food warehouse, such as product name, quantity and delivery date, are less sensitive, hence, the security level involved in private cloud infrastructure would be adequate. The evaluation implies that the database of R-CLATS should be moved to cloud, because a cloud database can be scaled easily and enables nearly instant updating and sharing of data across the enterprise.

In respect to the information repository, it is formed after meaningless raw data is preprocessed and processed into organized and interpretable information. The differences between features of the database and the information repository of R-CLATS mainly lie in the input source and data sensitivity. There is only one input source for the information repository, i.e. the database of R-CLATS. The data sensitivity of the information stored in the repository is relatively higher than that stored in the database, because information contains more meaningful content than the data. However, as explained in the last paragraph, information involved in the packaged food warehouse is relatively less sensitive than those involved in other industries, thus privacy and security are not top concerns when deciding whether or not to use a cloud-based information repository. In contrast, the nearly real-time update frequency offered by the continuously updating database and the users of information from various departments of the enterprise, make cloud infrastructure attractive in building the repository. Therefore, cloud-based information repository is preferred.

Concerning the components of the decision support analyses, the sources of input are both the database and information repository that are available internally. Besides, the analyses only take place upon product arrival, instead of being initiated continuously. Furthermore, the users of the analysed results are limited to the decision maker of SLAP. Finally, the sensitivity of SLAP decisions is low because the information is only valuable in terms of internal operational enhancement. Though the SLAP decisions are not sensitive, online accessibility to the analytical resources and the sharing of the decision across the enterprise are not necessary. Therefore, an on-premise development of the decision support analysing components is thus recommended to save the extra costs of employing AaaS.

To summarize, cloud-based database and information services known as DaaS and IaaS and the analyses modules developed locally are employed in R-CLATS. The details of each component are explained in following subsections.

3.3.1 Data-as-a-service

When employing DaaS, a cloud SQL database (C-DB) is preferred because when the warehouse has been using Microsoft (MS) software such as MS Excel and MS SQL, then a cloud SQL database is compatible with the documents originally stored in the on-premise server. The data flows involving the employment of a C-DB for R-CLATS development is shown in Figure 3.4.

The data sources related to R-CLATS that are found in the warehouse's computing system are mainly the Excel files, RFID system, internal system and SQL database. Besides, while the shippers look for order fulfilment services provided by the warehouse, they either provide the Excel files containing the shipment information or access to the ordering system of the warehouse to place a shipment order. The shipment information provided by the shippers are thus another source of data to the warehouse.

In order to employ a C-DB, data stored in an on-premise system has to be

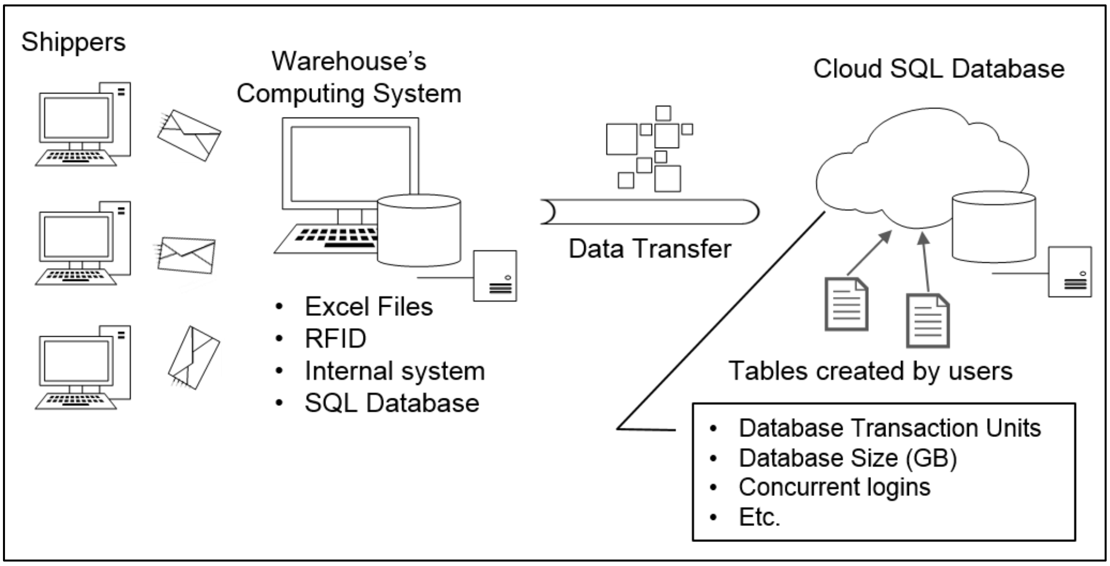


Figure 3.4 Data flows involving cloud SQL database employment

transferred to the C-DB. The most convenient way to do the data transfer is by linking the local SQL database to the C-DB through the interface of the CSP. Meanwhile, extra tables can be created in the C-DB through the server management tool provided by the service provider. If a local SQL is not available, the Excel files in .CSV format can be uploaded to the cloud storage location, and then be linked to the C-DB.

The choice of DaaS package depends on the computing resources that the warehouse needs in the first place. The computing resources in C-DB are often be measured by the CSP as the Database Transaction Units, Database Size in Gega Bytes (GB), and Concurrent logins, and workers are allowed to administer the C-DB, etc. Among these measurements, the Database Transaction Units are fundamental ones as they represent the measurements of the Central Processing Unit (CPU), input and output of data and transaction log and memory. Besides the computing resources, data security issues such as the disaster recovery plan and back up restoration plan should also be considered when choosing the right package. The C-DB user can chose a package according to the existing computing resource usage in the beginning. However, since scalability is available in C-DB, the C-DB package can always be adjusted easily through the CSP's interface.

3.3.2 Information-as-a-service

After storing the data into the C-DB, the IaaS is applied as a data integration platform. IaaS is initiated when the cloud data orchestration tool (C-DOT) is employed. As shown in Figure 3.5, while the C-DB can be linked to the C-DOT directly, the linkage between the local computer system and C-DOT is done through a data management gateway. Besides, data transfer, between C-DOT and the C-DB and local computing system of the warehouse respectively, relies on the data pipeline. The settings of the pipeline determine the specifications of the update activities between the databases and the C-DOT. For example, the update can be scheduled to be hourly or daily and the starting time of the daily update can be set.

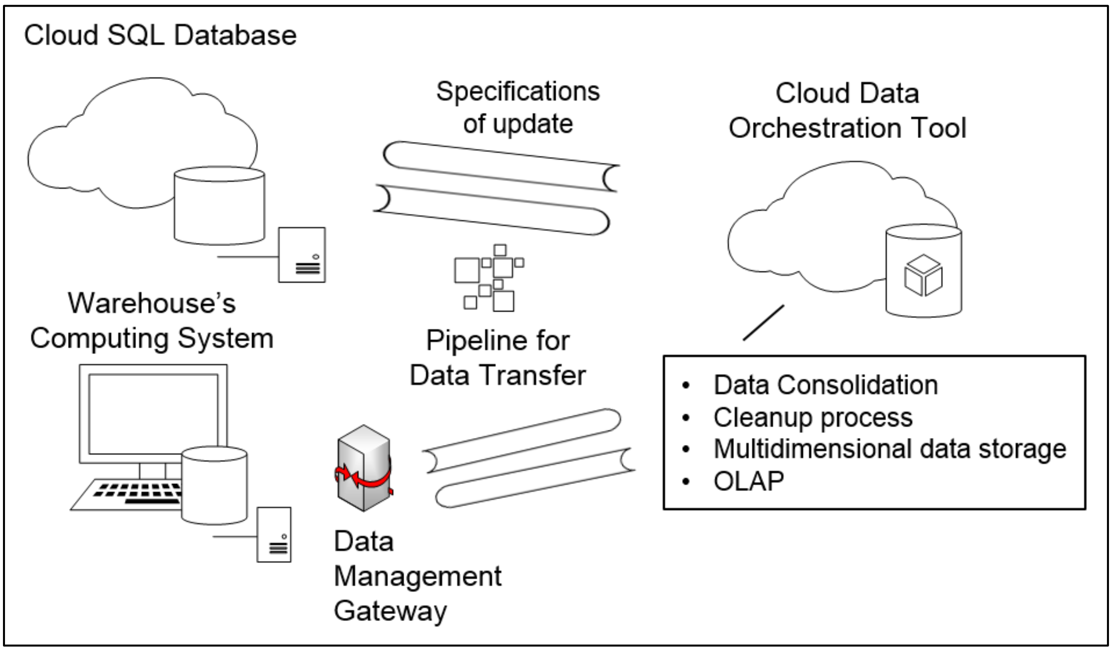


Figure 3.5 Data flows concerning the IaaS

The functions of C-DOT include but are not limited to data consolidation, data clean-up, multidimensional data storage and OLAP. In this research, raw data in C-DB has to be organized into a neat way in applying OLAP, in order to acquire meaningful information out of the raw data. Before making use of the data in the C-DB, data clean-up, also known as data preprocessing, is needed to ensure the quality of the data. There are three data preprocessing techniques that can help in building a neat centralized database, namely, data cleaning, data integration and data reduction (Romero & Ventura, 2007). Data cleaning means correcting inconsistent data, filling in missing data and removing noisy data. Data integration involves combining data that could be in different formats from various sources, into a more standardized form. Data reduction is the size reduction of data by aggregating data according to needs or by clustering similar values into groups. Preprocessed data from various data marts are then cross-referenced and integrated in the centralized database to form meaningful information. In this study, information such as sales rate, disposal rate, package material and storage requirements of different kinds of packaged food is needed because such information can be further processed in applying FARM, FL and ARM in the later modules.

Apart from having a neat database, enhancement in the analytical ability of R-CLATS and valuable information cultivation for the usage of various parties in the enterprise are pursued, therefore OLAP technology offered by C-DOT is employed. Generally, OLAP is applied in analysing sales data in three dimensions, commonly known as time, region and product. In this research, the dimensions can be time, region, type of product, sales volume and type of food packaged, chosen by the users of the information. Meanwhile, the "measures" obtained are used as the fuzzy input variables of R-CLATS. When the OLAP cube is completed, users can make use of its functions such as roll up, drill down, slice, dice and pivot, to easily acknowledge the characteristics of products that concern food safety. Since the information extracted through OLAP can provide an overview of the products' characteristics to users, the functions of ICM can be fulfilled and thus the analytical modules can then emerge.

3.4 Module 3: FARM variable selection module

When the data and information is consolidated in the ICM, they are ready to be extracted from the cloud repository and used in the analytical modules. The first analytical module, VSM, contains two major functions: (i) to select the most relevant input variables for the output variable, SKU storage time, and (ii) to predict the range of SKU storage times for different SKUs. In order to carry out the functions, three main submodules are involved. They are data preparation, fuzzy association rule mining, and knowledge evaluation and retention (Hui et al., 2016a). The components concerning the three submodules are shown in Figure 3.6 and explained in the following subsections.

3.4.1 Data preparation

To initiate the FARM process, data of all input and output parameters involving rule mining have to be prepared. Although most of the data and information are available in the cloud repository, some extra information could be needed after

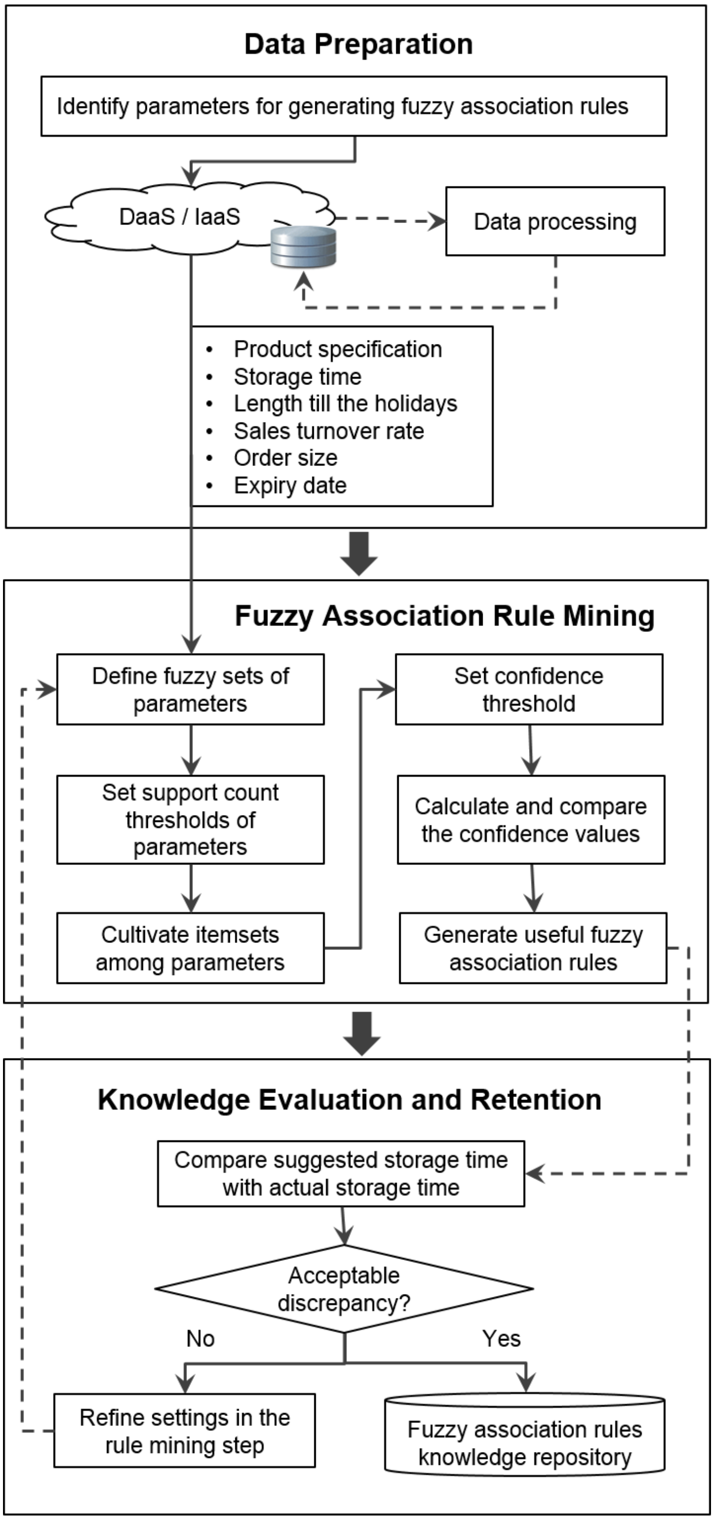


Figure 3.6 Components of the three submodules of VSM

determining the parameters involved. Therefore, in order to obtain all the relevant data, the parameters for generating fuzzy association rules are first identified. In terms of the input parameters selection, it can be done flexibly at the beginning of the rule mining process, because the purpose of VSM is to cultivate hidden patterns from different combinations of the potential factors. However, concerning the output parameter selection, it is fixed to reflect the SKU storage time, since SKU storage time is the resultant part of the rules.

After the parameters are determined, the cloud repository should be searched to see if it contains all the data needed. If some data are missing, data processing is conducted locally to obtain the needed data. To start the first round of rule mining, the following data are suggested to be extracted: product specification, length till the holidays, sales turnover rate, order size and expiry date.

3.4.2 Fuzzy association rule mining

This sub model is the core part of the VSM for generating the wanted fuzzy association rules. The first step of rules generation is to define the fuzzy sets of the parameters. The historical data saved in the cloud data warehouse are studied for obtaining the ranges of quantitative values of each parameter. After studying the past data, the membership functions and universe of discourse can be set accordingly. Then, the minimum support count thresholds of the parameters are defined for filtering out the itemsets that contain a small number of fuzzy counts, where the itemsets are cultivated among the parameters by using a mining algorithm. The detailed steps for implementing the mining algorithm are demonstrated in the case study section of this research to avoid duplication. While executing the mining algorithm, the minimum confidence thresholds are then set and compared with the confidence values of the qualified itemsets, in order to generate usable fuzzy association rules. At the end of this rule mining sub model, a number of fuzzy association rules describing the relationship between the input parameters and the SKU storage time are available. When determining the minimum support count thresholds and minimum confidence thresholds, a trial-and-error approach is suggested to be used (Lee et al., 2015).

3.4.3 Knowledge evaluation and retention

The effectiveness of the fuzzy association rules that are generated from the FARM submodule are evaluated in this submodule. Since the objective of the rule mining process is to find out the determinant factors of storage time and how these factors affect the storage time, the performance indicator of the rules is thus recommended to be the actual storage time of the SKUs. By comparing the range which the suggested storage time falls into with that of which the actual storage time falls into, a discrepancy value is obtained. The user of the system has to decide on an acceptable discrepancy level for comparison. If the discrepancy is too large, refinements would be made in the definition of the fuzzy sets or the mining algorithm for generating another set of rules. If the discrepancy is acceptable, the fuzzy association rule that accounts for the result would be stored in the fuzzy association rules knowledge repository, and in turn be used in the next analytical module for decision making in location assignment.

3.5 Module 4: Location assignment module

Since the range of SKU storage time is obtained in last module, the decision support function of the storage location assignment can be actualized in this module. LAM consists of two main submodules, fuzzy zoning and association rule mining. The major components of the submodules are shown in Figure 3.7.

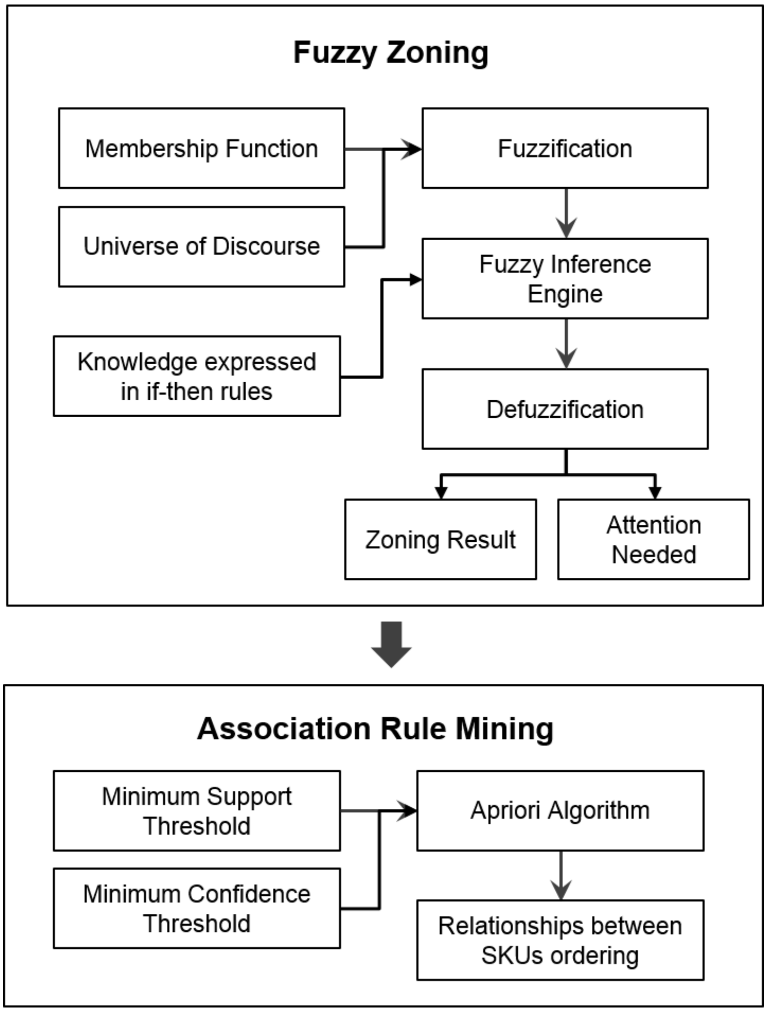


Figure 3.7 Components of the two submodules of LAM

The function of the fuzzy zoning submodule is to suggest the warehouse zone to be assigned to the SKUs and the attention needed when handling different SKUs. This submodule has three main steps: fuzzification, fuzzy inference engine analysis and defuzzification. Fuzzification is carried out after determining the membership function and universe of discourse of the input variables, while the fuzzy inference engine analysis is done by using knowledge of the packaged food handling. Such knowledge is expressed in if-then rules and retained in the inference engine.

While the fuzzy zoning submodule may suggest the same warehouse zone for a wide range of SKUs, the SKUs which are assigned to the same zone could have inter-relationships
that further determine the closeness of their locations (Hui et al., 2015). Therefore, the ARM submodule emerges to find out the inter-relationships among the SKUs through cultivating association rules from the ordering records. The rule mining process is initiated by setting the minimum support and confidence threshold, and completed through the Apriori algorithm. The revealed relationships between SKU orders are then used to improve the recommendations provided by R-CLATS. The rationale involved in these two submodules is explained in following subsections.

3.5.1 Fuzzy zoning

The major functions of this submodule are in offering suggestions on the most suitable locations and the attention needed for various packaged food, and retaining knowledge about how to assign packaged food according to the food's attributes. The suggestions are generated by FL. The three main steps for implementing FL are explained in detail in the following.

i. Fuzzification

To begin with, the variables have to be fuzzified. Fuzzification is needed when the data obtained are not yet in the right format to be inputted into the fuzzy system. The function of fuzzification is to convert input data set into fuzzy sets that can be analysed by the fuzzy inference engine. Fuzzification involves two determinant factors: membership function and universe of discourse. Membership function shows the characteristics of the fuzzy sets. The mathematical expression of membership function is:

$$D = \sum_{i-1}^{n} \frac{\mu_D(d_i)}{d_i}$$

where

D is the whole data set: D= $\{D_{1,} D_{2,} \dots D_n\}$;

d is an element of subset D ;

$\mu_D(d_i)$ denotes the membership function of element d_i.

As suggested by the domain experts who solve SLAP in the warehouse, the input variables concerning the storage location of packaged food are *Resistance to Temperature Variance, Effectiveness of Package, Damaged Rate, Receiving Quantity and Storage Time* which are obtained from VSM. However, if *Storage Time* is not available for a certain SKU because the parameters of that SKU do not comply with the fuzzy association rules generated in VSM, *Sales Turnover Rate* is used to replace *Storage Time* under this circumstance.

While *Resistance to Temperature Variance* reflects the storage requirements of food in terms of storage temperature and/or humidity, and *Effectiveness of Package and Damaged Rate* interpret the food package's susceptibility to the environment, they are determined respectively by the materials and shapes of the package, and the proportion of damaged products to the incoming products. Apart from food quality, operational efficiency of the warehouse should be considered. Organizing the warehouse according to *Receiving Quantity* of products yields a neat warehouse, while that according to *Storage Time* or *Sales Turnover Rate* of SKUs yields a shorter total travelling distance. The mathematical expression of membership functions of these six variables are shown in Table 3.2.

The universe of discourse is divided in zones that represent various membership values of a membership function. Take *Resistance to Temperature Variance* as an example, its universe of discourse is: *Resistance to Temperature Variance (RTV)* = {L, SL, SH, H},

Table 3.2 Mathematical expression of membership functions of the five input variables

Input Variable	Mathematical Expression	Denotation
Resistance to Temperature Variance (RTV)	$RTV = \sum_{i-1}^{n} \frac{\mu_{RTV}(rtv_i)}{rtv_i}$ $rtv = \{rtv_1, rtv_2, \dots rtv_n\}$	RTV = Whole data set rtv = Element of subset RTV
Effectiveness of package (EP)	$EP = \sum_{i-1}^{n} \frac{\mu_{EP}(ep_i)}{ep_i}$ $ep = \{ep_1, ep_2, \dots ep_n\}$	EP = Whole data set ep = Element of subset EP
Damaged Rate (DR)	$DR = \sum_{i-1}^{n} \frac{\mu_{DR}(dr_i)}{dr_i}$ $dr = \{dr_1, dr_2, \dots dr_n\}$	DR = Whole data set dr = Element of subset DR
Receiving Quantity (RQ)	$RQ = \sum_{i-1}^{n} \frac{\mu_{RQ}(rq_i)}{rq_i}$ $rq = \{rq_1, rq_2, \dots rq_n\}$	RQ = Whole data set rq = Element of subset RQ
Storage Time (ST)	$ST = \sum_{i-1}^{n} \frac{\mu_{ST}(st_i)}{st_i}$ $st = \{st_1, st_2, \dots st_n\}$	ST = Whole data set st = Element of subset ST
Sales Turnover Rate (STR)	$STR = \sum_{i-1}^{n} \frac{\mu_{STR}(str_i)}{str_i}$ $str = \{str_1, str_2, \dots str_n\}$	STR = Whole data set str = Element of subset STR

where L, SL, SH and H describe the level of resistance to temperature variance of a SKU in Low, Slightly Low, Slightly High and High respectively.

The universe of discourse can be defined after reviewing the historical data and interviewing the domain expert. The crisp values obtained from the C-DB can then be converted into linguistic terms according to the universe of discourse and membership functions. Fuzzification is then completed when the fuzzy sets are ready.

ii. Fuzzy inference engine analysis

After fuzzification, the input data is analysed by the fuzzy inference engine to provide solutions, i.e. recommendations in SLAP and the attention needed in SKU handling. The input and output variables of the fuzzy inference engine is summarized in Figure 3.8. While the output variables concerning storage location recommendation could be changed according to the environment of the warehouse, they are in general expressed as warehouse zones and vertical locations. Warehouse zones are the virtual division of a warehouse area according to the temperature stability of different regions of the warehouse, accessibility to the I/O Points of the warehouse, etc. Vertical location is the vertical division of a warehouse area, e.g. the various levels of the pallet racks and the levels of the stacked pallets.

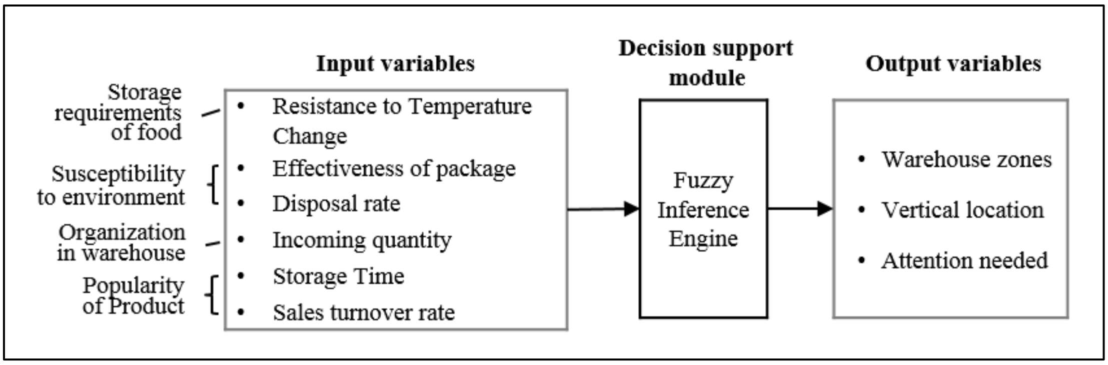


Figure 3.8 Input and output variables of the fuzzy inference engine

After defining the input and output variables, relationships between the input and output variables have to be determined. To do so, interviews with domain experts are carried out by a knowledge engineer, who is responsible for developing the system. The engineer then converts the knowledge captured into if-then rules and keeps those rules in the fuzzy inference engine. Apart from the knowledge contributed by the domain expert, variables and if-then rules can be added by the engineer where appropriate. The possible format of the if-then rules in this inference engine is:

IF *Resistance to Temperature Variance* is ______, *Effectiveness of Package* is _____, *Damaged Rate* is _____, *Receiving Quantity* is _____, and *Storage Time* is ____,

THEN *Warehouse zone* is _____, *Vertical location* is _____, and *Attention needed* is ____.

After specifying the if-then relationships in the inference engine, the engine can then process the input values into linguistic output variables, and go through defuzzification, i.e. a process converting linguistic output variables into numerical output values that are applicable to problem solving.

iii. Defuzzification

The defuzzification method adopted by the engine is called the center of area (COA). The equation of COA is:

$$Y = \frac{\sum_{j=1}^{n} y_j A_j}{\sum_{i=1}^{n} Ai}$$

where

Y is the center of area, indicating the defuzzified value of the linguistic output variable ;

y_j is the center of gravity, indicating the probability of occurrence of membership value j ;

A_j is the area involving the individual membership value j.

After defuzzification, the defuzzified numerical value suggests a precise storage location in terms of horizontal and vertical distribution in the warehouse. The degree of attention needed for each kind of product is recommended to the warehouse personnel as well.

3.5.2 Association rule mining

After determining the zone where a particular product should be allocated to in the fuzzy zoning submodule, the ARM is used in the ARM submodules to determine specific storage locations for SKUs within the zone. The ARM is applied to discover hidden patterns between products and customer orders. To unveil valid association rules from the sales data, domain experts have to first define:

Minimum support threshold (MST) = P (B∪ A) ,

Minimum confidence threshold (MCT) = P (B|A) , and

Lift = P (B|A)/P (B).

where A and B are different types of products and Lift indicates the “property of the relationship between products" (Chiang et al., 2014). For the detail implications of the above notations, one may refer to Section 2.4.3 in this thesis.

i. Application of ARM in this research

When determining the MST and MCT, a trial-and-error approach should be adopted. By using this approach, it prevents having too few rules if the thresholds are strictly defined. At the same time, it also avoids generating rules that are not reliable, which happens if the thresholds are loosely defined. Regarding Lift, when lift > 1, the suitability of allocating two products in the same place is higher and vice versa (Chiang et al., 2014). So lift should be set as greater than one. After setting the three thresholds, the Apriori algorithm is used to generate the association rules.

The brief idea of the usage of the Apriori algorithm in this submodule is to find which SKUs are commonly shipped out of the warehouse at the same time. This revealed pattern is done by analysing the outbound shipments records of the warehouse, in the same way as one analysing the sale transactions in a convenience store. For instance, when a sufficient number of shipment records show that brand A's cereal is often shipped with brand B's biscuits, then brand A's cereal should be located closer to brand B's biscuits. Therefore, as long as the rules generated from the algorithm meet the three thresholds, they can be used to propose the specific storage location for SKUs.

ii. Example of Apriori algorithm application

Suppose peanut butter, mixed nuts, dried mango and hazelnut spread are four items that are suggested to be allocated into the same zone by the fuzzy zoning submodule. The knowledge engineer then filters the monthly sales order to select only the transactions that simultaneously contain at least two out of the four items. The minimum support and confidence thresholds are set to be 20% and 80 % respectively. This means that the number of transactions that include both product A and B has to be at least 20% of the total sample size, and the number of transactions that involve product A also containing B has to meet 80% of the total sample size. After setting the two thresholds, the Apriori algorithm is used to analyse the selected sales order.

For easy reference, peanut butter, mixed nuts, dried mango and hazelnut spread are referred as P, M, D, H respectively in the rest of this section. Apriori steps are executed to filter out combinations that have support counts less than the minimum support counts threshold, i.e. 15 x 20% = 3 counts. The filtering steps are shown in Table 3.3.

Table 3.3 Sales order containing two or more selected items

Step 1

Sales order	The chosen items in the transactions
1	M,D,H
2	M,D,P
3	M,P,H
4	M,D
5	M,D
6	M,D
7	M,D
8	M,D
9	M,D
10	M,P
11	M,P
12	M,H
13	M,H
14	M,H
15	P,H

Step 2

Items	Support Count
M	**14**
D	**8**
H	**6**
P	**5**

Step 3

Itemset	Support Count
DH	1
PD	1
PH	2
MD	**8**
MH	**5**
MP	**4**

Step 4

Itemset	Support Count
MDH	1
MDP	1
MPH	1

Refer to ***Step 1*** in Table 3.3, 15 orders that contain at least two out of the four items are listed. In ***Step 2***, the support count of each item is counted. Since all of their support counts are greater than the threshold of 3 counts, they can be kept in formulating the itemset in the next step. In ***Step 3***, three out of six itemsets (the bolded itemset) have their support counts greater than 3, therefore those three itemsets are used to form the 3-itemsets listed in ***Step 4***. As the support count of all 3-itemsets cannot pass the threshold, the Apriori algorithm is stopped.

The qualified itemsets and their corresponding confidence and improvement calculation are shown in Table 3.4. Since the confidence threshold is set to be 80%, only the rule concerning item set “MH” (confidence = 83.25%, lift = 2.08) is validated. Mixed nuts and hazelnut spread are thus suggested to be stored together.

The performance of this module, LAM, can be enhanced by regular evaluation and refinement of the if-then rules in the fuzzy inference engine. Key Performance Indicators (KPIs) can be set up by the management according to the company’s needs. Generally, to fit the objectives of this system, the KPIs can include the

Table 3.4 Rules of successfully generated item sets

Condition *IF*	**(1) Support (Condition)**	**Result *THEN***	**(2) Support (Result)**	**(3) Support (Condition & Result)**	**(4) Confidence (3)/(1)**	**Lift (4)/(2)**
M	14/15 = 93.3%	D	8/15 = 53.3%	8/15 = 53.3%	57.13%	1.07
M	14/15 = 93.3%	P	5/15 = 33.3%	4/15 = 26.7%	28.62%	0.86
M	**14/15 = 93.3%**	**H**	**6/15 = 40%**	**5/15 = 33.3%**	**83.25%**	**2.08**

average time in storage location assignment, the disposal rate of products due to food packaging damage, the total order picking time and the accuracy of product locations. When the actual performance fails to meet the targets, rules examination and adjustment can be implemented through the user interface.

3.6 Summary

To summarize, the architecture of R-CLATS is composed of four module. The first two modules deal with efficient information retrieval and reliable information consolidation, while the last two modules make use of the consolidated information for executing the decision support analyses. DCM seeks to integrate RFID with the internal system of the warehouse to capture real-time and accurate data. The captured data is then processed by OLAP to offer meaningful information in the ICM. The ICM is executed in a cloud environment that enables scalability of the C-DB and C-DOT, where the scalability prepares the system in handling the unpredictable amount of e-orders. When the information is ready, it is used by FARM in the VSM for selecting determinant variables of SKU storage time prediction, and in subsequently predicting the range of SKU storage times. The predicted storage time and some other variables are analysed in the LAM with FL, in order to obtain the warehouse zones, the vertical location assigned to the SKUs, and the attention needed for SKU handling. Finally, the closeness between SKUs is revealed with ARM in the ARM submodule of the LAM, in order to further improve the recommendations offered by R-CLATS.

The feasibility of R-CLATS has to be verified. Therefore, a case study is implemented in the warehouse of a packaged food wholesaler in Hong Kong (HK). The details of the implementation are presented in next chapter.

Chapter 4 Implementation of R-CLATS - A Case Study in PMC

R-CLATS is proposed in this research to enable product traceability, variable selection and prediction of storage time, and decision support in SLAP in a packaged food warehouse. While the architecture of R-CLATS is illustrated in Chapter 3, the feasibility of the system has to be verified. Therefore, a case study is initiated in a packaged food warehouse to implement and evaluate the system, and is described in this chapter.

The company participating in the case study is called Princess Margaret China Limited (PMC). It is a small wholesaler of packaged food located in HK that was established in 2013. Its major business is importing packaged food such as chocolate, nuts and dried fruit from Western Europe and the United States, and then selling the food to major cities in China. It owns warehouses in Hong Kong and Shenzhen but the food, which usually arrives in pallets packed in containers larger than 20 foot, is always unloaded in the Hong Kong warehouse first. Since its major customers are other packaged food wholesalers and retailers, including some chain stores on both sides of the border, the products are mainly sold in pallets.

This chapter is comprised of three sections. Firstly, the current situation in PMC is studied to identify the problem areas in its warehouse. Secondly, the system implementation roadmap is illustrated. Finally, the details of R-CLATS implementation in PMC are presented.

4.1 Study of current situation

A background study of the operations and data flows of PMC is carried out. The flows and the problems found in these flow are presented in the following subsections.

4.1.1 Current workflow

The business model of PMC is shown in Figure 4.1. While the physical flows show the physical movements of the products, document flows state the documents incorporating the physical flows.

To begin with, the purchasing department places purchase orders (PO) to suppliers of different products according to the actual or anticipated demand, where the ordering unit is in pallet. Since these suppliers are mostly located in foreign countries, container, mostly in a 40’ container, before being shipped to Hong Kong. Most of such as the US and Europe, pallets of food are consolidated into a

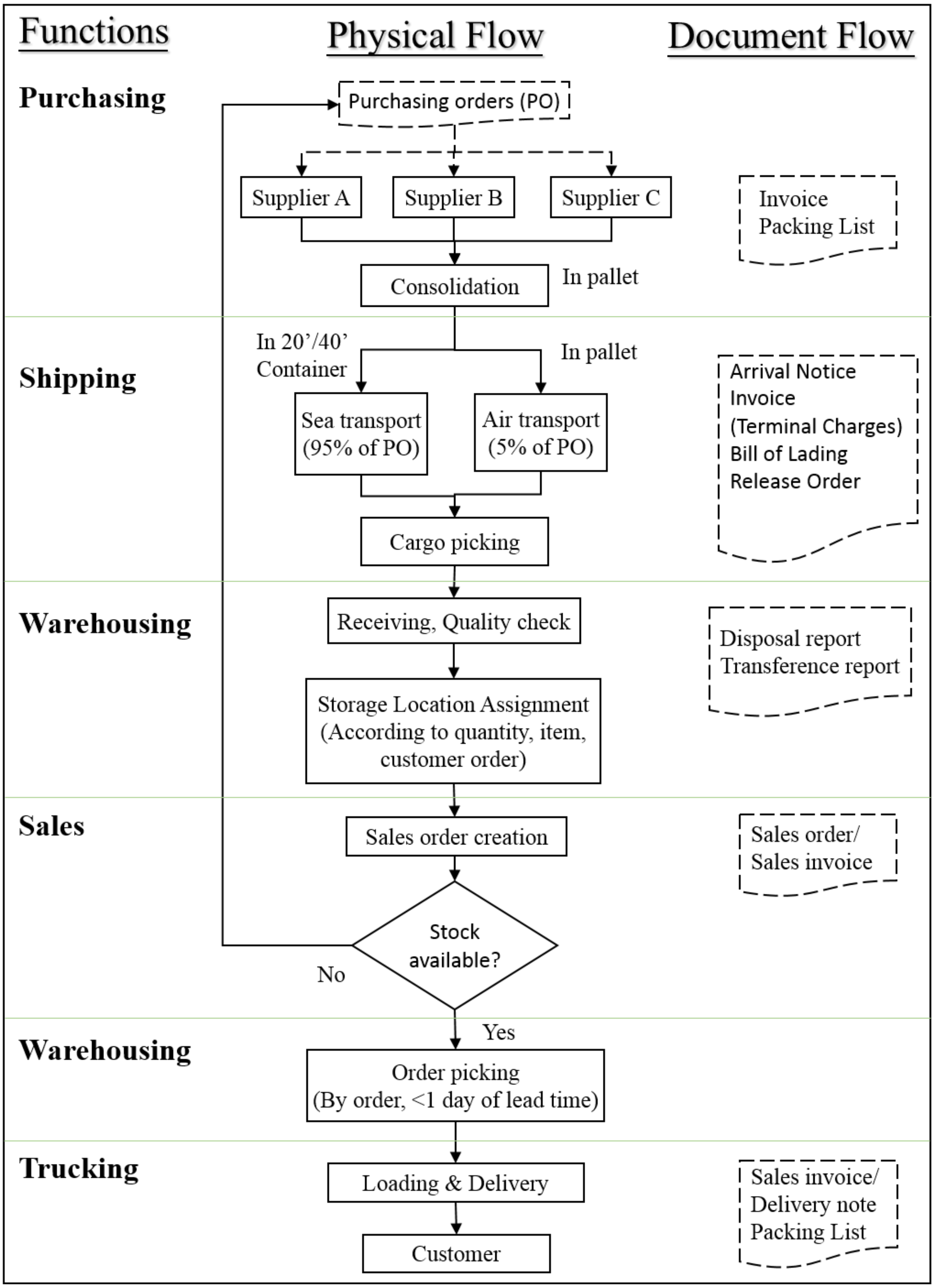


Figure 4.1 Product and document flows concerning the operations of PMC

the PO (around 95% of the total number of PO) are shipped by sea while the remaining 5% of the PO are transported by air, which it only happens when the products are urgently needed. When the containers arrive at the ports in Hong Kong, external freight forwarders handle the shipping documents and trucking of containers for PMC.

The warehouse operations of receiving and quality checking are undertaken when the containers arrive the warehouse of PMC in San Tin. During these operations, when damaged products are found, they are disposed of or transferred to the display room according the extent of damage. Disposal and transference reports are thus generated. The flawless items are assigned to different locations in the warehouse after the warehouse operator has finished the storage location assignment analysis according to the incoming quantity, product types and upcoming customer orders.

When there is a sales order, stock keepers will check if there is enough inventory to fulfil the order. If not, the sales department will ask the customer to place a sales order for PMC to proceed with the purchasing operations, or else the customer will be asked to wait for the product. If there is enough stock, a sales invoice will be issued and the order picking process will be initiated. If the operations run smoothly, the lead time in completing the order picking is usually less than one day, counting from the date of confirming an order. Finally, picked orders are delivered to customers by truck, either owned by PMC or rented by customers. Sales invoices or delivery notes are passed to customers with the deliveries.

4.1.2 Problem areas

For the receiving operations, when damaged products are found, they are disposed of or tansferred to the display room according the extent of damage. For the flawless items, allocation guidelines are unavailable but warehouse operators decide the storage location of each type of product mainly based on: 1. the existing location of that product if there is any, and 2. the incoming quantity. The rest of the unassigned pallets are allocated randomly in the warehouse. However, some products need special care in terms of storage temperature monitoring and physical handling. When the operators are not knowledgable about the storage details of the products and do not pay attention to the cause-effect realtionship between careless handling of specific products and damaging those product, the food quality and product disposal rate worsen.

Besides, a lack of allocation guideline renders slow decision making in SLAP, causing the food to be exposed in an open area, as shown in Figure 4.2, raising the risk of food deterioration. Furthermore, because the layout of the warehouse does not contain a passage path in between pallets, when pallets located internally are ordered, all pallets situated in front of the targeted pallet have to be moved out. An increase in movement of the pallets raises the chance of having the product damaged, as in the two examples shown in Figure 4.3, which are products damaged by a forklift.

Furthermore, in order to expand its business, PMC has started to consider setting up an e-retailing platform. However, its current workflows are not capable enough in dealing with more diversified SKUs and more time-sensitive order-picking.

The problem areas and the constraints of the warehouse layout emphasize the need for a SLAP DSS, which can analyze product and packaging characteristics, as well as predicting the storage time of products, in order to recommend suitable storage locations for SKUs. R-CLATS is thus proposed for PMC to assist in warehouse zoning and SKUs storage location assignments, which in turn improves customer satisfaction.

Figure 4.2 Unloaded products awaiting to be stored

Figure 4.3 Products damaged by forklift

4.2 Implementation roadmap

There are four phases in the implementation of R-CLATS, as shown in Figure 4.4: (i) Installation of RFID devices, (ii) Construction of cloud database and OLAP, (iii) Development of Variable Selection Module, and (iv) Development of Location Assignment Module.

In Phase 1, RFID hardware and software are configured in the warehouse and computers respectively, in order to ensure that the movements of products can be communicated to the users in a timely manner. While setting up the RFID hardware, the target area for RFID application is evaluated in order to select suitable RFID reader, tags and RFID tag printer. The configuration of the RFID software is set with the objective of communicating product locations to the users in an understandable way.

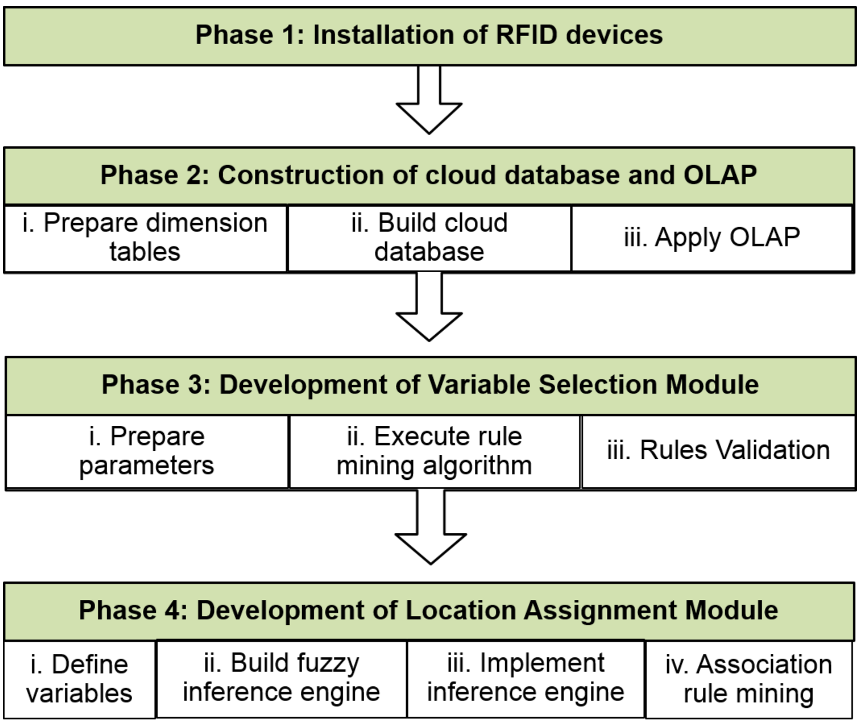


Figure 4.4 Phases of R-CLATS implementation

In Phase 2, data are collected and integrated from various local reports. The integrated data are then transferred and organized in a cloud centralized database. OLAP offered by the same CSP is then applied to the C-DB, in order to obtain the OLAP cube which provides instant analytical information to the users.

Phase 3 emerges when the first two phases are ready. In Phase 3, parameters of the FARM VSM are first defined in order to retrieve the right data from the C-DB. Afterwards, the rule mining algorithm of FARM is executed to obtain potential rules that explain the relevant input variables of storage time. Finally, the potential rules are validated to filter out the inaccurate ones.

Finally, the core components of running the fuzzy LAM are implemented in Phase 4 to generate the storage location recommendations. The components include defining the variables that will be processed in the system fuzzy inference engine, building the engine, implementing the engine and mining the association rules. User interfaces are created to provide user-friendly ways for users to do the analyses with R-CLATS.

While the above paragraphs give a brief idea of the implementation road map of R-CLATS, details of implementing each phase in PMC are presented in the following section.

4.3 System implementation

PMC initiates a pilot run of R-CLATS following the implementation roadmap. While the detailed steps of developing R-CLATS are explained in this section, evaluation of the implementation results is carried out in Chapter 5.

4.3.1 Installation of RFID devices

RFID hardware configuration is done based on the layout of the warehouse, with the objective of having full radio frequency coverage to the target area. Due to consideration of the investment costs in RFID readers and Antennas, only one warehousing area is equipped with RFID devices in this pilot run. For the northern main warehouse area of PMC, the connected sides of three adjoining containers are knocked through, making three containers into one warehousing area. The coverage area for the three containers is thus 12.04 m (L) x 7.05 m (W) x 2.39 m (H). Since the investment in an active RFID system is much higher than that of a passive system, PMC has adopted passive RFID readers and tags. Traditionally, a wired RFID reader instead of a wireless blue tooth reader is selected because the radio frequency of wireless readers that can be commonly found is from 125 kHz to 13.56 MHz. To cover the area of PMC’s warehouse, UHF long-range readers and tags are needed. An UHF long-range RFID integrated reader, UHF label tag and RFID label printer that complies with EPC Class 1 Generation 2 (ISO18000-6B/6C) are chosen. The locations of the RFID antennas are shown in Figure 4.5. Two antennas are placed in two corners of the ceiling, facing down, while the RFID tag is attached to the upper section of a pallet to guarantee an adequate response rate.

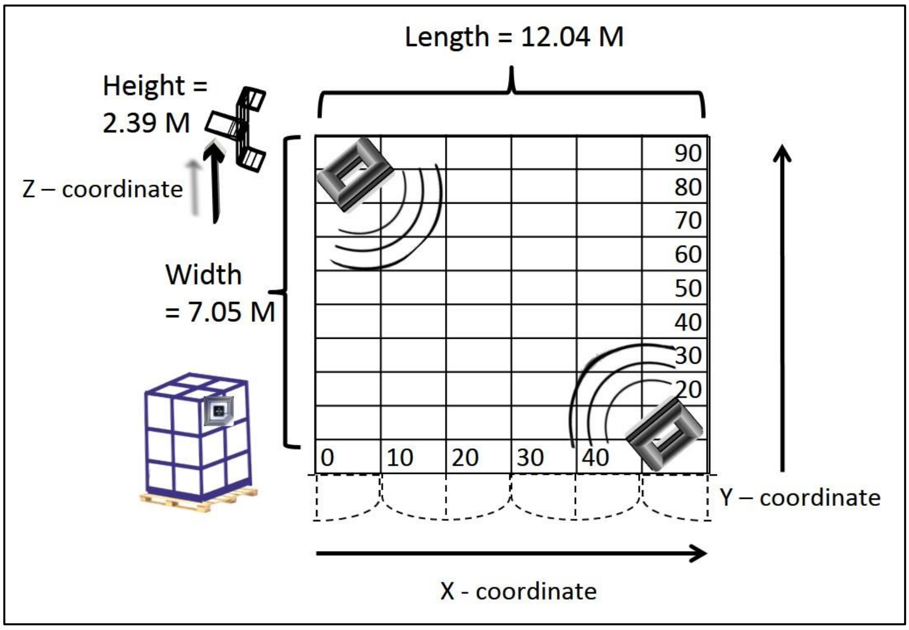


Figure 4.5 RFID devices set up in a warehousing area

To identify the locations of the pallets, the X-, Y- and Z- coordinates are set in the reader. Since the storage spaces are separated by the size of a standard pallet, the warehousing area is like a grid. The X-, Y- and Z- coordinates are counted from left to right, down to up and floor to ceiling respectively. As the locations of the pallets are rigid and follow the grid pattern of the warehouse, accurate coordinates of the pallets can be detected by antennas, and thus read by the reader. The dynamic data regarding the locations of the products, and inbound and outbound activities, are collected and decoded by the RFID reader. The data refreshes the inventory, sales and shipment records in the linked ERP. For the locations of the pallets, they are recorded in the slot management module of the ERP.

4.3.2 Construction of cloud database and OLAP

In this phase, a C-DB is built for organizing and filtering data that is useful for the analytical modules. Furthermore, the OLAP technology provide by the CSP is applied to the C-DB to enable easy extraction of relevant information.

i. Prepare dimension tables

Before building the C-DB, various dimension tables have to be retrieved or produced, and then be preprocessed. The major source of those tables is the ERP in use. Referring to Figure 4.6, *Sales*, *Disposal*, *Shipping* and *Product Information* reports can be retrieved in excel format from the ERP.

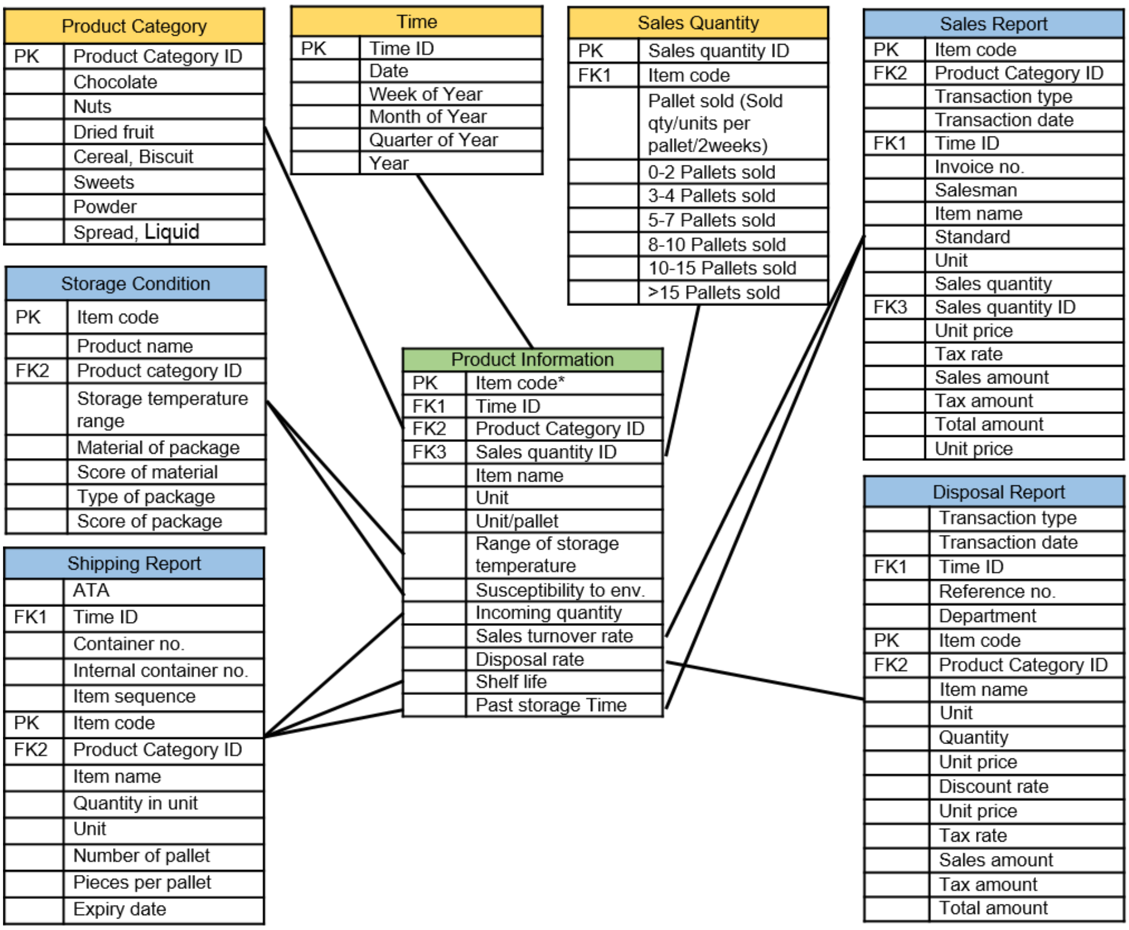


Figure 4.6 Structure of C-DB of PMC

In addition, to facilitate the OLAP application, dimension tables listing out items of each foreign key are prepared. In PMC's case, the three foreign keys are *Time*, *Product Category* and *Sales Quantity*, where *Sales Quantity* shows the sales volume of each product in terms of number of pallets sold in a given timeframe, i.e. 2 weeks. Furthermore, to reflect the storage requirements and package characteristics of the products, a dimension table recording the *Storage Condition* is produced for the static data involved. In the *Storage Condition* table, a score ranging from 1 to 9 is given to each type of package material and each type of package, where the type of package refers to the shape and size of the package. After summing up the two scores, the higher the total score means the more protective the package is. Dimension tables are then preprocessed with the three techniques mentioned in section 3, in order to obtain quality data for C-DB construction. The fact table named

Product Information shown in Figure 4.6 is the final output that the analytical modules likely need from the C-DB.

ii. Build cloud database

Regarding the construction of the C-DB, cloud SQL Database service is chosen by the case company as it is fully compatible with the on-premise MS office and SQL server. While the dimension tables *Storage Condition*, *Product Type* and *Date* are recording static data that do not require frequent updates, other tables contain dynamic data that are provided by the ERP. These tables with dynamic changes are expressed in the C-DB as a linked excel table so that whenever a new version replaces the old one and a new round of update is initiated to the C-DB, the C-DB is refreshed as well.

In terms of linkages between the dimension tables and the fact table, the primary key is the item code of the products, which is the code that is usually found on a certain section of the products' barcode. The product report generated from ERP is used as a basis for the fact table. The lines shown in Figure 4.6 illustrate the sources of additional data fields that are contributed by the linked dimension table. For the last six data fields of the fact table, i.e., from "Range of storage temperature" to "Shelf life", they are the "measures" of the fact table. The dimension tables of the three foreign keys are connected with the date, product category and sales fields of the tables, in order to facilitate information extraction from the OLAP cube in the later stages.

iii. Apply OLAP

The three foreign keys, *Time*, *Product Category* and *Sales Quantity*, are the dimensions

used in the OLAP. The SQL Server Management Studio and Business Intelligence Development Studio applicable to both local MS SQL Server and cloud SQL database are employed to create the OLAP cube in the C-DB. They are chosen due to their compatibility with the MS Excel and SQL server and their ease of application. The C-DB is connected to the SQL Server Management Studio and becomes the data source. An update in the SQL database can be reflected in the OLAP cube in real time. The fact table and the three dimension tables are inputted and associated with each other in the Business Intelligence Development Studio. For each dimension, hierarchies are set to enable the drill down and drill up functions of the cube. A new cube is produced by using the Cube Wizard function. After building, deploying and processing the cube and fixing any error encountered, the browser is used to examine the cube. The hierarchies of the three dimensions are drag and drop into the "column" and "row" fields depending on the demand of the users, while the "measures" are placed in the "details" field. Based on the processed real-time data presented by the OLAP cube, the company is able to make better decisions, not only in warehousing, but also in purchasing and sales.

4.3.3 Development of variable selection module

While the C-DB is ready in the last module, VSM can be developed to find the determinant factors and the potential range of storage time of different SKUs, in turn assisting the company to solve SLAP. The three stages of VSM development and the results of VSM implementation are explained in the following paragraphs.

i. Prepare parameters

<u>Step 1: Background study and parameters identification</u>

A background study was done to understand the operational details and information
concerning the SKUs. The aim of the study was to recognize the factors that could affect the storage time of SKUs, and in turn identify the parameters that would be used in the FARM algorithm. The study was accomplished by interviews and examination of the physical and information/ documentation flows in the company. Five parameters were identified from the study, represented by five alphabetic symbols in the following paragraphs. An introduction of the parameters is given in Table 4.1. While parameters from A to D are regarded as the input parameters that determine the storage time of SKUs, parameter E is the output parameter that shows the actual storage time resulting from different combinations of the input parameters. The if-then relationships between the input and output parameters would be discovered in the later stages.

Table 4.1 The identified parameters

Parameters	Representing Symbol	Meaning
Sales Turnover Rate	A	The ratio of sold quantity to incoming quantity in a given time period
Average Order Size	B	During a given time period, the average sold quantity of SKUs that are expressed in pallets for each order
Closeness to Holidays	C	The number of days between the date of sold and the date of local holiday
Shelf Life	D	The number of months between the receiving date of the pallet and the expiry date of that pallet of food
Actual Storage Time	E	The number of days between the receiving date of the pallet and its sold date

Step 2: Retrieve data from C-DB

Since the analytical modules, including the VSM, are run locally instead of in the C-DB, an on-premise database is then constructed to store the information needed for setting the itemsets in the next stage. Data are collected from the C-DB in accordance with the identified parameters and the specified range of the data creation date. For example, while the product report provides the basic information on SKUs, the sales report contains the data that are needed to calculate parameters A, B, C and E. The shipment report is related to parameters A, D and E. However, not all data from these reports are collected from the C-DB, but only those created in the last three months. Besides, since the existing reports do not contain information regarding local holidays, the related data are then added to the sales report in order to acquire parameter C. All reports are inputted into a MS Access database and linked by the unique item code of each SKU. Calculations are then done in the database to obtain all the parameters.

ii. Execute rule mining algorithm

Where the database is ready for parameters extraction, the FARM algorithm can be initiated. There are nine steps in cultivating useful fuzzy association rules.

Step 1: Define the membership function and universe of discourse

According to the past records of the parameters, the membership function and universe of discourse of each parameter are set, and are shown in Table 4.2. Take parameter B as an example, if the Average Order Size falls between 0.6 and 1.8 pallets, that order size is regarded as medium. An example of the membership functions of parameter B that is expressed in graphical format is shown in Figure 4.7.

Table 4.2 Membership function and universe of discourse of the parameters

Parameters	Range	Fuzzy Sets	Unit
Sales Turnover Rate (A)	0-100%	Low : 0-50 Medium : 25-75 High : 50-100	Percent
Average Order Size (B)	0-2.4 pallets	Small : 0-1.2 Medium : 0.6-1.8 Large : 1.2-2.4	Pallet
Closeness to Holidays (C)	1-60 days	Near : 0-30 Moderate : 15-45 Far : 30-60	Days
Shelf Life (D)	0-24 months	Short : 0-12 Medium : 8-16 Long : 12-24	Months
Actual Storage Time (E)	1-50 days	Short : 0-25 Medium : 12.5-37.5 Long : 25-50	Days

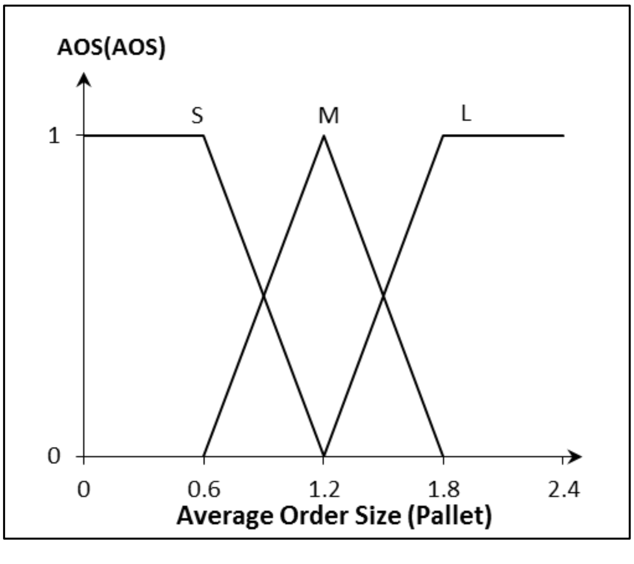


Figure 4.7 Membership functions of parameter B

Step 2: Transform the crisp parameter values into fuzzy sets

After defining the membership function of the parameters, seven past records concerning the parameters are acquired from the database to demonstrate the remaining steps of the rule mining algorithm. The seven past records are shown in Table 4.3. The crisp values of the past records are then transformed into fuzzy sets according to the membership functions defined. For example, the crisp value of parameter B of record 1 is 0.82, which yields a 0.63 membership value of "Small" and a 0.37 membership value of "Medium". The graphical expression of the fuzzy set of this example is shown in Figure 4.8. The rest of the transformed fuzzy sets of the parameters are shown in Table 4.4.

Table 4.3 The crisp values of the seven past records

Record	**Parameter**				
	A	***B***	***C***	***D***	***E***
1	0.90	0.82	5	8.67	1.33
2	0.89	1.23	2	9.13	5.50
3	0.02	0.14	6	11.50	14.00
4	0.07	0.35	43	6.87	33.00
5	0.48	1.10	4	19.80	11.00
6	0.82	1.32	4	8.00	8.00
7	0.57	0.74	22	11.87	20.00

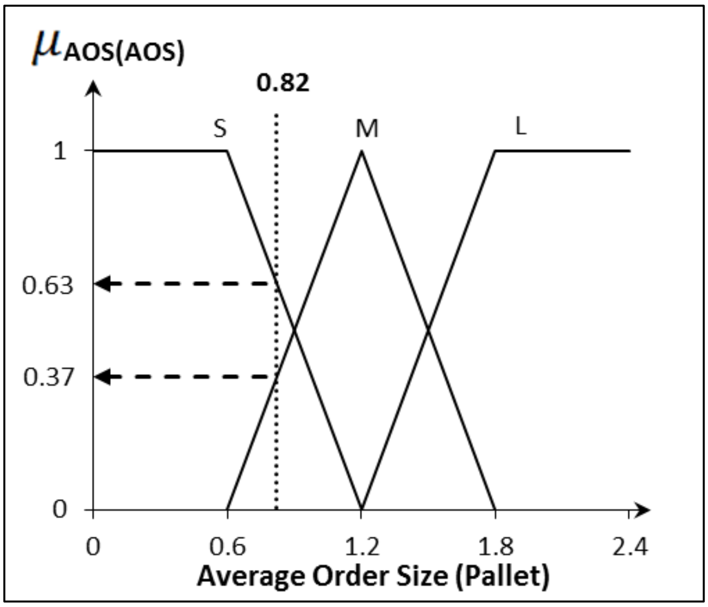


Figure 4.8 Fuzzy set of parameter B of record 1

Table 4.4 Fuzzy Sets and fuzzy counts of parameters

Record No.		**1**	**2**	**3**	**4**	**5**	**6**	**7**	**Fuzzy Counts**
	Low			1.00	1.00	0.08			2.08
A	***Medium***	0	0	0	0	0.92	0	0.72	1.64
	High	1.00	1.00				1	0.28	**3.28**
	Small	0.63		1.00	1.00	0.17		0.77	**3.57**
B	***Medium***	0.37	0.95	0	0	0.83	0.80	0.23	3.18
	Large		0.05				0.20		0.25
	Near	1.00	1.00	1.00		1.00	1.00	0.53	**5.53**
C	***Moderate***	0	0	0	0.13	0	0	0.47	0.60
	Far				0.87				0.87
	Short	0.55	0.48	0.08	0.85		0.67	0.02	**2.66**
D	***Medium***	0.45	0.52	0.92	0.15	0	0.33	0.98	3.34
	Long					1.00			1.00
	Short	1.00	1.00	0.88		1.00	1.00	0.40	**5.28**
E	***Medium***	0	0	0.12	0.36	0	0	0.60	1.08
	Long				0.64				0.64

Step 3: Define support counts threshold

The support counts threshold is used to filter out itemsets that have inadequate fuzzy counts, in order to preserve only those itemsets that have sufficient frequency of occurrence. The threshold values are defined through a trial-and-error method. The support counts threshold of the parameters is shown in Table 4.5.

Table 4.5 Fuzzy support counts threshold of the parameters

Parameters	**A**	**B**	**C**	**D**	**E**
Support counts threshold	2.2	2.2	2	2.3	1.2

Step 4: Obtain fuzzy counts of the parameters

In order to calculate the fuzzy counts of the potential 1st level itemsets (1-itemset), the membership values of each fuzzy class of each parameter are summed. For instance, referring to Table 4.4, "A.Low" is regarded as the fuzzy class "Low" of parameter A. The Fuzzy counts of "A.Low" is 1 + 1 + 0. 08 = 2.08, which is the summation of the number of occurrences of “A.Low”. The fuzzy counts of the rest of the fuzzy classes are calculated and shown in Table 4.4.

Step 5: Filtering and generation of 1-itemset

For the fuzzy classes under each parameter to be considered as the 1-itemset, the fuzzy counts have to be equal or greater than the support counts threshold set for the same parameter. For instance, for parameter A, only “A.High” has a fuzzy count of 3.28 that is greater than its threshold of 2.2. Furthermore, if there is more than one fuzzy class under the same parameter that has sufficient enough fuzzy counts, the one that involves the greatest fuzzy counts would represent the fuzzy characteristic of that parameter. The 1-itemsets of parameters A to E are then identified as “A.High”, “B.Small”, “C.Near”, “D.Medium” and “E.Short” respectively, as in the values shown in bold in the last column in Table 4.4.

Step 6: Define 2-itemsets and corresponding support threshold

The 1-itemsets are used to form the 2nd level itemsets (2-itemset) that contain fuzzy classes of two parameters. The potential 2-itemsets that are listed in Table 4.6 are different combinations of the 1-itemsets. Before continuing with the fuzzy counts calculation process, a filtering process is carried out. Taking the potential 2-itemset “A.High, D.Medium” as an example, the two support counts thresholds involved in this itemset are 2.2 and 2.3. The greater value 2.3 is selected as the support counts threshold of this 2-itemset. The threshold value is compared with the fuzzy counts of “A.High” and “D.Medium” respectively, i.e., 3.28 and 3.34. If one of the 1-itemset’s fuzzy counts is smaller than the support counts threshold 2.3, this 2-itemset would be eliminated. Since all fuzzy counts of the 1-itemsets are greater than the support counts threshold concerning the 2-itemsets, all potential 2-itesmsets shown in Table 4.6 are kept.

Step 7: Obtain fuzzy counts of potential 2-itemset

The fuzzy counts of 2-itemsets are obtained by summing up the smallest membership values that concern the 2-itemsets in Table 4.4. For instance, the records that contain “A.High, D.Medium” simultaneously are records 1, 2, 6 and 7.By summing up the smallest membership values of each record, i.e. 0.45, 0.52, 0.33 and 0.28 respectively, the fuzzy count of “A.High, D.Medium” is thus 1.58. All 2-itemsets’ fuzzy counts are calculated and listed in Table 4.6.

Step 8: Filtering and generation of 2-itemset

The fuzzy counts are then compared with their support counts threshold for generating the 2-itemsets. Only the ones with their fuzzy counts being equal or greater than their support counts threshold are counted as a 2-itemset. As suggested by the bold values shown under the column "Fuzzy Counts" in Table 4.6, the 2-itemsets are "A.High, C.Near", "A.High, E.Short", "B.Small, C.Near", "C.Near, D.Medium", "C.Near, E.Short" and "D.Medium, E.Short".

Table 4.6 Information concerns the potential 2-itemsets

Potential 2-itemset	**Support Counts Threshold**	**Fuzzy Counts**	**Confidence Value**
A.High, B.Small	2.2	0.91	
A.High, C.Near	2.2	**3.28**	
A.High, D.Medium	2.3	1.58	
A.High, E.Short	2.2	**3.28**	1
B.Small, C.Near	2.2	**2.33**	
B.Small, D.Medium	2.3	2.27	
B.Small, E.Short	2.2	2.08	
C.Near, D.Medium	2.3	**2.75**	
C.Near, E.Short	2	**5.28**	0.95
D.Medium, E.Short	2.3	**2.58**	0.77

Step 9: Obtain itemsets in higher levels

The rule mining algorithm continues to calculate the higher-level itemsets by repeating Steps 6 – 8, until the potential itemset is null, i.e. the fuzzy counts concerning the higher-level itemsets are no longer greater than the itemsets' support counts threshold. In this demonstration, there are five potential 3-itemsets and no 4-itemsets. The processing results concerning the potential 3-itemsets are shown in Table 4.7. Two of the 3-itemsets ("A.High, C.Near, E.Short", "C.Near, D.Medium, E.Short") are proven to be valid after going through the filtering processes.

iii. Rules Validation

Step 1: Filter by confidence value

For itemsets that contain two or more fuzzy classes, they are regarded as potential fuzzy association rules. However, the purpose of this module is to predict pallet storage time, therefore, only the itemsets that contain parameter E, which is the resultant part of the if-then rules, are kept for further evaluation. The evaluation is done through calculating the confidence values of the itemsets by equation (1) and (2). Equation (1) is used to validate a 2-itemset, while (2) is used to validate a 3-itemset. The 2-itemset “C.Near, E.Short” and the 3-itemset “C.Near, D.Medium, E.Short” are used to demonstrate the equations:

$$\frac{(C.Near \cap E.Short)}{C.Near} = \frac{5.28}{5.53} = 0.95 \tag{1}$$

$$\frac{(C.Near \cap D.Medium \cap E.Short)}{(C.\mathrm{Near} \cap D.Medium)} = \frac{2.58}{2.75} = 0.94 \tag{2}$$

There are in total five valid itemsets that contain parameter E. The confidence values of the five itemsets are shown in Table 4.6 and Table 4.7. The confidence values are compared with the confidence threshold for rule validation. The confidence threshold is set as 90%, therefore, four fuzzy association rules are generated in total. They are the itemsets in bold and italics in Tables 4.6 and Table 4.7.

Table 4.7 Information concerns the potential 3-itemsets

Potential 3-itemset	Support Counts Threshold	Fuzzy Counts	Confidence Value
A.High, C.Near, D.Medium	2.3	1.58	
A.High, C.Near, E.Short	2.2	**3.28**	1
B.Small, C.Near, D.Medium	2.3	1.90	
B.Small, C.Near, E.Short	2.2	2.08	
C.Near, D.Medium, E.Short	2.3	**2.58**	0.94

Taking the itemset “A.High, C.Near, E.Short” as an example for expressing it as a rule, this itemset states that:

IF the *Sales Turnover Rate* is high and *Closeness to Holidays* is Near,
THEN the *Actual Storage Time* is short.

Step 2: Validate with prediction discrepancy

The four fuzzy association rules are tested to prove their effectiveness in predicting the range of SKU storage time. Since Jain and Srivastava (2013) state that the performance of the data-mining-based predictive model is evaluated by its ability to predict accurately with new data, the four rules are thus validated through comparing the predicted range with the actual range of storage time of a newly arrived batch of food. The acceptable discrepancy is set by the management, where in PMC's case it is initially set as 20%, which means 8 out of every 10 batches of food should have an actual storage time that falls into the predicted range of storage time.

Three months' data are studied to calculate the rate of discrepancy between what the rules imply and the actual storage time. By selecting the records that comply with the "If" statements of the rules, the number of records involved is obtained. The actual storage time of these records are then fuzzified to determine the fuzzy classes that they belonged to. If the fuzzy class of the record complies with the "Then" statements of the rule, i.e., the storage time is short, the record is considered as "matching record", or else, it is counted as a "mismatched record". After counting the number of mismatched records, the discrepancy rate is obtained. The results of the rule validation are shown in Table 4.8.

Table 4.8 Results of rule validation

Fuzzy Association Rule	**No. of record Involved**	**No. of Matching record**	**No. of Mismatched record**	**Discrepancy**
If A.High, Then E.Short	54	48	6	11%
If C.Near, Then E.Short	71	61	10	14%
If A.High and C.Near, Then E.Short	42	37	5	12%
If C.Near and D.Medium, Then E.Short	10	6	4	40%

Referring to Table 4.8, the first three rules involve discrepancies smaller than 80%, therefore they are stored in a knowledge repository for decision support in the future. Where the discrepancy concerning the last rule exceeds the acceptable level, refinements have to be made in the rule mining algorithm in order to further investigate the significance of parameter D.

<u>User interface of VSM</u>

The specifications concerning the FARM algorithm can be edited by the user through the user interface of VSM as shown in Figure 4.9. The user can specify the range of data in terms

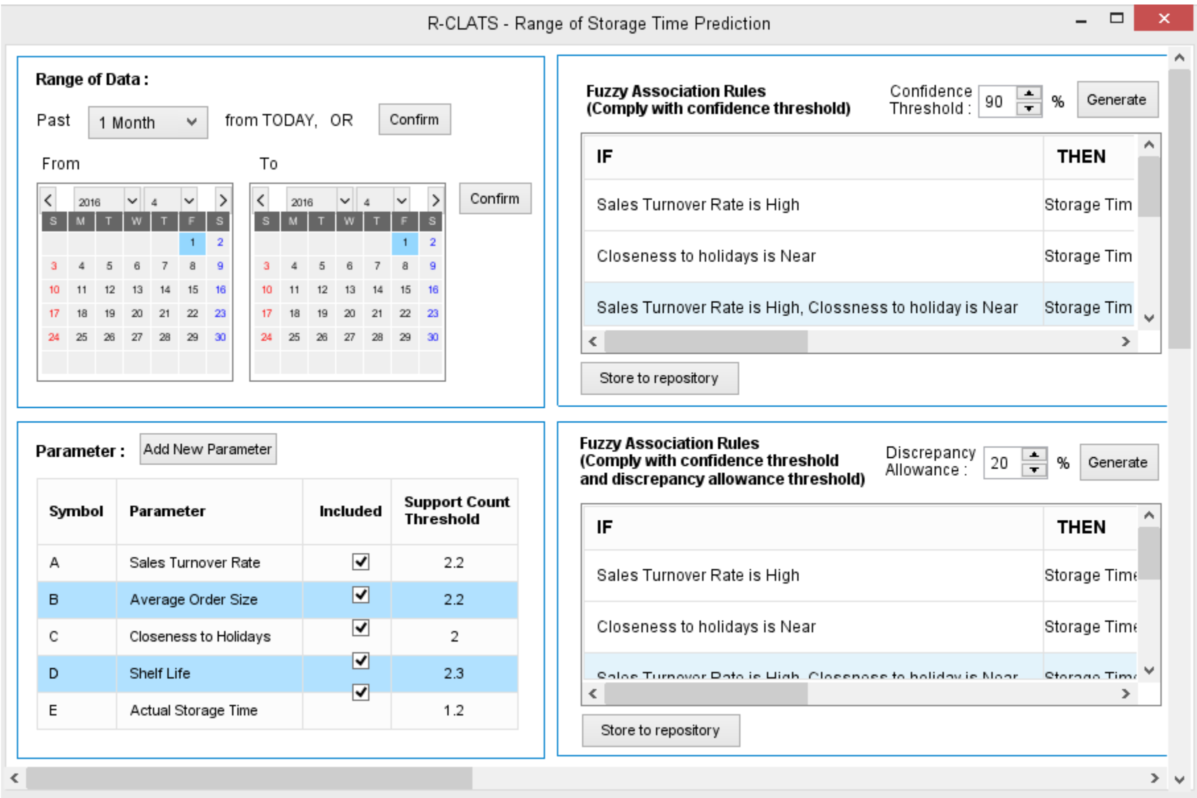


Figure 4.9 User interface of VSM

of date, the parameter involved, the support count and confidence thresholds, and the discrepancy allowance for rule filtering through the interface. There are two rule generation boxes where the upper one generates rules without considering the discrepancy allowance threshold, while the lower one generates rules with the discrepancy allowance threshold. The choice of using which rule generation box is made by the decision makers, who would decide whether they want more rules or more accurate rules. After generating the rules according to the thresholds, users can click on “Store to repository” to retain the rules in the database for future use. By clicking such button, the column “Predicted range of storage time” is added and filled up in the database according to the rules retained.

<u>Results of VSM implementation</u>

After going through the three stages of VSM development, VSM is implemented on the active SKUs that have been ordered and delivered in the past two months in PMC. 553 potential rules, involving more than 70 SKUs, have been cultivated and expressed in both 2-temsets and 3-itemsets. However, only the 268 rules which involve the parameter *Actual Storage Time* are kept. The 268 rules are then validated by the Confidence threshold and the Discrepancy threshold, in order to generate fuzzy association rules that can more accurately predict the range of SKU storage time. The Confidence threshold and discrepancy threshold are set to be 90% and 20% respectively. After filtering out the rules which contain confidence values and discrepancy rates smaller than the two thresholds, 221 rules remain and are stored into a knowledge repository.

Among the 221 rules, *Sales Turnover Rate and Average Order Size* are involved in 72% and 6% of the rules respectively. These results indicate that the most and least relevant parameter to storage time is *Sales Turnover Rate* and *Average Order Size* respectively. Therefore, *Average Order Size* could be excluded in the FARM execution in the future. Five examples of the validated rules are shown in Table 4.9. The range of SKUs storage time expressed in Short, Medium and Long, can then be used as one of the input variables of the fuzzy inference engine in LAM for determining storage locations.

Table 4.9 Examples of the validated fuzzy association rules

SKU	**Validated fuzzy association rules**		**Confidence Value**	**Discrepancy rate**
T30	**IF** **THEN**	*Sales Turnover Rate* is High, *Closeness to Holidays* is Near, *Actual Storage Time* is Short.	1.0	12%
Whole Almond 3lb	**IF** **THEN**	*Sales Turnover Rate* is High, *Shelf Life* is Medium, *Actual Storage Time* is Short.	0.98	11%
Peanut Butter 1360g x 2	**IF** **THEN**	*Shelf Life* is Medium, *Closeness to Holidays* is Near, *Actual Storage Time* is Short.	0.93	14%
Chocolate Assortment	**IF** **THEN**	*Sales Turnover Rate* is Medium, *Closeness to Holidays* is Near, *Actual Storage Time* is Medium.	0.91	19%
Oats 4530g	**IF** **THEN**	*Sales Turnover Rate* is Low, *Shelf Life* is Long, *Actual Storage Time* is Long.	0.91	16%

The frequency of executing VSM is not as high as that of executing LAM because once a set fuzzy association rules are generated, the LAM alone is able to handle the daily SLAP analysis. The daily SLAP handling method can thus be simplified. However, VSM should be executed from time to time to review the relevance of the parameters towards the range of SKUs storage time.

4.3.4 Development of location assignment module

As the predicted range of SKU storage time is obtained from last module, the next step is to form the knowledge base for completing the location assignment decision support function of R-CLATS. The four major tasks involved in developing LAM are to (i) define the variables, (ii) build a fuzzy inference engine, (iii) implement the inference engine, and (iv) cultivate association rules. The tasks completion details are explained in the following paragraphs.

i. Define the variables

<u>Step 1: Prepare floor plan and define output variables</u>

The first task of developing LAM is to identify and recognize the input variables that will be used in the fuzzy inference engine. There are four sources of information that help the knowledge engineer in identifying the input variables,(i) interviews with warehouse operators, including the domain experts, regarding their common practices in storage location, (ii) historical data concerning each product, (iii) knowledge of the knowledge engineer on the attributes of packaged food handling, and (iv) range of storage time obtained in VSM. For the information source of historical data, 2.5-month data that is collected during the peak season is studied. The data involves around 500 sales orders and 1,700 product transactions, which can adequately reflect the sales pattern, incoming quantity and damage rate of products.

Integrating the four information sources, there are six input variables identified, namely *Resistance to Temperature Variance, Effectiveness of Package*, *Damaged Rate*, *Receiving Quantity*, *Storage Time and Sales Turnover Rate*. *Resistance to Temperature Variance* indicates the acceptability of storage temperature change of the product. For example, chocolate often has a lower *Resistance to Temperature Variance* then cereal. *Effectiveness of Package* means how well the package is doing to protect the food content. This variable usually depends on the materials, shape and type of the package. For example, plastic polyethylene terephthalate (PET) film, which is shown in Figure 4.10, is highly sensitive to temperature change and insolation. Warehouse operators occasionally find the plastic film broken because of thermal expansion and contraction. Another example is the aluminium foil container, shown in Figure 4.11, which is more vulnerable than glass containers. Therefore an SKU containing aluminium canisters generally has a lower *Effectiveness of Package* than that contained in a glass container. *Damage Rate* measures the actual number of broken products out of all products available at a given time frame to examine the vulnerability of each product. *Receiving Quantity* counts the number of pallets for each product involved in the same incoming batch. *Storage Time* reflects the predicted range of time between the receiving date of that batch of SKU and the date when it is sold. *Sales Turnover Rate* is a complementary variable to *Storage Time* that serves similar purpose, they both suggest which products should be located closer to the retrieval points. However, since *Storage Time* is obtained from the VSM, it is more accurate than *Sales Turnover Rate* in reflecting the storage time of SKU. Therefore, *Sales Turnover Rate* is only applied when *Storage Time* obtained from VSM is unavailable. The six input variables are recognized by domain experts and warehouse operators as attributes that can assist R-CLATS to generate a SLAP solution, considering the product characteristics and popularity, environmental influences and tidiness of a warehouse.

Figure 4.10 Plastic film made of PET

Figure 4.11 Canister made of aluminium foil

<u>Step 2: Prepare floor plan and define output variables</u>

The output variables of the system are the locations in the warehouse and the suggested attention needed for different type of products. In order to separate the warehouse into sections, a floor plan of the warehouse is prepared after examination by the domain experts. Referring to Figure 4.12, PMC’s warehouse is comprised of 40-foot containers with air-conditioners. The volume of each container is 40 standard pallets, with 20 pallets stacked above the other 20 pallets.

The warehouse is divided into five virtual sectors, which comprise the first output variable, *Warehouse Section*, of the system, according to the retrieval time from the container doors and the stability of environment, i.e. temperature, humidity and insolation. The retrieval time and stability of the environment increases with increasing distance from the doors, therefore products being stored in sector 1 (lightest coloured) should be the ones that are relatively more popular and have a higher resistance to environmental changes. For the output value generated from the fuzzy inference engine, the defuzzified *Warehouse section* crisp value is rounded up to 0.5. If the decimal place is rounded to 5, i.e. the rounded value is 1.5, 2.5, etc., and the pallet should be placed in the inner row of the designated warehouse section. If the rounded decimal place is 0, i.e. the rounded value is 1.0, 2.0, etc., the pallet should be placed in the outer row of the designated warehouse section.

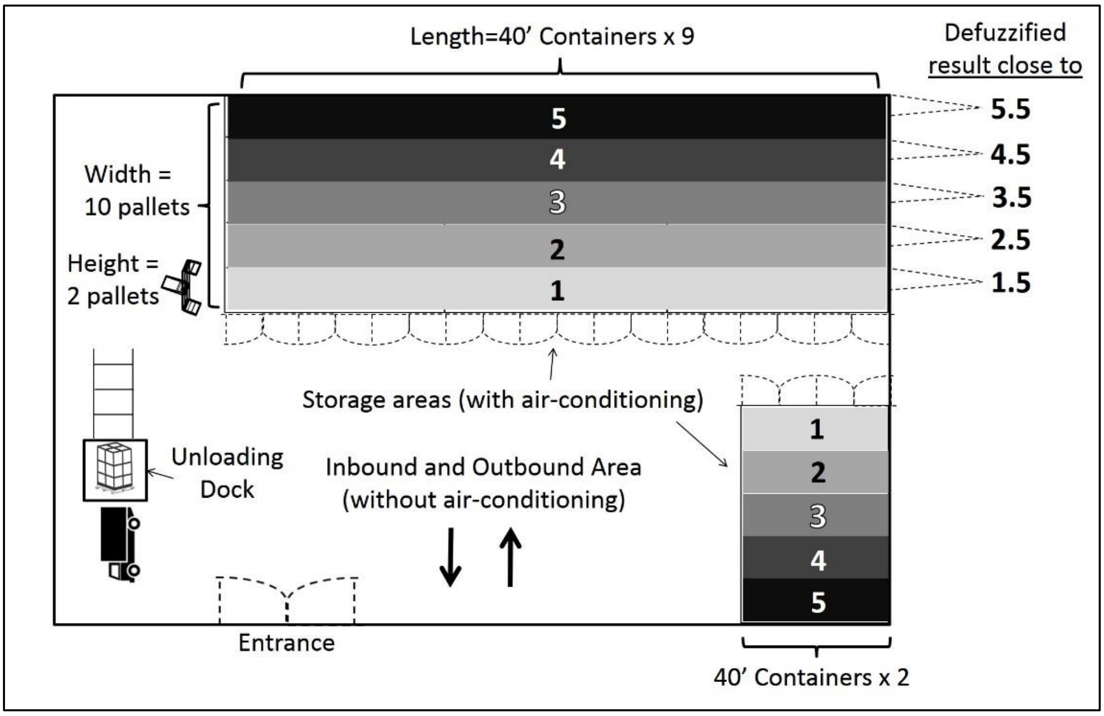


Figure 4.12 Floor plan of warehouse area

The second output variable is *Vertical Location.* Unlike some warehouses that contain racks for storing pallets up to several levels, PMC's warehouse only allows two pallets to be stored vertically. In terms of accessibility, pallets in the lower level, i.e. level 1, account for a lower accessibility, because they cannot be retrieved without removing the pallets placed above them. The second output variable of the inference engine is therefore the *Vertical Location* expressed as level 1 and level 2.

The final output variable is the *Attention Needed* for each type of product. Since it is observed that products with relatively high disposal rate are not treated with more attention in order to prevent damage, the final output variable is thus needed to identify these products for the stock keepers. Four levels of attention are proposed for this variable: none, little, much and full. The levels of *Attention Needed* are linked to different sets of Standard Operating Procedures (SOPs). For example, for products that require full attention, the stock keeper has to: (i) avoid temperature variance during all operations by such means as speeding up the order-picking or receiving processes, (ii) ensure that there are enough layers of plastic stretch film wrapped over the products to hold them in place, (iii) adjust the speed of forklift actions, including the speed of lifting and travelling, and (iv) avoid last-minute order-picking of those products. With the linkage between *Attention Needed* and SOPs, product damage can be avoided.

ii. Build a fuzzy inference engine

<u>Step 1: Experience learning</u>

After defining the variables of the fuzzy inference engine, the knowledge base regarding food storage has to be formed to complete the engine building. In order to form this knowledge base, experiential learning from the domain experts through interview and observation is initiated. The warehousing manager in PMC is identified as the key domain expert, who makes the operational decisions regarding SLAP. However, in order to avoid bias, other stock keepers in the company who have years of experience in SLAP handling are also considered as domain experts. Before interviewing the experts, the knowledge engineer prepares the questions by studying the historical data of the SKUs, especially those that involve a higher turnover and disposal rate. During the interview, the engineer asks follow-up questions to the experts according to their responses.

These questions can reveal the explicit knowledge of the experts regarding three areas: (i) definition of linguistic variables, (ii) the relationships between input linguistic variables and storage location allocation, and (iii) the relationships between input linguistic variables and levels of attention needed for handling different SKUs. For the first area, how the linguistic terms that are used to describe the six input variables of SKUs are explained by the experts. For example, if the acceptable storage temperature variation of the SKUs is around 5 degree Celsius, the level of *Resistance to Temperature Variance* of those SKUs can be expressed as low. Those SKUs are commonly under the category of chocolate. Using the same example to explain the second area, chocolate products have to be allocated to the warehouse zones that have a stable and low enough temperature. Concerning the third area, in addition to the interview, observation is carried out to examine which SKUs are treated with different levels of attention. For example, it is observed that more layers of plastic stretch film are wrapped over certain kinds of the products in order to hold the products in place. After learning the experience regarding the three areas, knowledge representation is implemented to achieve the knowledge.

Step 2: Set up fuzzy inference engine

The knowledge obtained in last step is regarded as procedural knowledge, which is about how a sequence of conditions (different characteristics of SKUs) related to the subsequent actions (where to locate, and handling with how much attention). The procedure knowledge is suitable to be represented by rules that commonly take the form of if-then format (Akerkar & Sajja, 2010). In order to achieve the knowledge expressed in fuzzy if-then rules, a fuzzy inference engine has to be built. The engine is constructed by the fuzzy toolbox of MATLAB® and Simulink® Release 2008a.

To begin with, fuzzification is implemented to transform the numerical values concerning the input variables into linguistic terms. The membership functions and universe of discourse of each input variable are defined, according to both the "definition of linguistic variables" offered by the domain experts in the last step and the historical data in the C-DB. The input variables are set in the engine by the membership function editor, as shown in Figure 4.13. The fuzzy sets for all input variables is listed in Figure 4.14.

The linguistic terms such as "Low", "Slightly Low" shown in Figure 4.14 are the qualitative descriptions of the universe of discourse. The triangular fuzzy membership functions are chosen over the Quasi or Trapezoidal fuzzy membership functions, since a smaller amount of data is required, enabling easy modification of the parameters (Piegat, 2001). Due to its simplicity, the staff in the company, who have little knowledge about FL, are still capable of maintaining the system.

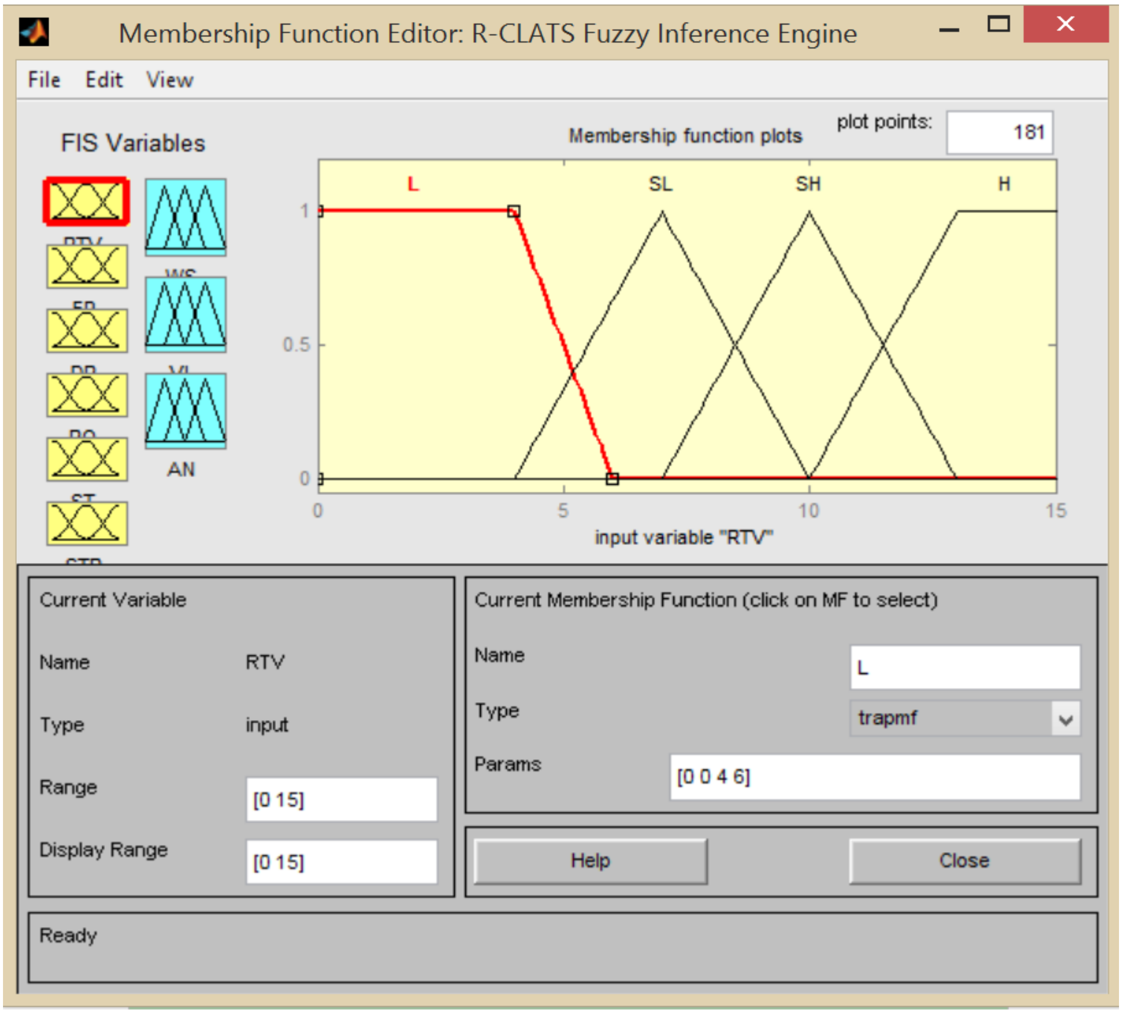


Figure 4.13 Membership function editor of the fuzzy inference engine

After fuzzification, the input and output variables are linked by generating the if-then rules. Based on the combinations of various membership functions of the first five input variables, 324 rules can be derived according to the content of the interview done in last step. In addition, another group of 324 rules is also derived, the only difference between two groups of rules is that the fifth input variable is *Sales Turnover Rate* instead of *Storage Time*. With this setting, the total of 648 rules can ensure that every SKU can be analysed with the fuzzy inference engine. All the rules are inputted and stored in the fuzzy inference engine to form a knowledge repository, as shown in Figure 4.15.

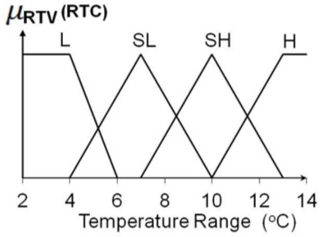
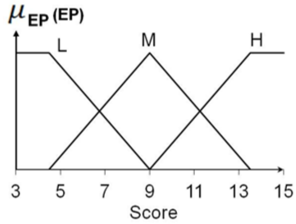
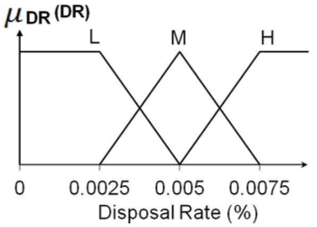
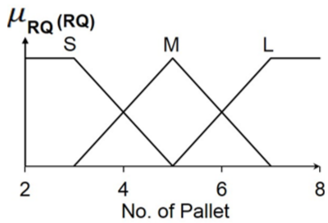
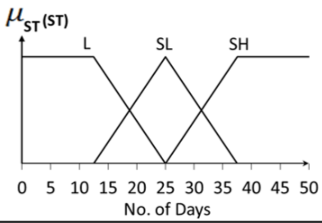
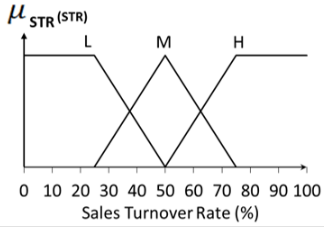
Input variables	Membership functions and Universe of discourse		
Resistance to temperature variance	Temperature range (°C)	Linguistic terms	
	< 6	Low	
	4-10	Slightly Low	
	7-13	Slightly High	
	>10	High	
Effectiveness of package	Score	Linguistic terms	
	< 9	Low	
	4.5-13.5	Medium	
	> 9	High	
Damaged rate	Disposal Rate	Linguistic terms	
	< 0.005	Low	
	0.0025-0.0075	Moderate	
	> 0.005	High	
Receiving quantity	No. of pallets	Linguistic terms	
	< 5	Small	
	3-7	Medium	
	> 5	Large	
Storage Time	No. of days	Linguistic terms	
	< 25	Short	
	12.5-37.5	Medium	
	25-50	Long	
Sales Turnover Rate	Sales turnover rate (%)	Linguistic terms	
	< 50	Low	
	25-75	Medium	
	> 50	High	

Figure 4.14 Membership functions of input variables

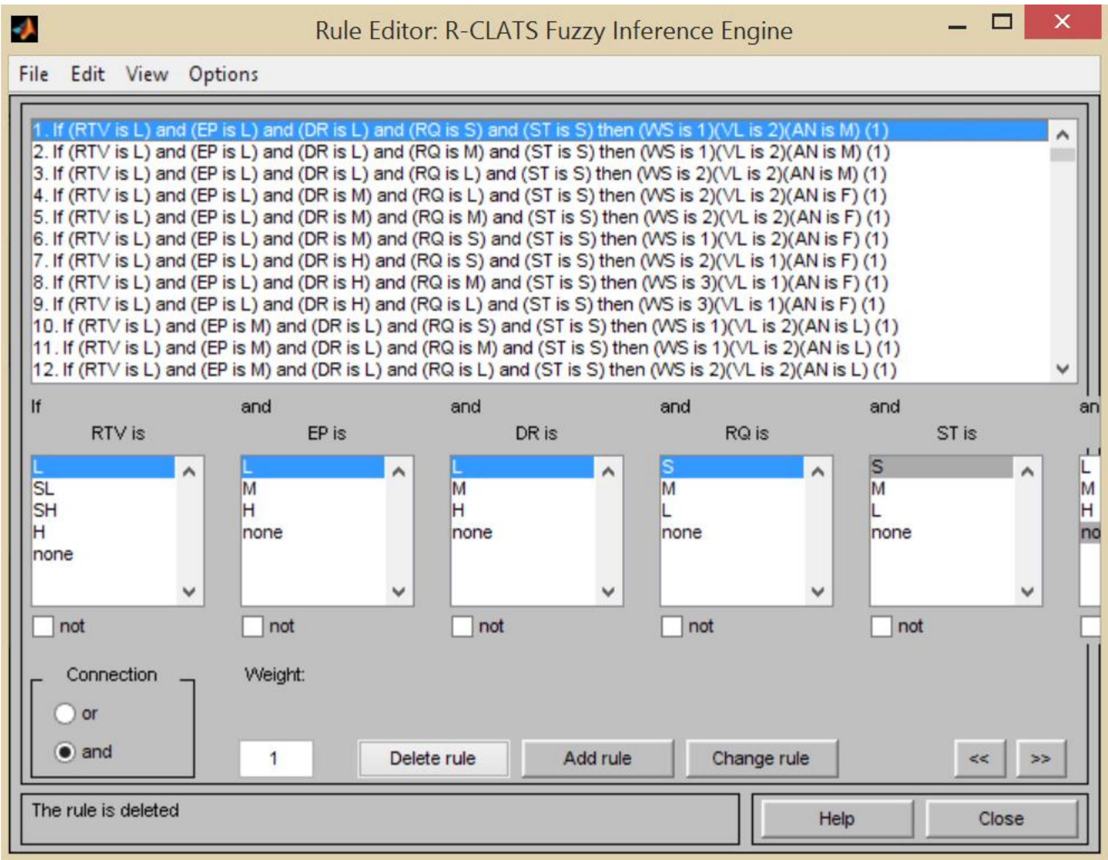


Figure 4.15 Knowledge repository comprised of if-then rules in the fuzzy inference engine

For clear illustration of the rules, they can be expressed in the rule block format shown in Figure 4.16. The outer parts of the block indicate different combinations of the six input variables, while the interior parts with the dotted outline show the output values in accordance with the input combinations. The values of only one output variable are shown in a rule block at a time. Figure 4.17 shows an example of the rule combinations concerning the *Warehouse section* that are expressed in rule block format. The rule indicated by the red cell in Figure 4.17 implies that, for a SKU:

IF *Resistance to Temperature Variance* is Low, *Effectiveness of Package* is Low, *Damaged Rate* is Low, *Receiving Quantity* is Small, and *Storage Time* is Short,

THEN *Warehouse section* is 1.

		1 Resistance to temperature variance		
		2 Effectiveness of Package		
		5. Storage Time (Short)		
3 Damaged Rate:		Low	Moderate	High
4. Receiving Quantity	Small	Warehouse Section/ Vertical Location / Attention Needed		
	Medium			
	Large			

Figure 4.16 Rule block for expressing if-then rules

		1. Resistance to temperature variance (Low)		
		2. Effectiveness of Package (Low)		
		5. Storage Time (Short)		
3 Damaged Rate:		Low	Moderate	High
4. Receiving Quantity	Small	1	1	2
	Medium	1	2	3
	Large	2	2	3

Figure 4.17 An example of a rule block concerning *Warehouse section*

Some examples of the complete rules are:

IF *Resistance to Temperature Variance* is Slightly Low, *Effectiveness of Package* is High, *Damaged Rate* is Medium, *Receiving Quantity* is Large, and *Storage Time* is Short,
THEN *Warehouse section* is 2, *Vertical level* is 2, and *Attention needed* is Little.

IF *Resistance to Temperature Variance* is Low, *Effectiveness of Package* is Low, *Damaged Rate* is High, *Receiving Quantity* is Medium, and *Storage Time* is Medium,
THEN *Warehouse section* is 4, *Vertical level* is 1, and *Attention needed* is Much.

IF *Resistance to Temperature Variance* is Slightly High, *Effectiveness of Package* is High,
Damaged Rate is Low, *Receiving Quantity* is Small, and *Storage Time* is Long,
THEN *Warehouse section* is 3, *Vertical level* is 1, and *Attention needed* is None.

After inputting the rules, output surface graphs such as those that are shown in Figure 4.18, can be generated from the engine to review the relationships between the variables.

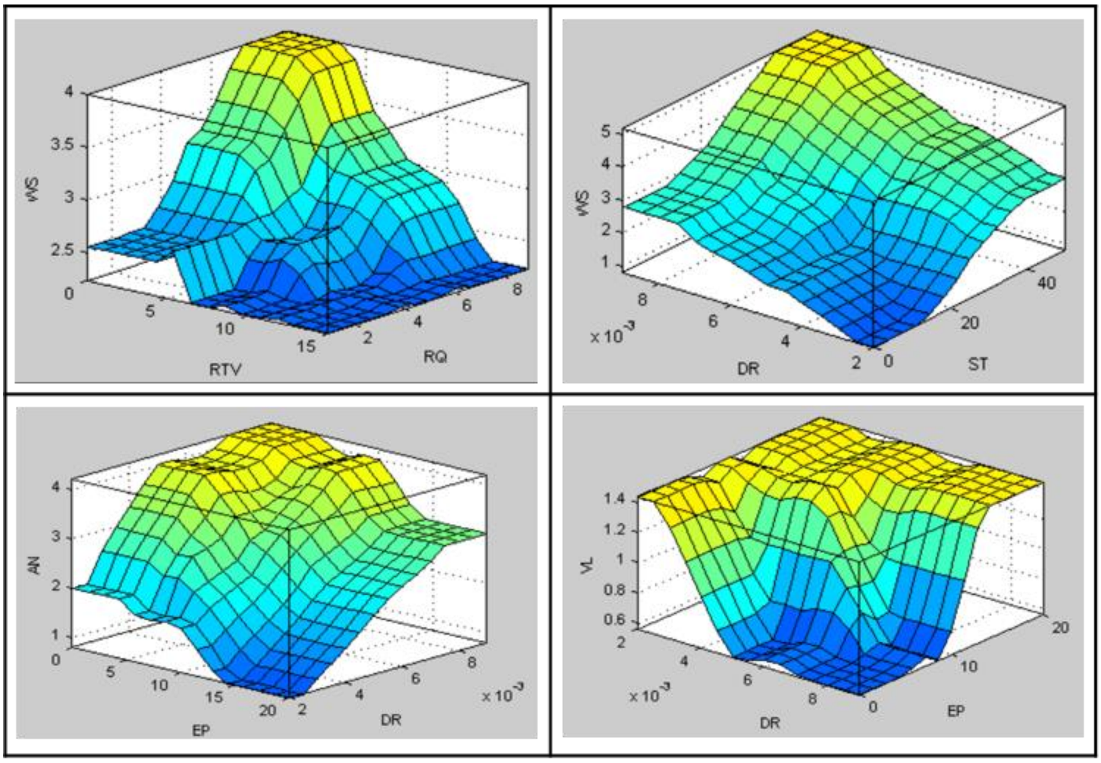


Figure 4.18 Fuzzy inference system output surface

iii. Implement inference engine

After determining the fuzzy sets and if-then rules, data on the arriving products is inputted into the system for testing the allocation guidelines generation process. While the fuzzy inference engine developed by the Matlab fuzzy toolbox is the core analytical component of the system, the backend jobs of the system are done in C++ programming language. The backend jobs include extracting the relevant data from the C-DB, filling in the fuzzy inference engine with the data, and expressing the outputs obtained from the engine into understandable phrases for the users. Users can run the system easily through the Product Allocation Guideline Generator user interface, which is shown in Figure 4.19.

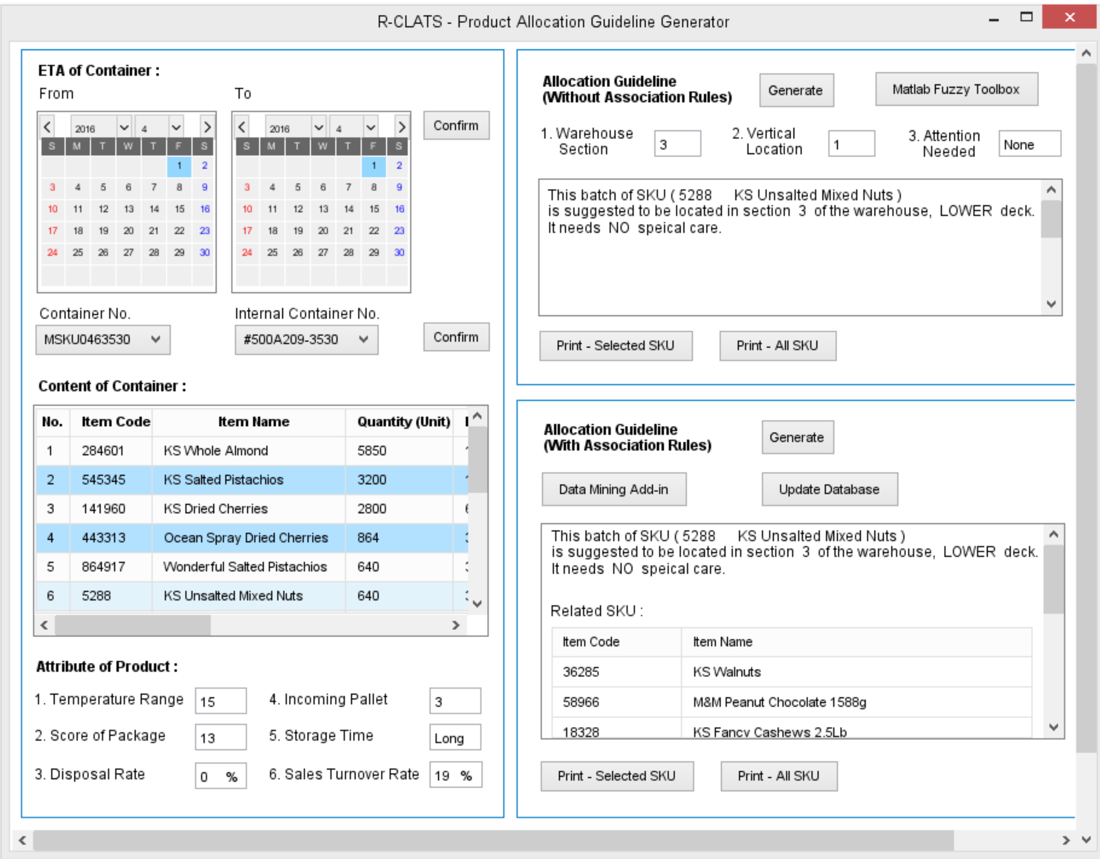


Figure 4.19 User interface of R-CLATS

For illustrating the processes, analyses regarding three of the arriving 40-foot high cube containers are examined. There are two ways to initiate the analysis. Firstly, the user can retrieve the contents of the container by indicating the container number in the box at the left. The backend programme searches the C-DB, and then retrieves and shows the attributes of the involved products in the user interface. The user can check if the attributes shown are valid. If they are not entirely valid, manual corrections can be made through the user interface. In case the system is unable to retrieve the data automatically, which can happen if the data sources in the ERP are not updated in time, a second method is used. The second method is to manually input the input variables of the products such as that shown in Table 4.10 into the interface for analysis.

Table 4.10 Input and output values of variables of the three containers

Product Name	Temperature Range (°c)	Score of Package	Disposal Rate (%)	No. of Incoming Pallet	Storage Time	Sales Turnover Rate (%)	Warehouse Section	Vertical Location	Attention Needed
	Input Variables						Outputs		
Container 1									
KS Dried Cherries	10	8	1.3333%	6	Short	100%	2	1	Much
KS Whole Almond	10	8	0.0000%	15	Short	82%	1	2	None
KS Unsalted Mixed Nuts	15	13	0.0000%	3	Long	19%	3	1	None
KS Salted Pistachios	10	8	0.0000%	10	Medium	38%	2.5	1	None
Ocean Spray Dried Cranberry	10	8	0.0000%	3	Long	25%	3	1	None
Wonderful Salted Pistachios	10	8	0.0051%	3	Short	100%	1	2	Little
Container 2									
Lindor Truffles	6	8	0.0000%	8	Medium	64%	2	2	Little
KS Salted Mixed Nuts	15	13	0.0667%	29	Long	21%	5	1	Much
Coachs Oats Whole Grain Oatmeal	20	6	0.0130%	3	Short	71%	2	1	Full
Container 3									
Mauna Loa Macadamias, Honey	15	7	0.0000%	5	Short	133%	1	2	None
Mauna Loa Macadamias, Onion	15	7	0.0000%	5	Short	100%	1	2	None
Mauna Loa Macadamias, Variety	15	7	0.0000%	15	Short	133%	1	2	None
Mauna Loa Macadamias, Salted	15	7	0.0000%	15	Short	100%	1	2	None

After the attributes of the products are ready, by clicking the “Generate” button in the box located at the upper right corner of the interface, the backend programme will initiate the analysis run by the inference engine by inputting the attributes into it. The defuzzified output crisp values generated by the engine are rounded up and linked to the linguistic terms associated with them by the backend programme. The recommendations in linguistics phrases are then shown to the user through the user interface. To modify the fuzzy inference engine, the user may click the “Matlab Fuzzy Toolbox” button to retrieve the engine. Figure 4.20 shows the defuzzified output values for each product in the containers captured from the fuzzy toolbox of MATLAB. The analytical results of the three containers are listed in the last three columns of Table 4.10. Warehouse operators can then react according to the suggestions provided by R-CLATS. However, if the warehouse operators want to obtain more comprehensive allocation guidelines which include the relationships between SKUs, they can use the box located at the lower right corner of the interface. Such box initiates the ARM process, which is explained in the next subsection.

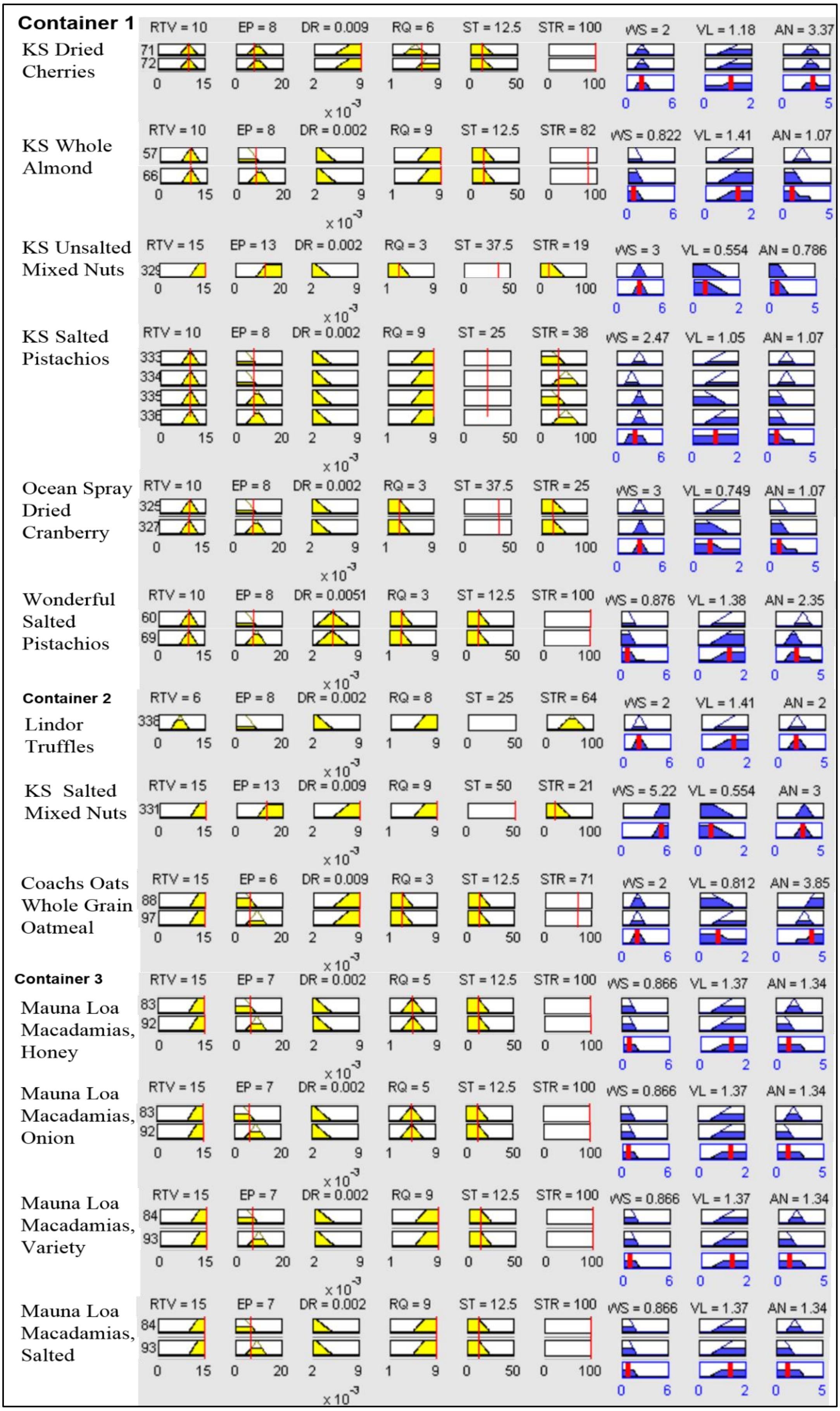

Container 1
KS Dried Cherries
RTV = 10 EP = 8 DR = 0.009 RQ = 6 ST = 12.5 STR = 100 WS = 2 VL = 1.18 AN = 3.37
KS Whole Almond
RTV = 10 EP = 8 DR = 0.002 RQ = 9 ST = 12.5 STR = 82 WS = 0.822 VL = 1.41 AN = 1.07
KS Unsalted Mixed Nuts
RTV = 15 EP = 13 DR = 0.002 RQ = 3 ST = 37.5 STR = 19 WS = 3 VL = 0.554 AN = 0.786
KS Salted Pistachios
RTV = 10 EP = 8 DR = 0.002 RQ = 9 ST = 25 STR = 38 WS = 2.47 VL = 1.05 AN = 1.07
Ocean Spray Dried Cranberry
RTV = 10 EP = 8 DR = 0.002 RQ = 3 ST = 37.5 STR = 25 WS = 3 VL = 0.749 AN = 1.07
Wonderful Salted Pistachios
RTV = 10 EP = 8 DR = 0.0051 RQ = 3 ST = 12.5 STR = 100 WS = 0.876 VL = 1.38 AN = 2.35
Container 2
Lindor Truffles
RTV = 6 EP = 8 DR = 0.002 RQ = 8 ST = 25 STR = 64 WS = 2 VL = 1.41 AN = 2
KS Salted Mixed Nuts
RTV = 15 EP = 13 DR = 0.009 RQ = 9 ST = 50 STR = 21 WS = 5.22 VL = 0.554 AN = 3
Coachs Oats Whole Grain Oatmeal
RTV = 15 EP = 6 DR = 0.009 RQ = 3 ST = 12.5 STR = 71 WS = 2 VL = 0.812 AN = 3.85
Container 3
Mauna Loa Macadamias, Honey
RTV = 15 EP = 7 DR = 0.002 RQ = 5 ST = 12.5 STR = 100 WS = 0.866 VL = 1.37 AN = 1.34
Mauna Loa Macadamias, Onion
RTV = 15 EP = 7 DR = 0.002 RQ = 5 ST = 12.5 STR = 100 WS = 0.866 VL = 1.37 AN = 1.34
Mauna Loa Macadamias, Variety
RTV = 15 EP = 7 DR = 0.002 RQ = 9 ST = 12.5 STR = 100 WS = 0.866 VL = 1.37 AN = 1.34
Mauna Loa Macadamias, Salted
RTV = 15 EP = 7 DR = 0.002 RQ = 9 ST = 12.5 STR = 100 WS = 0.866 VL = 1.37 AN = 1.34

Figure 4.20 Analysis results generated by Matlab fuzzy tool box

iv. Association rule mining

Though the fuzzy inference engine has recommended a zone for SKU allocation, association rules mining is implemented to further shorten the order picking time where possible. MS SQL Server Data Mining Add-in is employed to implement the rule mining, due to its easiness in use and compatibility with the MS SQL Server and MS office software that PMC is using. An Apriori algorithm is applied as the back end algorithm to cultivate the rules. The details of the implementation are explained as follows:

Step 1: Configuration of data source from SQL

Since PMC has installed the Microsoft SQL Server 2012 in their local computer, a free application of the Microsoft® SQL Server® 2012 Data Mining Add-in is feasible. The sales report contains all data needed for ARM, therefore the data source can either be the sales report generated from the ERP, or the transferred Sales report extracted from the C-DB. After installing the add-in, the database in the SQL server is connected to MS Excel, and then the sales data in the database can be imported into the Excel sheet as shown in Figure 4.21.

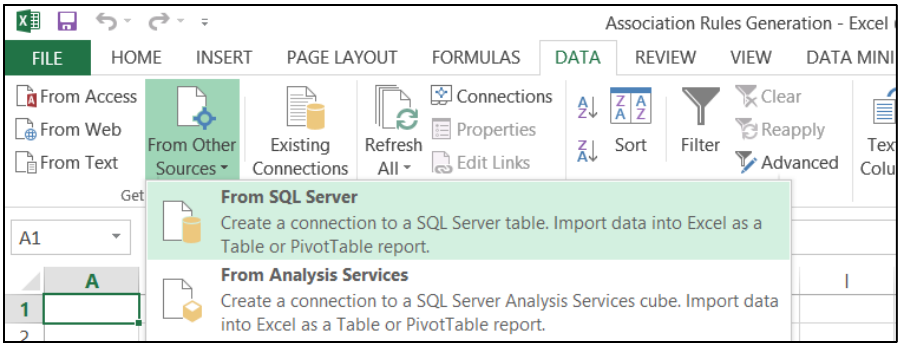


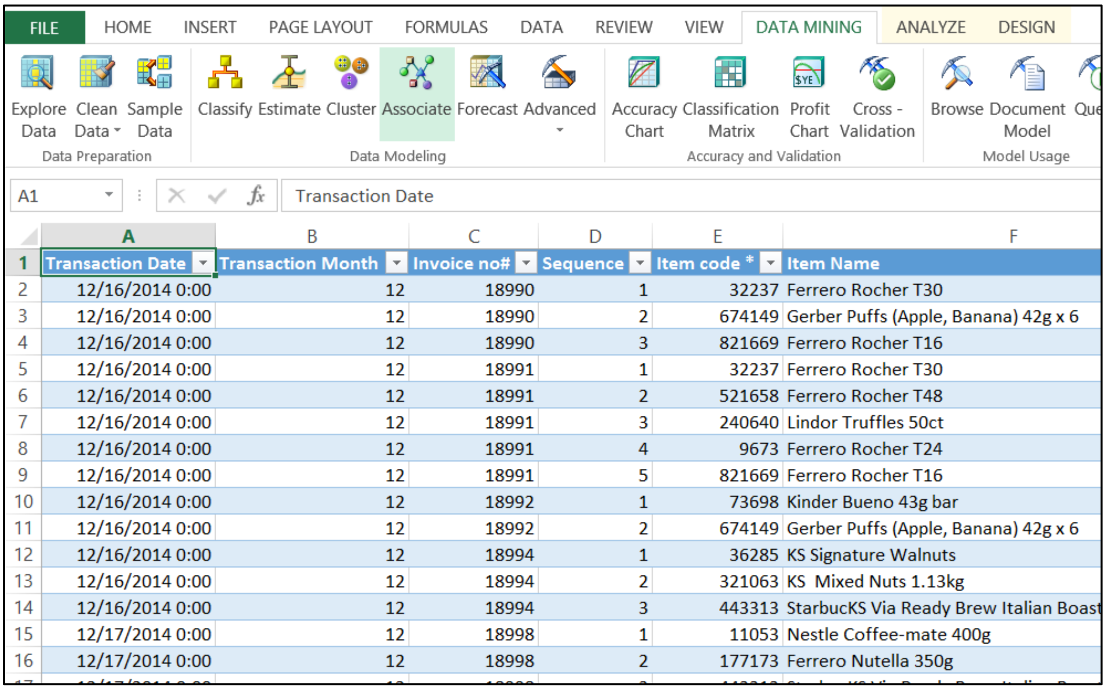
Figure 4.21 Sales data importing from SQL server to Excel

Around 500 sales orders incurred in the peak season are imported to the Excel sheet for the association rule mining analysis. Since the demand of packaged food is the greatest during the peak season, analysing the peak season's data is sufficient to reveal the ordering patterns and relationships between products in the largest extend.

Step 2: Executing the Association Rule Mining Tool

Since the sales report in the SQL server database is chosen to be directly extracted from the ERP, the sales data imported from the SQL server are thus in Excel format that is ready to be used by the ARM tool, i.e. each row shows an item instead of showing a transaction that may include several items (refer to Figure 4.22).

The compatible format saves the steps of reformatting the data in a proper way for the tool to analyse.



	A	B	C	D	E	F
1	Transaction Date	Transaction Month	Invoice no#	Sequence	Item code *	Item Name
2	12/16/2014 0:00	12	18990	1	32237	Ferrero Rocher T30
3	12/16/2014 0:00	12	18990	2	674149	Gerber Puffs (Apple, Banana) 42g x 6
4	12/16/2014 0:00	12	18990	3	821669	Ferrero Rocher T16
5	12/16/2014 0:00	12	18991	1	32237	Ferrero Rocher T30
6	12/16/2014 0:00	12	18991	2	521658	Ferrero Rocher T48
7	12/16/2014 0:00	12	18991	3	240640	Lindor Truffles 50ct
8	12/16/2014 0:00	12	18991	4	9673	Ferrero Rocher T24
9	12/16/2014 0:00	12	18991	5	821669	Ferrero Rocher T16
10	12/16/2014 0:00	12	18992	1	73698	Kinder Bueno 43g bar
11	12/16/2014 0:00	12	18992	2	674149	Gerber Puffs (Apple, Banana) 42g x 6
12	12/16/2014 0:00	12	18994	1	36285	KS Signature Walnuts
13	12/16/2014 0:00	12	18994	2	321063	KS Mixed Nuts 1.13kg
14	12/16/2014 0:00	12	18994	3	443313	StarbucKS Via Ready Brew Italian Boast
15	12/17/2014 0:00	12	18998	1	11053	Nestle Coffee-mate 400g
16	12/17/2014 0:00	12	18998	2	177173	Ferrero Nutella 350g

Figure 4.22 Sales Data imported from SQL server

Referring to Figure 4.23, after data importing, the ARM tool (referred as "Associate Wizard") is initiated. The transaction ID and item are set by choosing the correct columns in the table. Also, the minimum support and confidence thresholds (referred as "Minimum support" and "Minimum rule probability" in the interface) are set in the tool to determine the strictness of rules generation.

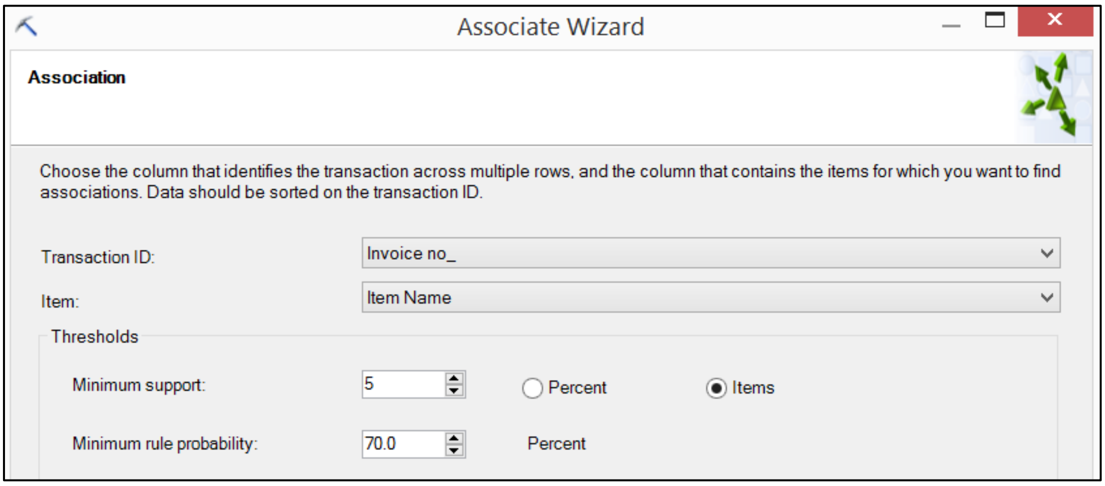


Figure 4.23 Initiation of the ARM tool

A trial-and-error approach is used to define suitable thresholds. The trial results of PMC state that the minimum support and confidence thresholds should be set to be 5 items and 70% respectively. Referring to Figure 4.24, the rules generated by the associate wizard are shown. 60 rules are found to comply with the two thresholds. The rules indicate which items are sold with which other items in the same transaction. For example, a type of Fish Oil and DHA product is always (confidence=100%) sold with a type of calcium supplement (the highlighted rule). The “Importance” of the rules is calculated according to the number of transactions of the involved items. For PMC, the rules with low “Importance” are still usable, because the unpopular items should also be well located. As long as the rules meet the minimum confidence threshold, they can be references for the warehouse operator.

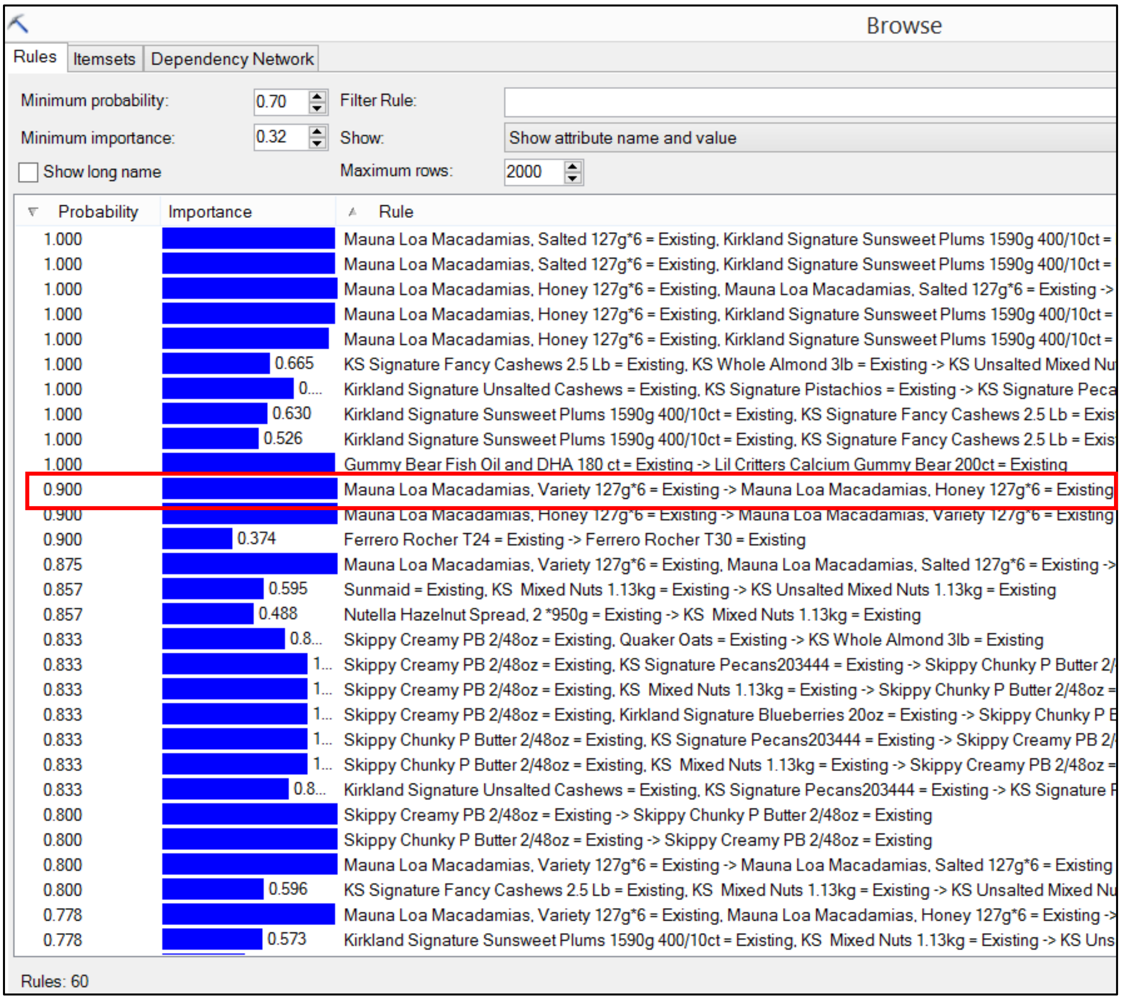


Figure 4.24 Rules generated by the Associate Wizard

In Figure 4.25, the itemsets in different sizes are listed by the associate wizard. The itemsets are the combinations of 2 or more items found in the same transaction that exist more than 5 times in the database. They are all potential association rules that have not been filtered by the confidence threshold. Since only the relationships between two or more products are of interest to the decision maker, the minimum itemsets size can be set to 2.

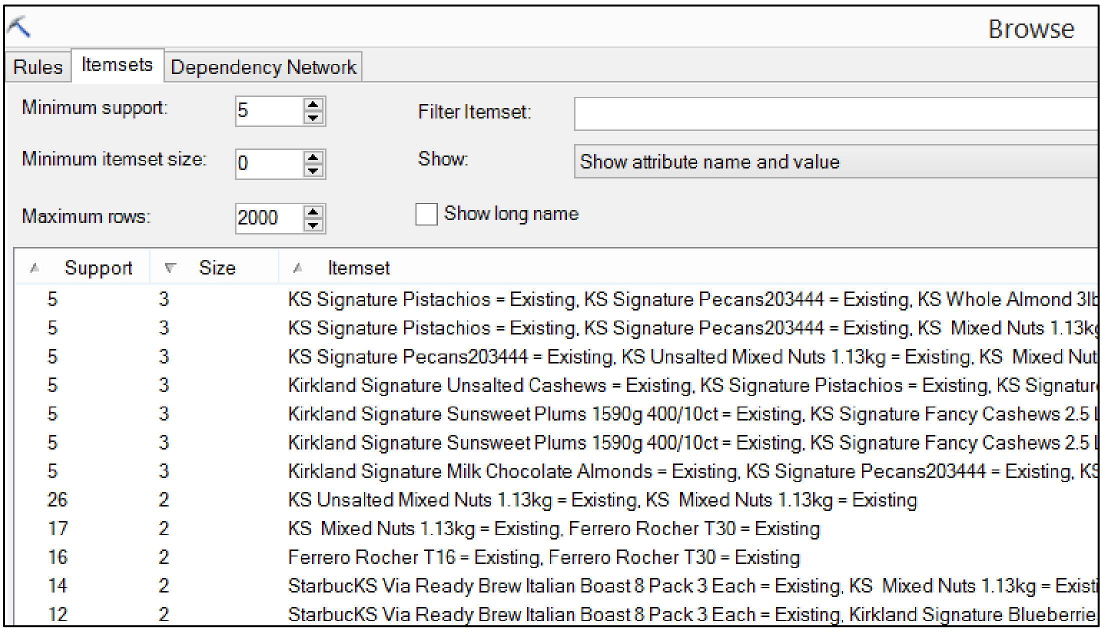


Figure 4.25 Items sets discovered by the Associate Wizard

Finally, the rules are exported from the rules browser to an Excel sheet for further processing and record, as shown in Figure 4.26.

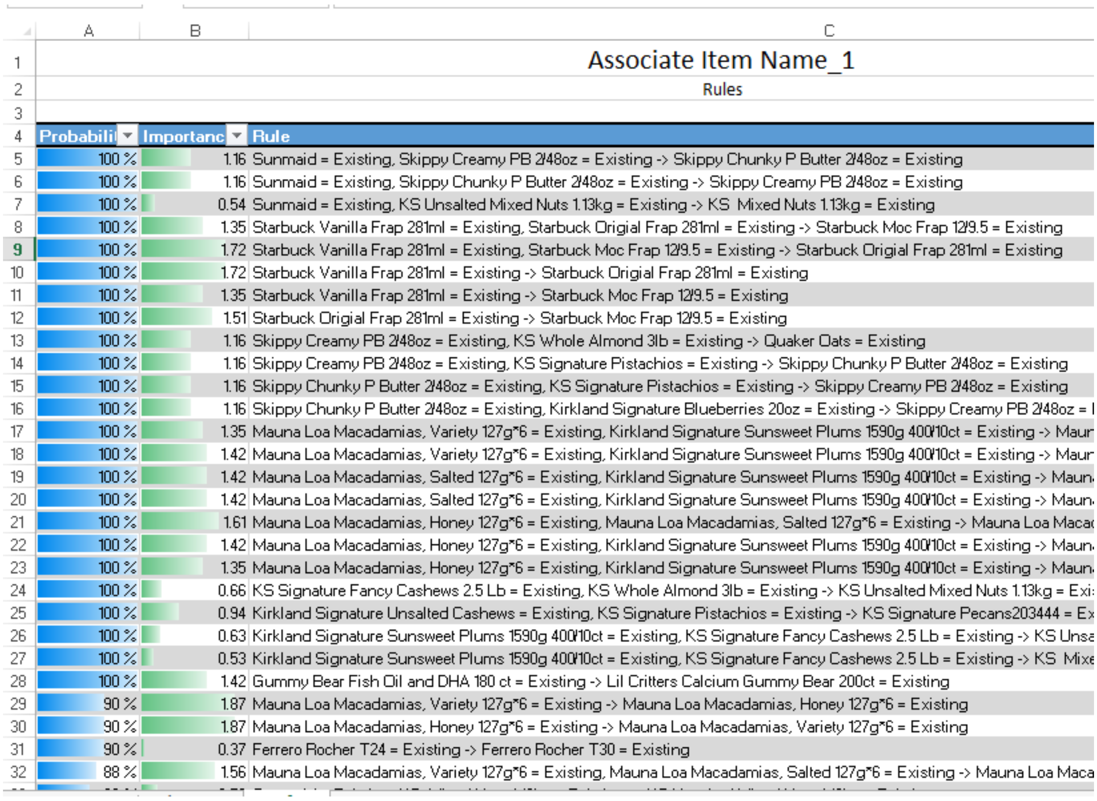


Figure 4.26 Association rules being copied to an Excel sheet

User Interface Application

When warehouse operators choose to generate allocation guidelines with a new set of association rules, they can use the functions in the box located at the lower right corner of the interface shown in Figure 4.19. By clicking the “Data mining Add-in” button, the SQL server data mining add-in enabled file is opened and the steps in implementing ARM can be completed. After rule mining, users can click the “Update Database” button in the interface to refresh the database with the new rules. Finally, the user can click the “Generate” button to obtain the allocation guideline that includes the results of ARM.

After the system is ready, SOPs regarding PMC’s storage location assignment operations are established to make use of the analysis results. A document recording the new set of SOPs that contain the usage of R-CLATS is created. The file, namely, Storage Location Assignment Standard Operating Procedures, is shown in Figure 4.27. It describes the steps that the parties involved should take from before the arrival of a container to after the dispatching of a container. With the report, the related parties, i.e. warehousing clerk and stock keeper, are trained to comply with the SOPs when handling storage location assignment.

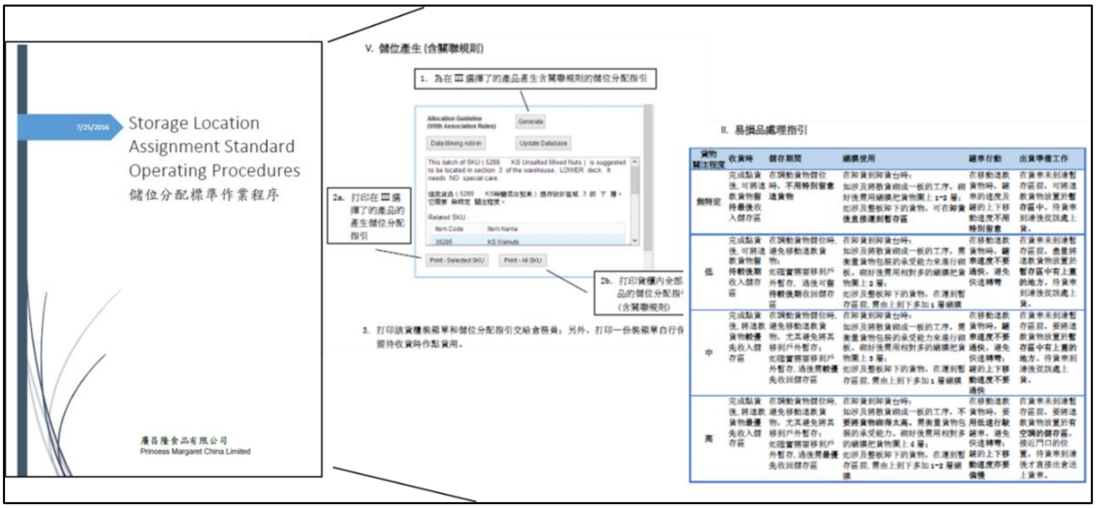


Figure 4.27 Storage Location Assignment Standard Operating Procedures for PMC

4.4 Summary

To summarize, a case study is done in PMC to initiate a pilot run of R-CLATS. Given the problems facing PMC, i.e., lack of allocation guidelines, slow decision making in SLAP, and inadequacy in e-fulfilment, R-CLATS is impemented in the compnay to improve its SLAP-related operations. The four phases of implementation, namely, Installation of RFID devices, Construction of cloud database and OLAP, Development of Variable Selection Module, and Development of Location Assignment Module, are successfully carried out. The methods of system development, data extraction, variable definition and knowledge base construction methods are demonstrated in this chapter. How the user interfaces are incorporated with the backend programmes, such as Matlab fuzzy toolbox and MS SQL Server Data Mining Add-in, in order to run the analyses, is also illustrated. For each analytical module, KPIs are set by the management to evaluate performance. After collecting the first-round of the KPI figures, the management sets a target value for each KPI. According to the latest value of the KPIs, the if-then rules in the fuzzy toolbox and parameters and thresholds concerning the data mining approaches are adjusted. Moreover, the membership functions and fuzzy sets can be refined when necessary. The system design is proven to be applicable in this chapter. The effectiveness of the system, however, is evaluated in the next chapter.

Chapter 5 Results and Discussion

The problems facing a packaged food warehouse are studied in this research, where such problems are mainly related to the decision making in SLAP. In order to assist the decision makers in the warehouse, R-CLATS is proposed. This system applies RFID, cloud infrastructure, FARM, FL and ARM to perform different functions that aim at improving the activities and decision making in the warehouse. The design and feasibility of R-CLATS is tested and described in the last chapter while the performance and contribution of the system are evaluated in this chapter. This chapter is divided into five sections. Firstly, a comparison between the current and the proposed approaches in performing the warehouse activities is done. Secondly, a performance evaluation of R-CLATS is implemented through analysing figures of several indicators obtained from the case study. Thirdly, a validation of the fuzzy-based methodology is initiated. Fourthly, the contribution of this research towards the related research area is reviewed by a comparison between the existing work and R-CLATS. Finally, a cost analysis on system implementation is carried out to acknowledge the cost effectiveness of the system.

5.1 Comparison of current and proposed approach

In this section, the proposed approach is evaluated through comparing the warehouse activities involved in both the traditional and R-CLATS approaches. Five warehouse activities are chosen according to the scope of this study. These five activities include product receiving, product tracking, storage location assignment, vulnerable product handling and knowledge retention. The differences in these warehouse activities under both approaches are observed from the case study of PMC and summarized in Table 5.1. In general, the traditional approach adopted by PMC mainly relies on manual resources such as experience, memory and personal judgment. In contrast, the R-CLATS approach uses technologies and computer resources in the decision making and information recording. The differences between the two approaches involving particular warehouse activities are summarized in Table 5.1, and are then explained in detail.

Table 5.1 A comparison of warehouse activities under the traditional and R-CLATS approaches

Warehouse Activities	Traditional Approach	R-CLATS Approach
Product receiving	Manual data input to record newly received product	Automatic recording of newly received products through RFID application
Product tracking	Rely on personal memories to remember product location, usually cannot recall the locations of different product lots	Use X-, Y- and Z- coordinates set with the RFID system to record locations of different product lots
Storage location assignment	Based on experience and personal judgment to allocate products in the warehouse	Based on recommendations provided by the system that are obtained through multiple analytical processes
Vulnerable product handling	Treat product damaging as inevitable and take no or little precautionary action	Identify vulnerable products by the system and suggest SOPs to handle those products to prevent product damaging.
Knowledge retention	Do not perform knowledge retention	Packaged food handling-related knowledge is retained in the knowledge base embedded in the system

i. Product receiving

Traditionally, when a container arrives at the warehouse, stock keepers would check the received quantity and quality of the products before storing them in the storage area. After the checking, the form used to record the details of the received products would be sent to the office. A clerk would then manually input the information into the ERP system. With R-CLATS, after checking the quantity and quality of the products, the tags which contain the information are placed on the pallets. When the pallets pass the RFID antennas, the relevant information including product location expressed in specific coordinates is recorded into the ERP automatically. The automatic data capturing ability enable a timely, quick and accurate data entry to refresh the system. Human resources for the related manual work involved are thus saved.

ii. Product tracking

Under the traditional approach, stock keepers rely on their memory to remember the locations of different products. Sometime, when the same SKU is stored in different containers and arrive at different times, the SKU would be stored in a separate area. The reliance in memory to recall product locations renders slow order picking, especially when the order states specifically the expiry date requirement of the food, which happens quite often. In such a case, stock keepers have to spend extra time to search for the right product as remembering the locations of pallets with different expiry dates is almost impossible. After using R-CLATS, the product locations with the expiry date information are available instantly. The RFID technology embedded in the system enables automatic product tracking. Therefore, even if pallets are moved around the warehouse, the most updated locations are known. Furthermore, in case there is a product recall due to food contamination, the specific product lot can be located easily.

iii. Storage location assignment

Before applying the DSS, warehouse operators allocate products to various locations according to their experience and personal judgement. Though factors such as storage temperature and popularity of a product are sometime considered during the decision making process, not all relevant factors are included, especially when the decision maker is inexperienced. Besides, the decision making time is often quite long due to complexity of the SLAP. After using R-CLATS, warehouse operators can allocate products based on recommendations offered by the system. Since the system takes the relevant factors in consideration and goes through multiple analytical processes before generating the recommendations, the allocation guideline is more comprehensive. Moreover, since a computer system is not affected by emotional feelings such as stress brought by time constraints, it can offer consistent solutions to users within a predictable duration. With the help of the system, warehouse operators can save time in SLAP handling to undertake other warehouse operations.

iv. Vulnerable product handling

Traditionally, product damage seems to be inevitable to stock keepers. They take little or even no precautionary action to prevent product damage, instead, they transfer the defective products to a display room or simply dispose them when they found. In such cases, loss incurred in the damaged product is not minimized. The R-CLATS approach, on the other hand, helps to identify vulnerable products according to historical data. Moreover, different sets of SOPs are suggested according to the extent of the vulnerability of the products to the stock keepers. The SOPs are with the allocation guideline and SOPs, and stock keepers become more aware of the vulnerable products. Subsequently, even though there are still defective products, the number of damaged products caused by careless product handling is reduced.

v. Knowledge retention

The warehouse which adopts the traditional approach usually does not have the means to retain knowledge or does not even attempt knowledge retention. Various operational decisions are mostly based on experience. Knowledge transfer between warehouse personnel most commonly takes the form of oral communication. These kinds of knowledge management practices easily cause knowledge loss. In contrast, knowledge retention is a major component of the R-CLATS approach since the analysis processes are based on the knowledge expressed in rules that are stored in the system. Therefore, when developing and refining the system, knowledge related to packaged food handling is retained. Moreover, the knowledge embedded in the system is improved whenever refinement of the decisive rules is made according to the KPI evaluation results.

In summary, various warehouse activities are facilitated by R-CLATS. The performance of the system should therefore be evaluated to understand to what extent the system help in achieving more efficient and effective storage operations in a packaged food warehouse.

5.2 Performance evaluation

The effectiveness of R-CLATS has to be evaluated through comparing KPIs involved in different fields concerning a packaged food warehouse. Figures for seven KPIs are collected in the case company for evaluation. For PMC, the seven KPIs are categorized into three aspects, namely, operational efficiency, quality of products and tracking ability. PMC’s management plans to review the outcome regularly every month during the peak season, and every two months during the quiet season. The pilot run in PMC lasted for 6 months, where around 4 months were used for work involved in phase 1 to phase 4 of the implementation, and the remaining 2 months were for observing the implementation results. During the observation period, 35 forty-foot high cube containers arrived at the warehouse. The KPIs were measured before and after implementing R-CLATS for one and two months for calculating the improvement rate in using the system. The results concerning each KPI are explained in the following subsections.

5.2.1 Operational efficiency

The KPIs that are used to evaluate the operational efficiency of the warehouse are Time spent on SLAP, Average Order Picking Time and Average time spent in data entry. The results concerning each KPI are listed in Table 5.2.

The KPI, the Average Time Spent on SLAP, is measured by the average time difference between when the batch of pallets finish discharging at the unloading dock, and when that batch of pallets is fully stored in the warehouse. After the implementation of R-CLATS for one month, an 11.8% reduction in the Average Time Spent on SLAP is achieved. A higher percentage of 19.6% of the same KPI is achieved after 2-months of implementation. The improvement is explained by warehouse operators being able to make location assignment decisions in a quicker manner, after referring to the recommendations provided by the system instead of manually deciding the locations for every SKU.

Table 5.2 Comparison of KPIs related to operational efficiency

KPIs	Before R-CLATS	After R-CLATS (1 month)	After R-CLATS (2 month)	Improvement (1 month)	Improvement (2 month)
Average Time Spent on SLAP	51 mins	45 mins	41 mins	11.8 %	19.6 %
Average Order-picking Time (< 4 pallets)	38 mins	26 mins	23 mins	31.6 %	39.4 %
Average Order-picking Time (>= 4 pallets)	55 mins	43 mins	42 mins	21.8 %	23.6 %
Average Time Spent in Data Entry	152 mins	112 mins	104 mins	26.3%	31.6%

Regarding the KPI “Average Order-picking Time”, it starts to count after an order is communicated to the stock keeper until the ordered pallets are picked up and are ready to be delivered. This KPI is separated into two category according to number of pallets involving in the orders, because the layout of PMC's warehouse renders a more time consuming order picking process for large orders. However, the average time spent on order-picking for both categories is cut by more than 20% after using R-CLATS. The results imply that the storage locations suggested by the system incur shorter travelling distance and less unnecessary movements of pallets. The results concerning small orders (<4 pallets) are better than that of large orders because the travelling from I/O points to the inner pallets is unavoidable if the order involves more pallets.

For the KPI "Average Time Spent in Data Entry", it is measured by the average time spent on manual data input/ correction and data validation in the system per day. These activities have to be triggered by product receiving, order fulfilment and product disposal activities that cause the movements of products in the warehouse. The average time spent in data entry is cut by 26.3 % and 31.6 % after applying R-CLATS for one and two months respectively. The reason for the improvement is that RFID automatically records the date, SKU and number of the product movements in the warehouse. The manual data entry work is thus reduced. However, since the clerk stills needs to validate the changes made by RFID, and the system is not applied to the whole warehouse yet, so the improvement rate is not as high as expected.

The improvements in all KPIs related to operational efficiency indicate that R-CLATS is able to enhance the warehouse's efficiency by speeding up its decision making, order picking and data entry operations. Besides, better results are found after implementing the system for 2 months. This shows the adaptability of the warehouse personnel in making use of the system, and the learning ability of the system through rules adjustment.

5.2.2 Quality of product

While it is proven in the last section that R-CLATS can enhance the operational efficiency of the warehouse, the quality of recommendations offered by R-CLATS in terms of product well-being has to be measured by another set of KPIs. These KPIs include disposal rate and return/ exchange rate of product. The results of these PKI measurement before and after R-CLATS implementation are shown in Table 5.3.

Table 5.3 Comparison of KPIs related to quality of product

KPIs	Before R-CLATS	After R-CLATS (1 month)	After R-CLATS (2 month)	Improvement (1 month)	Improvement (2 month)
Product Disposal Rate	0.0067 %	0.0052%	0.0048%	22.4%	28.4%
Product Return /Exchange Rate	2.3 %	2.0 %	1.9%	13.0%	17.4%

Product Disposal Rate calculates the ratio of the disposed quantity to the received quantity of each item in a month, where the reason for disposal has to be product damage, instead of other reasons such as being expired. After applying R-CLATS, the Product Disposal Rate decreases by 22.4 % and 28.4% in one and two months respectively. This implies that the SOPs suggested in the product allocation and handling guideline have raised the attention of stock keepers when dealing with vulnerable items. Another reason for the improvement is that SKUs that are relatively vulnerable are moved to the inner warehouse sections to avoid unnecessary contact with the forklifts and extra movements.

The Product Return/Exchange Rate calculates the ratio of the returned or exchanged quantity to the sold quantity of all items in a month. The reason for product return or exchange has to be the discovery of product damage, instead of other reasons such as food expiry. The Product Return/Exchange Rate has a light improvement of 13 %. The improvement can be originated from the lower disposal rate. As a lower disposal rate means the absolute amount of defective products is smaller, the number of problematic products for the customer is thus smaller too. However, the results are not as significant as other KPIs be because the defective products are hidden in the inner carton of the pallets, which cannot be detected, with or without the system.

The results of the KPIs shown in Table 5.3 indicate that product quality can be better maintained when the recommendations provided by R-CLATS are followed.

5.2.3 Product traceability

Since offering product traceability to the warehouse operation is another purpose of developing R-CLATS, the tracking ability of the system is thus measured by two KPIs, Location Accuracy and Accuracy of Stock Taking. The results of these KPIs are summarized in Table 5.4.

Location Accuracy is obtained by calculating the percentage of cases in which the product locations of three randomly selected products suggested by the ERP, match the actual product locations. Before adopting R-CLATS, the warehouse did not record the storage locations of products in their system. Therefore the Location Accuracy is not calculated before R-CLATS implementation. After using R-CLATS, the product locations retrieved from the system can 100% match the exact locations of the SKUs selected from the warehouse area covered by RFID. It implies that the system offers a promising product tracking ability to the warehouse.

Table 5.4 Comparison of KPIs related to tracking ability

KPIs	Before R-CLATS	After R-CLATS (1 month)	After R-CLATS (2 month)	Improvement (1 month)	Improvement (2 month)
Location Accuracy	–	100%	100%	100%	100%
Accuracy of Stock Taking	82.4%	90.7%	89.7%	10.0%	8.9%

In addition, the Accuracy of Stock Taking of the warehouse is enhanced too. This KPI measures how many SKUs have a matched record between the quantity provided by the ERP and the quantity counted during the monthly stock taking, given a total of 194 SKUs in the warehouse. This KPI can reflect whether R-CLATS can track the movement of pallets, especially for the outbound movements, in order to prevent product loss. The Accuracy of Stock Taking is improved from 82.4 % to 90.7% and 89.7% after applying the system. Therefore in general, RFID is adequate for serving the purpose of retrieving real-time data and tracking products, in turn enhancing the product traceability in the warehouse. The accuracy, however, has not reached 100% because only a part of the warehouse area is using the system. For the rest of the pallets, manual recording of the outbound quantity is still adopted, which may involve human error during rush hours.

The comparison results suggest that all KPIs are improved. The improvement achieved after implementing the trial run of R-CLATS proved that the system is able to offer a quick and quality solution to SLAP for warehouse operators. It provides allocation guidelines and retains product handling knowledge to enhance operational efficiency, maintain product quality and enable product traceability.

5.3 Validation of the fuzzy-based methodology

Although R-CLATS is proven to be effective and efficient in helping a packaged food warehouse in the last stage, the methodology of using FL as the prime analytical techniques has to be verified to validate the system. In this section, R-CLATS is compared with a rule-based system (RBS). The RBS has the same, input variables, output variables and relationships between the variables as the R-CLATS. The difference between the two systems is that the variables of the RBS are not fuzzified, they only contain rigid categories to compare the input and output crisp values. The comparisons are done using 54 SKU records from three 40' incoming containers of PMC. The first 10 sets of results generated by the two systems are shown in Table 5.5 as an example.

The results generated are converted into two indicators for the results comparisons, the indicators being travelling distance and product retrieving duration. The average travelling distance and product retrieving duration involving the storage locations in the PMC

Table 5.5 The outcomes generated from the same sets of data by R-CLATS and RBS

Output Variables:		Warehouse Section		Vertical Level	
Record	**SKU Item Number**	**R-CLATS**	**RBS**	**R-CLATS**	**RBS**
1	58959	1.5	2	2	2
2	740652	2	2	1	1
3	36285	2.5	2	1	1
4	576921	2.5	3	1	1
5	803364	2.5	3	2	2
6	203444	2.5	3	1	1
7	611239	3.5	4	1	1
8	18328	3.5	4	2	1
9	411016	3.5	4	2	1
10	879520	3	3	1	1

warehouse are listed in Table 5.6. The Average travelling distance from XY to the I/O point indicates how many meters on average, are involved in retrieving a pallet located in Warehouse Section X and Vertical Level Y, to the I/O point of the warehouse. The Average product retrieving duration from XY to the outbound area means how many minutes on average, does it take to retrieve a pallet located in Warehouse Section X and Vertical Level Y, to the outbound area for delivery preparation. Since retrieving pallets that are placed at level 1 involve double effort by taking away the pallets above, larger values can be found where the indicators concern vertical level 1.

After calculating the two indicators of the 54 SKU records, the Total travelling distance and Total product retrieving duration concerning the records are obtained and shown in Table 5.7. R-CLATS outperforms RBS at 4.6% and 6.1% in terms of travelling and product retrieving duration respectively.

The results comparison of R-CLATS and RBS prove that FL is able to provide a more precise storage location then the traditional approach that rigidly categorizes variables. This

Table 5.6 Average travelling distance and product retrieving duration involving the storage locations

	Vertical Level (Y)	Warehouse Section (X)									
		1	**1.5**	**2**	**2.5**	**3**	**3.5**	**4**	**4.5**	**5**	**5.5**
Average travelling distance from XY to I/O point (meter)	**1**	1.2	3.6	6.0	8.4	10.8	13.2	15.6	18.0	20.4	22.8
	2	0.6	1.8	3.0	4.2	5.4	6.6	7.8	9.0	10.2	11.4
Average product retrieving duration from XY to outbound area (minute)	**1**	0.83	0.87	2.67	3.82	4.95	6.05	7.22	8.68	9.88	10.5
	2	0.52	0.26	2.38	3.47	4.57	5.65	6.82	8.23	9.58	10.1

precision helps to avoid placing pallets in the inner area, rendering shorter travelling distance and product retrieval time, and thus a more efficient order-picking process. The precision exists because variables, including *Warehouse section* and *Vertical level*, can be separated in detail under fuzzification. Due to this advantage, the more warehouse sections and vertical levels the warehouse has, the more benefits the R-CLATS would bring to the decision maker.

Table 5.7 Results comparisons of R-CLATS and RBS

	R-CLATS	**RBS**	**Difference**	**Difference in percentage**
Total travelling distance from XY to I/O point (meter)	483.6	507.0	- 23.4	- 4.6%
Total product retrieving duration from XY to outbound area (minute)	249.1	265.3	- 16.2	- 6.1%

5.4 Comparison with existing work

Besides improving the operations in a packaged food warehouse, the contribution of this paper towards the related research area is reviewed by a comparison between the existing work and R-CLATS. They are compared in terms of objectives, tools, product tracking ability and decision support ability. The results of comparison are summarized in Table 5.8.

RFID has been embedded in operational systems to enable the product tracking ability. For instance, Mainetti et al. (2013) proposed a RFID-based system to track the movements of vegetables. However, the information gathered by RFID was solely used for tracking the product and maintaining the product information along the chain, but not applied in decision support. On the other hand, Yeh et al. (2011) did make use of the real-time information obtained by RFID in decision making, but the decision was related to replenishment rather than SLAP. Their work is thus not adequate in the field of decision support in SLAP.

Besides the applications of RFID in product tracking, existing work is done in improving the automatic data retrieval technologies. For example, Li & He (2014) formulated a model incorporated with artificial immune network to mitigate collision problem of RFID reader, while Zhou et al. (2013) presented a metric for evaluating fingerprint-based Wi-Fi localization more efficiently and reliably. The objectives of these kinds of work, however, are different from that related to the proposal of a decision support system. Therefore these approaches cannot directly help the decision makers who work in the operational fields.

To help the decision maker, researchers have proposed various RFID-based DSS (RFID-DSS). Chow et al. (2006) and Tan and Chang (2010) illustrated the usage of RFID-DSS in allocating warehouse equipment and providing better service in restaurant respectively. In their work, the decision support functionality of the system were well performed. However, RFID was applied to track equipment or to read membership card, instead of tracking products. Therefore, they are not the suitable DSS that can handle SLAP and enable product traceability at the same time. Choy et al. (2014) did propose a RFID-DSS that seeks to tackle SLAP. The product tracking ability of the system, however, was not evaluated. Besides, the objective of the system is to enhance the order-picking efficiency in the warehouse, therefore the attributes considered were not comprehensive enough to include the storage requirements of products, particularly that of food products.

Table 5.8 Comparison between R-CLATS and existing systems

Proposed and existing systems	**Objective(s)**	**Tool(s)**	**Product Tracking**	**Decision Support Ability**
R-CLATS	To assign storage locations that can both improve operational efficiency and maintain food quality, and to enable food tracking	RFID, OLAP, FARM, FL, ARM	Well-performed	Relatively high - attributes considering the popularity, storage requirements and vulnerability of food package are considered to generate comprehensive assignment and handling guidelines. The range of SKU storage time can be predicted.
RFID-based fresh vegetable tracing and tracking system (Mainetti et al., 2013)	To improve the data collection and maintenance procedures concerning the fresh vegetables supply chain	RFID, NFC	Well-performed	Not applicable - the proposed system aims to improve the data collection and maintenance processes, therefore does not provide the decision support functionality
Intelligent service-integrated platform (Yeh et al., 2011)	To actively monitor inventory status of malls and stores, in order to replenish at the right time	RFID, software agent	Well-performed	Relatively high - sales quantity is instantly reflected to the database, which provides up-to-date information for decision making in replenishment
AINetHE-RA (Li & He, 2014)	To mitigate the RFID reader collision problem	Artificial immune network	Not applicable	Not applicable - the proposed approaches aims to evaluate or improve the existing tools, therefore does not provide the decision support functionality
Localization entropy performance metric (Zhou et al., 2013)	To propose a novel performance metric for evaluating the accuracy of fingerprint-based Wi-Fi localization	Centro-symmetric N x M model, logarithmic attenuation model	Not applicable	

RFID-RMS (Chow et al., 2006)	To allocate warehouse material handling equipment effectively so as to maximize the use of it	RFID, CBR, UWB, integral-linear programming	Not applicable	Relatively high - time is reduced to select the appropriate resource package, while real time location of equipment is available to facilitate quick equipment allocation
RFID-based e-restaurant system (Tan & Chang, 2010)	To provide better customer- centered service for members of restaurants	RFID, WLAN, PDA	Not applicable	Relatively high - past consumption records and preferences are retrieved in real-time for accurate food recommendations
RFID-SAS (Choy et al., 2014)	To suggest storage locations that can enhance the order-picking efficiency	RFID, FL	Not evaluated	Reasonable - basic attributes such as product dimensions, volume and popularity are considered to generate assignment guidelines that target on reducing order-picking time

After reviewing the aforementioned approaches, three limitations of the existing work for helping the packaged food industry are implied. First of all, integrative approaches that include both tracking and decision support functions are still sparse. Secondly, even if the integrative approaches are proposed, they are not aimed to solve the SLAP in packaged food industry. Finally, despite of the availability of a RFID-based SLAP handling system, its objective is similar to that of other SLAP handling approaches. It seeks to enhance operational efficiency but overlooks the importance of food quality maintenance. These limitations highlight the need of R-CLATS for the packaged food industry. Unlike non-edible products, packaged food products have to comply with specific storage requirements. In addition, product tracking ability of the system is crucial to the safety in food supply chain. R-CLATS applies RFID, OLAP, FARM, FL and ARM to provide allocation guidelines that improve both operational efficiency and product well-being in a warehouse. Besides, it enables reliable real-time product tracking with RFID. Furthermore, it can predict the range of SKU storage time. Therefore R-CLATS, which integrates the usage of RFID, FARM, FL and ARM, is believed to be a novel approach for solving the storage-related problems in the packaged food industry.

5.5 Cost analysis on system implementation

After reviewing R-CLATS in terms of its operational performance enhancement ability methodology and novelty, its cost effectiveness is evaluated in this section. A cost analysis regarding the implementation of R-CLATS is initiated. The results of the analysis is summarized in Table 5.9.

In Table 5.9, the total cost of implementing the system is around HK$ 321800, which include the costs for purchasing RFID equipment, cloud infrastructure and the labour costs for physical mounting, and system set up. Meanwhile, the maintenance cost and the operational costs involved before and after implementing the system, i.e. average labour costs for order-picking and data entry, and average costs incurred in product disposal and missing per month are listed in the table.

Table 5.9 Cost Analysis of R-CLATS implementation

	Implementation Cost (HK$)	**Before Implementa-tion (HK$)**	**After Implementa-tion (HK$)**
RFID equipment including antennas, tags and readers, physical mounting, and cloud infrastructure	237,800	-	-
System set up [a]	84,000	-	-
Maintenance cost per month [b]	-	-	17,000
Average labour cost for order-picking per month	-	50,000	35,000
Average labour cost for data entry per month	-	13,000	9,100
Average cost incurred in product disposal and product missing per month	-	43,000	26,000

[a] Labour costs of two full-time system developers
[b] Labour cost for a system operator and cost for cloud infrastructure

The saving brought by R-CLATS per year can thus be calculated as:

[(Average labour cost for order-picking per month before implementation -Average labour cost for order-picking per month after implementation) +(Average labour cost for data entry per month before implementation -Average labour cost for data entry per month after implementation) +(Average cost incurred in product disposal and product missing per month before implementation -Average cost incurred in product disposal and product missing per month after implementation) - Maintenance cost per month after implementation] x 12

= HK$ [(50,000-35,000) + (13,000-9,100) + (43,000-26,000) - 17,000] x 12
= HK$ 226,800.

According to the calculated saving per year, the expected break-even point of R-CLATS implementation is:

HK$ (Money invested / saving per year) = HK$ (321,800 / 226,800 per year) = 1.4 years

Based on the calculation, it takes around 1.4 years to justify the investment in R-CLATS. However, since the system will bring continuous savings to the warehouse as the system is continuously improved, it is likely that the proportion of the costs to the savings would be less than expected. Subsequently, the company can justify the investment in less than 1.4 years.

Furthermore, the above cost analysis is based on the pilot run of the system. If the system is applied in full-scale in the warehouse, the proportion of the initial set up costs and the maintenance costs to the year savings tends to be smaller. Given the company size of a SME, the RFID implementation costs would increase according to the size of the warehouse labour. Meanwhile, the system set up costs and maintenance would not increase much because these two costs involving a small-sized or an expanded R-CLATS system should be similar. On the other hand, the saving brought to the company would be larger as the operational efficiency and product disposal would be further improved. Therefore, a shorter break-even point would be achieved if the system is run on full scale.

5.6 Summary

In this chapter, R-CLATS is evaluated thoroughly from reviewing the effectiveness and efficiency that it brought to the warehouse operations, its methodology, to its novelty in academia and cost effectiveness. It is proven that R-CLATS is able to offer allocation and product handling guidelines that bring higher operational efficiency, product quality and traceability to a packaged food warehouse. In addition, the locations obtained through FL are proven to be more precise than that obtained through rigid rule-based reasoning. Furthermore, it is a novel integrative DSS that enables product tracking and comprehensive SLAP handling for the packaged food industry. Finally, the cost analysis has justified the investment made in R-CLATS with the savings that it brought. Overall, R-CLATS brings positive impacts to the packaged food warehouse and the related research areas.

Chapter 6 Conclusions

The performance, methodology, novelty and cost effectiveness of R-CLATS are evaluated in the last section. The results show that the system is able to provide decision support functions to the warehouse operator, who can in turn make better decisions in SLAP. Subsequently, the operational efficiency, product quality maintenance and product traceability in the warehouse is enhanced. After the system validation, conclusions on the research are given in this chapter. A summary of the research is first presented. Afterwards, the contribution of the research is reported in accordance with the research objectives. Finally, the limitations of the system and future work are suggested.

6.1 Summary of the research

For the packaged food industry, the increasing concern for food safety and the emergence of e-retailing have brought great challenges to the packaged food e-fulfilment warehouses. In general, these warehouses have been facing problems in lacking allocation guidelines, knowledge retention mechanisms, storage time prediction mechanisms and an accurate real-time tracking system. This research proposes an intelligent DSS that can assist the warehouses in tackling the problems. The literature review identifies the specific warehouse operations that should be handled, to study the automatic data retrieval technologies and cloud-based DSS and to learn about various data mining and artificial intelligence techniques. It is learned from the literature that SLAP is the major operational problem that needs to be focused on. Besides, technologies such as RFID and cloud computing, and techniques such as FARM, FL and ARM are the suitable components for developing the intelligent system. Subsequently, a system called R-CLATS is proposed to serve the research objectives.

R-CLATS is composed of four modules. DCM automatically retrieves data regarding the received products and the movements of products through RFID. The data retrieved is then organized and integrated to generate information in ICM, which applies CDB and OLAP. The information generated is used in VSM and LAM. In VSM, FARM is selected as the data mining technique to find the most relevant parameters for the range of SKU storage times, and then to predict the storage time of various SKUs. Finally, LAM provides recommendations in product allocation and handling plan to warehouse operators, with the usage of FL and ARM.

The feasibility of the system is tested through a case study initiated in a packaged food company PMC. Before applying the system, PMC lacked allocation guidelines to handle packaged food which needs special care. It also was not equipped with a product tracking system, which supports remediation measures during food contamination outbreaks. In contrast, after applying R-CLATS, the operational efficiency and effectiveness of the warehouse are enhanced. To be specific, the case company adopts R-CLATS to recognize vulnerable products, in order to take precautions to avoid damage. As a result, the number of damaged product and the frequency of product return/exchange requested by the customers are reduced. Besides, product traceability becomes available in the warehouse. The case study proves that the design of the system is feasible and the case company is benefited from applying it.

To further validate the system, its performance, fuzzy-based methodology and cost effectiveness are evaluated. The results of KPIs measured before and after R-CLATS implementation show that the system can improve the operational performance of a packaged food warehouse. Moreover, the fuzzy-based methodology can out-perform traditional systems that use rigid crisp intervals, because fuzziness can offer more precise solutions. Finally, the cost analysis shows that investment in R-CLATS implementation can be justified, especially if in a full-scale implementation in the warehouse.

6.2 Contributions of the research

Recalling the objectives of this research, (i) to design a comprehensive system for packaged food storage, (ii) to employ efficient and reliable technologies for data retrieval and consolidation, (iii) to predict the range of storage time of packaged food products, and (iv) to establish a decision support module with AI for decision support and knowledge base construction, the contributions of this research in relation to these research objectives are summarized as follows:

(i) R-CLATS is able to provide comprehensive services for the packaged food industry. It successfully integrates a DSS with a RFID tracking system to offer more accurate, comprehensive and timely assistance in packaged food warehouse operation. The enhanced Location Accuracy reflects the effectiveness of the system in raising the product traceability in the warehouse. In the past when such a system is not available, the effort and resources needed in tracking the lot numbers of products was unaffordable for the company. With the help of RFID, R-CLATS automatically records every movement in the warehouse, including the storage location and lot number for each batch of products, into the ERP in real time. Besides, as mentioned in Chapter 5, R-SALTS can offer comprehensive SLAP solutions to the warehouse operator, in turn enhancing the operational efficiency and maintaining the food quality in a packaged food warehouse. All components of R-CLATS thus contribute to a more efficient and safer supply chain for packaged food.

(ii) This research demonstrates a successful integration between RFID, cloud infrastructure and a local decision support system. The usage of RFID enhances the visualization of the real-time situation in a warehouse in order for the system to offer timely and accurate decision support. In addition, the partial employment of cloud-based resources, i.e., applying only DaaS and IaaS but not AaaS, brings the benefits of using a scalable database, which can cope with unexpected increase or decrease of the data amount under the dynamic e-retailing business environment. Meanwhile, this practice can save the cost of unnecessarily buying computing resources for analytical modules development.

(iii) The methodology of using FARM in variable selection and range of storage time prediction in the VSM is a novel yet practical approach in the field. The fuzzy component of FARM enables a description of the parameters, which gives a more detailed explanation of the relationship between the parameters. Meanwhile, besides the confidence and support count thresholds, the discrepancy threshold further strengthens the rule selection process. Therefore, the system only keeps the rules that have strong prediction power for further usage.

(iv) In the LAM of the system, FL is integrated with ARM to offer more comprehensive product allocation and handling guidelines. This integrative approach is sparsely found in the existing literature but is proven to be effective for SLAP handling. While previous study related to SLAP mainly aimed at improving operational efficiency, R-CLATS takes the initiative of applying FL to consider imprecise factors, such as vulnerability and sensitivity to external environment for SLAP handling. This application of FL can provide recommendations that fit the storage requirements of packaged food. Meanwhile, ARM can effectively cultivate the ordering patterns of the SKUs. The integrative approach can therefore demonstrate how to generate SLAP solutions that can both improve the operational efficiency of the warehouse and maintain the product quality. Moreover, the system is also a knowledge base which stores packaged food handling knowledge. The VSM and LAM module, which make use of FARM, FL and ARM, are able to generate, retain and apply if-then rules to offer decision support. These If-then rules represent the knowledge of the domain experts regarding their product handling and decision making methods. Therefore, the knowledge base constructed and embedded in R-CLATS can be treated as a way to prevent knowledge loss in the industry.

In summary, after design and implementation, the system is validated. Through comparing the validation results with the stated research objectives, it can be concluded that the research objectives are met. Moreover, with appropriate modifications, the methodology proposed in this research can contribute to industries other than the packaged food industry.

6.3 Limitation of the system

While the system can contribute to both the packaged food industry and the related research areas, the study has the following limitations:

(i) Though the proposed system is designed to fit the needs of the packaged food warehouse, the parameters of FARM, variables processed by the fuzzy inference engine used in the developed R-CLATS, are based on the requirements of the case company. These variables have to be modified case by case when applied in other companies.

(ii) Since the pilot run of R-CLATS is only applied in part of the warehouse area in the case company, the results of the implementation are affected by operations carried out in the other warehouse area without R-CLATS. For example, given the height limitation of PMC’s warehouse, only two pallets can be stored vertically. Therefore, the improvements obtained from assigning the locations into different vertical location are not comprehensively reviewed.

(iii) FARM and ARM generate rules according to the actual relationships found among the historical data with various thresholds. From time to time, the thresholds have to be reviewed based on the latest data. However, the definition of the thresholds are currently based on the trial-and-error approach which is quite time consuming. The system implementation process is thus slowed down.

(iv) The variables used in the fuzzy inference engine are currently defined based on the opinions given by domain experts and the knowledge engineer, therefore some potential variables could be omitted. Besides, several input variables are weighted equally in the fuzzy inference engine. However, in the real situation, some variables could be more important than the others. These variable determination issues could affect the quality of the recommendations given by the system.

In summary, there are four issues that should be investigated in order to improve the system, namely, the generalization of the system application, constrained validation of the system contribution, slow thresholds definition, and variable determinations for fuzzy inference engine. These limitations could be improved if appropriate modifications are made to the system. The ways to further improve the system in accordance with the four limitations are presented in the future work section.

6.4 Future work

In spite of the success of R-CLATS in fulfilling the research objectives, the system can be further improved to cope with the limitations and to contribute more to the relevant research areas. The future work related to the four limitations includes studying the system applications in other industries, implementing R-CLATS in other packaged food warehouses with less physical constraints, developing a programme thresholds definition, and conducting a survey for variables determination.

(i) Although the system aims to support the packaged food industry, which is a core part of the food industry, the whole food industry actually needs to deal with food safety concerns. The storage sector of a food supply chain is also critical to the maintenance of food's quality. Future study can modify the parameters, membership functions and variables in the analytical models of R-CLATS, in order to develop a DSS system for improving the storage operations of fresh food, or even that of other products.

(ii) To comprehensively validate the capability of the system, the research can be further proceeded in the case company and along the whole supply chain. For the case company, R-CLATS can be applied in full-scale in the warehouse to obtain a full review of its performance. Besides, the usage of the cultivated association rules could be extended to the purchasing area to improve the turnover rate of the warehouse. Furthermore, the research can be extended to the whole life of the packaged food supply chain through applying R-CLATS in different storage facilities along the chain. For example, the manufacturers and retailers of packaged food also equip with storage facilities for temporarily storing the food. By changing the components of R-CLATS according to their storage environment, the operational efficiency and food safety of the whole chain could be enhanced. With a larger number of case studies, a more objective evaluation of the implementation results can be done.

(iii) Regarding the effort involved in the threshold definitions in the VSM and ARM implementation, it is considered as time-consuming if the definition mainly relies on human resources. However, if the trial-and-error is done by machine automatically, human resources could be saved. Therefore, a programme can be developed to automatically process the trials with different combinations of thresholds, and generate a report summarizing the testing results. The system user can then determine the final thresholds based on the report. Human resources can thus be saved and the thresholds trials can be done more thoroughly.

(iv) In order to identify the parameters and variables for the system in a more comprehensive way, a survey can be implemented. Questionnaires can be distributed to various packaged food warehouses to collect opinions from different domain experts. The questionnaires would contain questions asking about their practice in SLAP and product handling, as well as the factors that they think would be important to storage time prediction and location assignment. Moreover, the relative importance of different factors should be studied, and then be reflected in the engine through adjusting the weighting of the variables.

With the above suggestions for future work, the proposed system could provide decision support functionality to the whole food industry or even to other industries. In addition, the recommendations provided by the system could be more precise and the human resources needed in maintaining the system could be reduced.

References

(No. of reference: 131)

- Accorsi, R., Manzini, R., and Bortolini, M. (2012). A hierarchical procedure for storage allocation and assignment within an order-picking system. A case study. *International Journal of Logistics Research and Applications, 15*(6), 351-364.
- Accorsi, R., Manzini, R., and Maranesi, F. (2014). A decision-support system for the design and management of warehousing systems. *Computers in Industry, 65*(1), 175-186.
- Agatz, N. A. H., Fleischmann, M., and van Nunen, J. A. E. E. (2008). E-fulfillment and multi-channel distribution – A review. *European Journal of Operational Research, 187*(2), 339-356.
- Ahn, T., Ryu, S., and Han, I. (2007). The impact of Web quality and playfulness on user acceptance of online retailing. *Information and management, 44*(3), 263-275.
- Akerkar, R. A. , and Sajja, P. S., (2010). *Knowledge-based systems*. Sudbury, Massachusetts: Jones and Bartlett Publishers.
- Amin, S. T., and Alrub, A. M. A. (2014). The Role of MKIS In Decision Making: A Conceptual Framework. *Interdisciplinary Journal of Contemporary Research In Business, 5*(9), 551-569.
- Andriulo, S., Elia, V., and Gnoni, M. G. (2015). Mobile self-checkout systems in the FMCG retail sector: A comparison analysis. *International Journal of RF Technologies, 6*(4), 207-224.
- Arendarenko, E. (2009). A study of comparing RFID and 2D barcode tag technologies for pervasive mobile applications. *Master's Thesis, University of Joensuu, Finland*.
- Ballestín, F., Pérez, Á ., Lino, P., Quintanilla, S., and Valls, V. (2013). Static and dynamic policies with RFID for the scheduling of retrieval and storage warehouse operations. *Computers and Industrial Engineering, 66*(4), 696-709.
- Barnes, C. (2016). Omni-Channel Retail — Challenges and Opportunities for Packaging Innovation. *Integrating the Packaging and Product Experience in Food and Beverages: A Road-Map to Consumer Satisfaction*, 59-76.
- Biji, K. B., Ravishankar, C. N., Mohan, C. O., and Gopal, T. K. S. (2015). Smart packaging systems for food applications: a review. *Journal of Food Science and Technology*, 52 (10),6125-6135.
- Bose, I., and Pal, R. (2005). Auto-ID: Managing anything, anywhere, anytime in the supply chain. *Communications of the ACM, 48*(8), 100-106.
- Bottani, E., Cecconi, M., Vignali, G., and Montanari, R. (2012). Optimisation of storage allocation in order picking operations through a genetic algorithm. *International Journal of Logistics Research and Applications, 15*(2), 127-146.
- Brunazzi, G., Parisi, S., and Pereno, A. (2014). The instrumental role of food packaging. *The Importance of Packaging Design for the Chemistry of Food Products* (pp. 57-86): Springer International Publishing.

- Burkard, R. E., Fruhwirth, B., and Rote, G. (1995). Vehicle routing in an automated warehouse: Analysis and optimization. *Annals of Operations Research, 57*(1), 29-44.
- Chabanne, H., Urien, P., and Susini, J. F. (2011). *RFID and the internet of things*. London : Wiley.
- Chan, F. T. S., and Chan, H. K. (2011). Improving the productivity of order picking of a manual-pick and multi-level rack distribution warehouse through the implementation of class-based storage. *Expert Systems with Applications, 38* (3), 2686-2700.
- Chatterjee, P. (2010). Causes and consequences of 'order online pick up in-store'shopping behavior. *The International Review of Retail, Distribution and Consumer Research, 20*(4), 431-448.
- Chebolu-Subramanian, V., and Gaukler, G. M. (2015). Product contamination in a multi-stage food supply chain. *European Journal of Operational Research, 244*(1), 164-175.
- Chen, J. C., Cheng, C. H., and Huang, P. B. (2013). Supply chain management with lean production and RFID application: A case study. *Expert Systems with Applications, 40*(9), 3389-3397.
- Chen, M. C., and Wu, H. P. (2005). An association-based clustering approach to order batching considering customer demand patterns. *Omega , 33* (4), 333 – 343.
- Chiang, D. M. H., Lin, C. P., and Chen, M. C. (2011). The adaptive approach for storage assignment by mining data of warehouse management system for distribution centres. *Enterprise Information Systems, 5*(2), 219-234.
- Chiang, D. M. H., Lin, C. P., and Chen, M. C. (2014). Data mining based storage assignment heuristics for travel distance reduction. *Expert Systems, 31*(1), 81-90.
- Chirici, L., and Wang, K. (2013). A'Lean'Fuzzy Rule to Speed-Up a Taylor-Made Warehouse Management Process *Digital Product and Process Development Systems* (pp. 61-72): Springer.
- Cho, S., Hong, H., and Ha, B. C. (2010). A hybrid approach based on the combination of variable selection using decision trees and case-based reasoning using the Mahalanobis distance: For bankruptcy prediction. *Expert Systems with Applications, 37*(4), 3482-3488.
- Chow, H.K., Choy, K.L., Lee, W.B., and Lau, K.C. (2006). Design of a RFID case-based resource management system for warehouse operations. *Expert Systems with Applications, 30*(4), 561-576.
- Choy, K.L., Lam, H.Y., Lin, C., Lee, C.K.H. (2013). *A hybrid decision support system for storage location assignment in the fast-fashion industry.* Proceeding of the Portland International Conference on Management of Engineering and Technology (PICMET'13), San Jose, California, USA, 28 July - 1 August 2013, pp. 468-473.
- Choy, K.L., Ho, G.T.S., and Lee, C.K.H. (2014). A RFID-based storage assignment system for enhancing the efficiency of order picking. *Journal of Intelligent Manufacturing*, 1-19.

- Chuang, Y. F., Lee, H. T., and Lai, Y. C. (2012). Item-associated cluster assignment model on storage allocation problems. *Computers and industrial engineering, 63* (4), 1171 -1177.
- Cortez, P., Cerdeira, A., Almeida, F., Matos, T., and Reis, J. (2009). Modeling wine preferences by data mining from physicochemical properties. *Decision Support Systems, 47*(4), 547-553.
- Coskun, V., Ok, K., and Ozdenizci, B. (2012). Near field communication- From theory to practice. Hoboken, N.J: Wiley.
- Costa, C., Antonucci, F., Pallottino, F., Aguzzi, J., Sarriá, D., and Menesatti, P. (2013). A review on agri-food supply chain traceability by means of RFID technology. *Food and Bioprocess Technology*, 6(2), 353-366.
- Da Silva, D. D., De Vasconcelos, N. V. C., and Cavalcante, C. A. V. (2015). Multicriteria Decision Model to Support the Assignment of Storage Location of Products in a Warehouse. *Mathematical Problems in Engineering, 2015*, 1-8.
- Delgado, M., Marín, N., Sánchez, D. and Vila, M. A.(2003). Fuzzy association rules: general model and applications. *Proceeding of the 2003 IEEE International Conference on Fuzzy Systems (FUZZ), St. Louis, Missouri, USA, 25-28 May 2003,11*(2), pp. 214-225.
- Demirkan, H., and Delen, D. (2013). Leveraging the capabilities of service-oriented decision support systems: Putting analytics and big data in cloud. *Decision Support Systems, 55*(1), 412-421.
- Desai, E., and Shajan, M. G. (2012). A review on the operating modes of Near Field Communication. *International Journal of Engineering and Advanced Technology (IJEAT), 2*(2), 322-325.
- Deshmukh, R. (2014). Review on Radio Frequency Identification Technology. *International Journal of Electronics, Communication and Soft Computing Science and Engineering (IJECSCSE), 3*(2), 1.
- Dong, M., Li, H., Ota, K., Yang, L. T., and Zhu, H. (2014). Multicloud-based evacuation services for emergency management. *IEEE Cloud Computing, 1*(4), 50-59.
- Dixon, B. E., Simonaitis, L., Goldberg, H. S., Paterno, M. D., Schaeffer, M., Hongsermeier, T., . . . Middleton, B. (2013). A pilot study of distributed knowledge management and clinical decision support in the cloud. *Artificial intelligence in medicine, 59*(1), 45-53.
- Drobnik, O. (2015). *Barcodes with iOS : bringing together the digital and physical worlds*. Shelter Island, NY: Manning.
- Elwakil, E., and Zayed, T. (2014). Construction knowledge discovery system using fuzzy approach. *Canadian Journal of Civil Engineering, 42*(1), 22-32.
- Ene, S., and Öztürk, N. (2012). Storage location assignment and order picking optimization in the automotive industry. *The International Journal of Advanced Manufacturing Technology, 60*(5-8), 787-797.
- Euromonitor International. (2014). *Global Confectionery Overview: Key Categories, Countries and Trends to 2019.* Euromonitor International.

- Fontana, M. E., and Cavalcante, C. A. V. (2014). Using the efficient frontier to obtain the best solution for the storage location assignment problem. *Mathematical Problems in Engineering, 2014,*1-10.
- Fouad, R. H., Samhouri, M. S., and Qamar, A. M. (2012). An Intelligent Preventive Maintenance Scheduling in ERP Systems: A Fuzzy Logic Approach. *International Journal of Advancements in Computing Technology, 4*(23), 651-661.
- Fujiwara, K., Sawada, H., and Kano, M. (2012). Input variable selection for PLS modeling using nearest correlation spectral clustering. *Chemometrics and Intelligent Laboratory Systems, 118*, 109-119.
- Ghiotto, A., Vuong, T. P., Tedjini, S., and Wu, K. (2008). Design of Passive Ultra-High Frequency Radio-Frequency Identification Tag. *29th General Assembly of URSI, Chicago, USA, 7-16 August 2008*,
- Ghosh, S., and Kundu, P. K. (2015). MATLAB Simulation of RFID Communication Protocol for Sensor Data Acquisition. *Sensors and Transducers, 188*(5), 91-95.
- Gill, A. (2014). A Fuzzy Set Theoretic Approach to Warehouse Storage Decisions in Supply Chains.*Supply Chain Management Under Fuzziness* (pp. 471-488): Springer Berlin Heidelberg.
- Glover, F., and Greenberg, H. J. (1989). New approaches for heuristic search: A bilateral linkage with artificial intelligence. *European Journal of Operational Research, 39*(2), 119-130.
- Goyal, S., and Goyal, G. K. (2012). A novel method for shelf life detection of processed cheese using cascade single and multi layer artificial neural network computing models. *ARPN Journal of Systems and Software*, *2*(2), 79-83.
- Gu, J., Goetschalckx, M., and McGinnis, L. F. (2007). Research on warehouse operation: A comprehensive review. *European Journal of Operational Research, 177*(1), 1-21.
- Guo, Z. X., Wong, W. K., and Guo, C. (2014). A cloud-based intelligent decision-making system for order tracking and allocation in apparel manufacturing. *International Journal of Production Research, 52*(4), 1100-1115.
- Hansen, W. R., and Gillert, F. (2008). RFID for the optimization of business processes. Chichester, England Hoboken, NJ: John Wiley and Sons.
- Ho, G. T., Ip, W., Wu, C.H., and Tse, Y. K. (2012). Using a fuzzy association rule mining approach to identify the financial data association. *Expert Systems with Applications, 39*(10), 9054-9063.
- Hora, M., Bapuji, H., and Roth, A. V. (2011). Safety hazard and time to recall: The role of recall strategy, product defect type, and supply chain player in the US toy industry. *Journal of Operations Management, 29*(7), 766-777.
- Huang, M. L., Hung, Y. H., and Chen, W. Y. (2010). Neural network classifier with entropy based feature selection on breast cancer diagnosis. *Journal of medical systems, 34*(5), 865-873.

- Hui, Y. Y. Y., Choy, K. L., Ho, G. T. S., Lam, C. H. Y., Lee, C. K. H., and Cheng, S. W. (2015). An intelligent fuzzy-based storage assignment system for packaged food warehousing. *Proceeding of the Portland International Conference on Management of Engineering and Technology (PICMET'15), Portland, Oregon, USA, 2-6 August 2015*, pp. 1869-1878.
- Hui, Y. Y. Y., Choy, K. L., Ho, G. T. S. and Lam, C. H. Y. (2016a). A Fuzzy Association Rule Mining Framework for Variables Selection Concerning the Storage Time of Packaged Food. *Proceeding of the 2016 IEEE International Conference on Fuzzy Systems (FUZZ), Vancouver, Canada, 24-29 July 2016,* pp. 671-677.
- Hui, Y. Y. Y., Choy, K. L., Ho, G. T. S., Carman K.M. Lee, C.K.H. Lee and Lam, H.Y. (2016). A RFID-based Storage Location Assignment and Tracking System for Packaged Food Industry. *Expert Systems* (Submitted for 3rd review).
- Hui, Y. 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-Fulfilment Warehouse. *International Journal of Engineering Business Management, 2016, 8*, pp.1-15.
- Iqbal, R., Ahmad, A., and Gilani, A. (2014). NFC based inventory control system for secure and efficient communication. *Computer Engineering and Applications Journal*, *3*(1), 23-33.
- Jain, N., and Srivastava, V. (2013). Data Mining techniques: A survey paper. *International Journal of Research in Engineering and Technology, 2*(11), 2319-1163.
- Jain, N. K., Gajjar, H., Shah, B. J., and Sadh, A. (2015). A Conceptual Framework for Measuring E-fulfillment Dimensions: A Consumer Perspective. *Journal of Internet Commerce*, *14*(3), 363-383.
- Jain, R., Singh, A. R., Yadav, H. C., and Mishra, P. K. (2014). Using data mining synergies for evaluating criteria at pre-qualification stage of supplier selection. *Journal of Intelligent Manufacturing, 25*(1), 165-175.
- Juan-Verdejo, A., and Baars, H. (2013). Decision support for partially moving applications to the cloud: the example of business intelligence. *Proceeding of 2013 International Workshop on Hot Topics in Cloud Services, Prague, Czech Republic, 20-21 April 2013*, pp. 35-42
- Kim, B. S., and Smith, J. S. (2012). Slotting methodology using correlated improvement for a zone-based carton picking distribution system. *Computers and Industrial Engineering, 62* (1), 286-295.
- Kim, M., Li, D., and Hong, S. (2013). A Robust and Invisible Digital Watermarking Algorithm based on Multiple Transform Method for Image Contents. *World Congress on Engineering and Computer Science 2013, San Francisco, USA, 23-25 October 2013*, pp. 23-25.
- Kofler, M., Beham, A., Wagner, S., and Affenzeller, M. (2015). Robust Storage Assignment in Warehouses with Correlated Demand. *Computational Intelligence and Efficiency in Engineering Systems* (pp. 415-428): Springer.

- Koufteros, X., Droge, C., Heim, G., Massad, N., and Vickery, S. K. (2014). Encounter Satisfaction in E-tailing: Are the Relationships of Order Fulfillment Service Quality with its Antecedents and Consequences Moderated by Historical Satisfaction? *Decision Sciences, 45*(1), 5-48.
- Kumari, L., Narsaiah, K., Grewal, M.K., and Anurag, R.K. (2015). Application of RFID in agri-food sector. *Trends in Food Science and Technology, 43*(2), 144-161.
- Lam, C.H.Y., Chung, S.H., Lee, C.K.M., Ho, G.T.S., and Yip, T.K.T. (2009). Development of an OLAP based fuzzy logic system for supporting put away decision. *International Journal of Engineering Business Management, 1*(2), 7-12.
- Lam, C. H.Y., Choy K.L., and 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, H.Y., Choy, K.L., Ho, G.T.S., Kwong, C.K. and Lee, C.K.M. (2013). A real-time risk control and monitoring system for incident handling in wine storage. *Expert Systems with Applications, 40*(9), 3665-3678.
- Lang, G., and 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), 2532-2548.
- Lee, C. K. H., Tse, Y. K., Ho, G. T., and Choy, K. L. (2015). Fuzzy association rule mining for fashion product development. *Industrial Management and Data Systems, 115*(2), 383-399.
- Lee, C. K. H., Choy, K. L., Ho, G. T. S., and Lin, C. (2016). A cloud-based responsive replenishment system in a franchise business model using a fuzzy logic approach. *Expert Systems, 33*(1), 14-29.
- Leeland, A. M. (2011). *Case-based reasoning : processes, suitability and applications*. New York: Nova Science Publishers.
- Leung, K. H., Choy, K. L., Tam, M. C., Lam, C. H. Y., Lee, C. K. H., and Cheng, S. W. Y. (2015). A hybrid RFID case-based system for handling air cargo storage location assignment operations in distribution centers. *Proceeding of the Portland International Conference on Management of Engineering and Technology (PICMET'15), Portland, Oregon, USA, 2-6 August 2015*, pp. 1859-1868
- Leung, K. H., Choy, K. L., Tam, M. C., Hui, Y. Y. Y., Lam, C. H. Y., Tsang, P. P. L. (2016a). A knowledge-based decision support framework for wave put-away operations of e-commerce and O2O shipments. *Proceeding of the 6th International Workshop of Advanced Manufacturing and Automation (IWAMA 2016), University of Manchester, UK, 10-11 November 2016, 7(5),* pp. 495-507.
- Leung, K. H., Cheng, S. W. Y., Choy, K. L., Wong, D. W. C., Lam, H. Y., Hui, Y. Y. Y., Tsang, Y. P., Tang, V. (2016b). A Process-oriented Warehouse Postponement Strategy for E-commerce Order Fulfillment in Warehouses and

Distribution Centers. *Managerial Strategies and Solutions for Business Success in Asia* (pp.21-34): IGI-Global, DOI: 10.4018/978-1-5225-1886-0.ch002.

- Li, J., Moghaddam, M., and Nof, S. Y. (2015). Dynamic storage assignment with product affinity and ABC classification—a case study. *The International Journal of Advanced Manufacturing Technology,* 1-16.
- Li, X. L., and Liu, B. (2014). Rule-Based Classification. In Aggarwal, C. C. (Ed.), *Data classification: algorithms and applications* (pp. 121-156): CRC Press.
- Li, Z., Li, J., and He, C. (2014). Artificial immune network-based anti-collision algorithm for dense RFID readers. *Expert Systems with Applications, 41*(10), 4798-4810.
- Lin, D. and Wadhwa, V. (2008). Efficiency gets a new identity: barcode and RFID in the supply chain. *Quality Progress, 41*(2), 20.
- Liu, H., Sun, J., Liu, L., and Zhang, H. (2009). Feature selection with dynamic mutual information. *Pattern Recognition, 42*(7), 1330-1339.
- López, B. (2013). Case-based reasoning: a concise introduction. *Synthesis Lectures on Artificial Intelligence and Machine Learning, 7*(1), 1-103.
- Lu, Y., Liu, Z., and Ma, L. (2016). Competing Through Logistics Management: Studies on E-Retailing in China. *E-Retailing Challenges and Opportunities in the Global Marketplace,* 256-275.
- Ma, C. Y., and Wang, X. Z. (2009). Inductive data mining based on genetic programming: automatic generation of decision trees from data for process historical data analysis. *Computers and Chemical Engineering, 33*(10), 1602-1616.
- Mainetti, L., Mele, F., Patrono, L., Simone, F., Stefanizzi, M.L., and Vergallo, R. (2013). An RFID-based tracing and tracking system for the fresh vegetables supply chain. *International Journal of Antennas and Propagation, 2013*(531364), 1-15.
- Mann, K. S., and Kaur, N. (2015). Cloud-deployable health data mining using secured framework for Clinical decision support system. *Proceeding of International Conference and Workshop on Computing and Communication (IEMCON), Vancouver, Canada, 15-17 October 2015,* pp. 1-6.
- Manzini, R., Bindi, F., Ferrari, E., and Pareschi, A. (2012). Correlated Storage Assignment and Iso-Time Mapping Adopting Tri-Later Stackers. A Case Study from Tile Industry *Warehousing in the Global Supply Chain* (pp. 373-396): Springer.
- Marsh, K., and Bugusu, B. (2007). Food packaging—roles, materials, and environmental issues. *Journal of Food Science, 72*(3), R39-R55.
- Marston, S., Li, Z., Bandyopadhyay, S., Zhang, J., and Ghalsasi, A. (2011). Cloud computing—The business perspective. *Decision Support Systems, 51*(1), 176-189.
- McEntire, J. C., Arens, S., Bernstein, M., Bugusu, B., Busta, F. F., Cole, M., …Ohlhorst, S. (2010). Traceability (product tracing) in food systems: an IFT

report submitted to the FDA, volume 1: technical aspects and recommendations. *Comprehensive Reviews in Food Science and Food Safety, 9*(1), 92-158.

- McHugh, S., and Yarmey, K. (2012). Near field communication: Introduction and implications. *Journal of Web Librarianship, 6*(3), 186-207.
- Mell, P., and Grance, T. (2010). The NIST definition of cloud computing. *Communications of the ACM, 53*(6), 50.
- Mkansi, M., Qi, B., and Green, G. (2011). A Literature Review On Management Of Supply And Distribution In The UK Online Grocery Retailing: A Resource-Based View. *Proceeding of UK Academy for Information Systems Conference 2011, Oxford, UK, 11-13 April 2011*, Article No. 32.
- Nava-Díaz, S. W., Chavira, G., Hervás, R., Villarreal, V., Bravo, J., Martín, S., and Castro, M. (2009). NFC approach: towards a simple interaction. *Proceedings of IADIS International Conference on Mobile Learning 2009, Barcelona, Spain, 26-28 February 2009.*
- Nepomuceno, M. V., Laroche, M., and Richard, M. O. (2014). How to reduce perceived risk when buying online: The interactions between intangibility, product knowledge, brand familiarity, privacy and security concerns. *Journal of Retailing and Consumer Services, 21*(4), 619-629.
- Nettleton, D. (2014). Commercial data mining : processing, analysis and modeling for predictive analytics projects. Amsterdam: Morgan Kaufmann.
- Ngai, E. W. T., Xiu, L., and Chau, D. C. K. (2009). Application of data mining techniques in customer relationship management: A literature review and classification. *Expert Systems with Applications, 36*(2), 2592-2602.
- Nofal, M. A., and Fouad, K. M. (2015). Developing Web-based Semantic and Fuzzy Expert Systems using Proposed Tool. *International Journal of Computer Applications, 112*(7), 38-45.
- Obeidat, M., North, M., Richardson, R., Rattanak, V., and North, S. (2015). Business Intelligence Technology, Applications, and Trends. *International Management Review, 11*(2), 47.
- Oh, S., Cha, J., Ji, M., Kang, H., Kim, S., Heo, E., . . .Yoo, S. (2015). Architecture design of healthcare software-as-a-service platform for cloud-based clinical decision support service. *Healthcare Informatics Research, 21*(2), 102-110.
- Olson, D. L., Delen, D., and Meng, Y. (2012). Comparative analysis of data mining methods for bankruptcy prediction. *Decision Support Systems, 52*(2), 464-473.
- Palmer, R. C. (2001). *The bar code book : comprehensive guide to reading, printing, specifying, and applying bar code and other machine-readable symbols* (Revised and expanded 4th ed.). Peterborough, N.H: Helmers Pub.
- Papetti, P., Costa, C., Antonucci, F., Figorilli, S., Solaini, S., and Menesatti, P. (2012). A RFID web-based infotracing system for the artisanal Italian cheese quality traceability. *Food Control, 27*(1), 234-241.

- Pereira de Abreu, D. A., Cruz, J. M., and Paseiro Losada, P. (2012). Active and intelligent packaging for the food industry. *Food Reviews International, 28*(2), 146-187.
- Piegat, A. (2001). *Fuzzy modeling and control*(Studies in fuzziness and soft computing, vol.69). New York: Physica-Verlag Heidelberg.
- Rajabi, A., Ebrahimirad, V., and Yazdani, N. (2013). Decision Support-as-a-Service: An Energy-aware Decision Support Service in Cloud Computing. *Proceeding of 2013 5th Conference on Information and Knowledge Technology (IKT), Shiraz, Iran, 28-30 May 2013*, pp.71-76.
- Rajola, F. (2013). Customer relationship management in the financial industry organizational processes and technology innovation (2nd ed., pp. 109-125). Berlin New York: Springer.
- Rathod, N. A., and Ladhake, S. A. (2012). Detecting and decoding algorithm for 2D barcode. *International Journal of Emerging Technology and Advanced Engineering (IJETAE), 2*(11), 199-202.
- Ravinchandra, K. A. L., Abdulla, R., and Thang, K. F. (2016). Smart Stock Management Control. *International Journal of Applied Engineering Research, 11*(1), 492-500.
- Robertson, G. L. (2013). *Food packaging : principles and practice* (3rd ed.). Boca Raton, FL: CRC Press, Taylor and Francis.
- Romero, C., and Ventura, S. (2007). Educational data mining: A survey from 1995 to 2005. *Expert Systems with Applications, 33*(1), 135-146.
- Rose, M., and Fernandes, A. (2013). *Persistent organic pollutants and toxic metals in foods*. Oxford: Woodhead Publsihing.
- Roth, A. V., Tsay, A. A., Pullman, M. E., and Gray, J. V. (2008). Unraveling the food supply chain: strategic insights from China and the 2007 recalls. *Journal of Supply Chain Management, 44*(1), 22-39.
- Roy, A., and Chatterjee, R. (2013). A survey on fuzzy association rule mining methodologies. *IOSR Journal of Computer Engineering, 15*(6), 1-8.
- Shah, V. (2010). RFID: a brief overview. *International Journal of Manufacturing Technology and Management, 21*(3-4), 316-323.
- Sharma, P., Nair, V., and Jyotishi, A. (2014). Patterns of Online Grocery Shopping in India: An Empirical Study. *Proceeding of 2014 International Conference on Interdisciplinary Advances in Applied Computing, Amritapuri, India, 10-11 October 2014*, Article No. 29
- Shi, Z. (2011). *Advanced artificial intelligence*. Singapore Hackensack, NJ: World Scientific.
- Sotoca, J. M., and Pla, F. (2010). Supervised feature selection by clustering using conditional mutual information-based distances. *Pattern Recognition, 43*(6), 2068-2081.
- Subramanian, N., Gunasekaran, A., Yu, J., Cheng, J., and Ning, K. (2014). Customer satisfaction and competitiveness in the Chinese E-retailing: Structural

equation modeling (SEM) approach to identify the role of quality factors. *Expert Systems with Applications, 41*(1), 69-80.

- Tan, T.H., and Chang, C.S. (2010). Development and evaluation of an RFID-based e-restaurant system for customer-centric service. *Expert Systems with Applications, 37*(9), 6482-6492.
- Teo, K. B. (2011). *Process-driven warehouse operations : the practitioner's definitive guide*. Singapore: Straits Times Press Reference.
- Trebar, M., Grah, A., Melcon, A. A., and Parreno, A. (2011). Towards RFID traceability systems of farmed fish supply chain. *International Conference on Software, Telecommunications and Computer Networks (SoftCOM)*, 19th Split, 15–17 September, Croatia, 1–6.
- Vanelslander, T., Deketele, L., and Van Hove, D. (2013). Commonly used e-commerce supply chains for fast moving consumer goods: comparison and suggestions for improvement. *A Leading Journal of Supply Chain Management, 16*(3), 243-256.
- Verma, M., Srivastava, M., Chack, N., Diswar, A. K., and Gupta, N. (2012). A comparative study of various clustering algorithms in data mining. *International Journal of Engineering Research and Applications (IJERA), 2*(3), 1379-1384.
- Verma, V., Sharma, D., and Sheth, J. (2016). Does relationship marketing matter in online retailing? A meta-analytic approach. *Journal of the Academy of Marketing Science*, *2016*(44), 206-217.
- Vishkaei, B. M., Rashti, M. E., and Vishkaei, B. M. (2011). A Fuzzy Multi-Objective Class Based Storage Location Assignment. *International Journal of Applied Operational Research , 1* (1), 19-33.
- Vlachos, I. P. (2014). A hierarchical model of the impact of RFID practices on retail supply chain performance. *Expert Systems with Applications, 41*(1), 5-15.
- Wutthisirisart, P., Noble, J. S., and Chang, C. A. (2015). A two-phased heuristic for relation-based item location. *Computers and Industrial Engineering, 82*, 94-102.
- Xiao, Z., Zhang, J., Li, D., and Chen, C. (2015). Trust in Online Food Purchase Behavior: An Exploration in Food Safety Problem for Produce E-retailers. *Advance Journal of Food Science and Technology, 8*(10), 751-757.
- Yang, P., Miao, L., Xue, Z., and Qin, L. (2013). 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.
- Yeh, K.C., Chen, R.S., and Chen, C.C. (2011). Intelligent service-integrated platform based on the RFID technology and software agent system. *Expert Systems with Applications, 38*(4), 3058-3068.
- Ząbkowski, T. S., and Szczesny, W. (2012). Insolvency modeling in the cellular telecommunication industry. *Expert Systems with Applications, 39*(8), 6879-6886.
- Zhang, L., and Oh, L. B. (2013). *Determinants of Multichannel Consumer Switching Behavior: A Comparative Analysis of Search and Experience Products.*

Proceeding of 12th Wuhan International Conference on E-Business (WHICEB 2013), Wuhan, China, May 25-26, 2013, pp. 205-212.

- Zhou, M., Tian, Z., Xu, K., Yu, X., and Wu, H. (2013). Theoretical entropy assessment of fingerprint-based Wi-Fi localization accuracy. *Expert Systems with Applications*, *40*(15), 6136-6149.
- Zhu, X., Zhang, Q., Zhang, L., and Yang, J. (2014). Consumers' Demand and Online Promotion of the Food Retailing Through the E-Commerce Websites in China. *Advance Journal of Food Science and Technology*, *6*(1), 102-111.