AN APPROACH FOR THE PERISHABLE PRODUCT LOGISTICS BASED ON REAL-TIME MONITORING WITH RADIO FREQUENCY IDENTIFICATION (RFID)

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An Approach for the Perishable Product Logistics based on Real-time Monitoring with Radio Frequency Identification (RFID)

By

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CERTIFICATE OF ORIGINALITY

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Abstract

Food and plasma are essential in our lives. Spoilage or contamination of these products can lead to serious consequences. Most of them belong to perishable products. Perishable products are products that only have a short shelf-life. Transportation involving Third-Party Logistics companies (3PL) is a weak point in product management. The damage caused by deterioration in the quality of perishable products during transportation is often responsible for great monetary losses. Consequently, it is necessary to improve the management of such perishable products. However, the efficient monitoring of such products and effective data management are big challenges for researchers.

Radio frequency identification (RFID) technology provides a potential efficient way to improve the management of perishable products. RFID is an emerging technology that has been increasingly used in logistics and supply chain management (SCM) in recent years, since it can offer a long read range, large data capacity, and multiple readings at the same time.

This research aims to study the transportation management of perishable products based on the real-time monitoring of the entire supply chain of perishable products from manufacture to retail using RFID technology. The study proposes a system called the Monitoring-based Decision Support System (MDSS), which integrates three modules for the major functions, namely a Real-time Monitoring Module (RMM) with enabling RFID for quality evaluation, a Forecasting and Warning Module (FWM) for arrival time prediction and emergency warning, and a Decision Support Module (DSM) for vehicle and emergence management.

The value degeneration process is firstly introduced in the MDSS. Several mathematical models are used to describe the different categories of perishing that are applied to the system. Based on mathematical models, data and evaluation results from RMM, environmental factors and product information are transmitted to FWM for forecasting and warning judgments. If anything abnormal occurs the corresponding information is then transmitted to DSM for emergency management. DSM also helps develop the vehicle schedule before transportation.

RMM is designed with RFID technology and sensor networks. The module introduces a hybrid algorithm that combines *k*-Nearest Neighbour algorithm (*k*-NN) with Artificial Neural Networks (ANN) to evaluate the product quality. FWM applies Fuzzy Case-based Reasoning (CBR) in its forecasting function, and fast Rule-based Reasoning (RBR) in its warning function. In DSM, an Improved Quantum-inspired Evolutionary Algorithm (IQEA) and Genetic Algorithm (GA) are applied to create an optimal schedule for vehicle management before the transportation of perishable products. These two algorithms aim to solve vehicle schedule problems at different scales. In addition to static optimisation, DSM can also help cope with any emergency. Using heuristic approaches, DSM adjusts the vehicle schedule and provides suggestions on how to cope with any emergency.

Finally, a particular case is studied to test the performance of the system. The results from the case study show that MDSS has a positive effect on perishable product management, especially during transportation. For further research, the system can be extended to managing perishable products over the entire supply chain, including storage, retail and recall, in addition to delivery.

Publications Arising from the Thesis

In the process of conducting the study, 4 international journal papers, 3 conference papers and 1 book chapter have been published. 1 international journal paper will be accepted after revision. 1 international journal paper is under review.

Journal Articles

1. **Wang, L. X**., Kwok, S. K., Ip, W. H., Ng, P. H., (2009). Transportation visualization of perishable products with a RFID and Sensor network. *IJIAP International Journal of Information Analysis and Processing*, 2(2): 35-42.
2. **Wang**, **L.,** Kwok, S. K., Ip, W. H., (2010). A Radio Frequency Identification and Sensor-based System for the Transportation of Food, *Journal of Food Engineering*, 101: 120-129.
3. **Wang, L.,** Kwok, S. K., Ip, W. H., (2011). A radio frequency identification-based quality evaluation system design for the wine industry. *International Journal of Computer Integrated Manufacturing* 25(1): 11-19.
4. **Wang, L.,** Kwok, S. K., Ip, W. H., (2012). Design of an Improved Quantum-Inspired Evolutionary Algorithm for a transportation problem in Logistics System, *Journal of Intelligent Manufacturing*, 23: 2227-2236.
5. **Wang, L.,** Ting, S. L., Ip, W. H., (2013). Design of Supply-chain Pedigree Interactive Dynamic Explore (SPIDER) for food safety and implementation of Hazard Analysis and Critical Control Points, *Computers and electronics in agriculture,* 90: 14-23.

6. **Wang, L.,** Ng, C. K., Ip, W. H., (2012). Design of a Radio Frequency Identification (RFID) based Monitoring and Vehicle Management System, *Transportation Research Part C: Emerging Technologies*. (Submitted)

Conference Proceedings

1. **Wang, L.,** Kwok, S. K., Ip, W. H., (2010). Design of an Improved Quantum-Inspired Evolutionary Algorithm for a transportation problem. In: *The 6th International Conference on Intelligent Manufacturing & Logistics Systems*, February, 2010, Hsinchu, Taiwan
2. **Wang, L.,** Ho, G. T. S., Ip, W. H., (2011). Intelligent Optimization Method: Research about an Improved Quantum-Inspired Evolutionary Algorithm. In: *The Fourth China Conference on Data Mining*, 6-8 May, 2011, Guangzhou, Guangdong, P.R. China.
3. **Wang, L.,** Ip, W. H., (2011). A Soft Case-based Reasoning System for Travelling Time Estimation. In: *Future Computing 2011*, September, 2011, Rome, Italy.

Book Chapter

1. **Wang, L.,** Kwok, S. K., (2010). Radio Frequency in Packaging, Inventory Control and Tracking in the Food Processing Industry. In: Awuah, G.B., Ramaswamy H.S., Tang, J. ed., 2012. *Electro-Technologies for Food Processing: Book Series Volume 3, Radio Frequency Heating in Food Processing: Principles and Applications.* United States, CRC Press. Ch. 35.

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List of Abbreviations

3PL	Third-Party Logistics companies
AI	Artificial Intelligence
ANN	Artificial Neural Network
CBR	Case Based Reasoning
CDMA	Code Division Multiple Access
CGA	Classical Genetic Algorithm
CIF	Cost Insurance and Freight
CNY	Chinese Yuan
CYMS	Container Yard Management System
DEHP	Bis(2-ethylhexyl) Phthalate
DINP	Diisononyl phthalate
DSM	Decision Support Module
EPC	Electronic Product Code
EQA	Earliest Query Answering
FDA	Food and Drug Administration
FTA	Fault Tree Analysis
FWM	Forecasting and Warning Module
GA	Genetic Algorithm
GPRS	General Packet Radio Service
GPS	Global Positioning System

GQ-GA	General Quantum Genetic Algorithm
HACCP	Hazard Analysis and Critical Control Points
HCES	Heuristic of Checking Embedded Strings
IQEA	Improved Quantum-inspired Evolutionary Algorithm
k-NN	*k*-Nearest Neighbour algorithm
MDSS	Monitoring-based Decision Support System
NP	Non-Polynomial
PSO	Particle Swarm Optimisation
QA	Quantum Algorithm
Q-bit	Quantum-bit
QEA	Quantum-inspired Evolutionary Algorithm
RBR	Rule-based Reasoning
RFID	Radio Frequency Identification
RMM	Real-time Monitoring Module
SCM	Supply Chain Management
TDLTE	Time-Division Long-Term Evolution
TSP	Traveling Salesman Problem
USDA	The United States Department of Agriculture
VRP	Vehicle Routing Problem
VRPTW	Vehicle Routing Problem with Time Windows
VRPTWSD	Vehicle Routing Problem with Time Windows and Split Deliveries
WHO	World Health Organization

CHAPTER 1 INTRODUCTION

1.1 Research Background

Perishable products, such as seafood, fruit, plasma, and so on, are products that only have a short shelf-life. This characteristic leads to difficulties in long distance transportation, yet with the arrival of globalisation long distance transportation is playing an increasingly important role in people's daily lives. The transportation of perishable products is an important branch of logistics, which in the literature is known as the "cold chain" (Gong and Liang, 2006; Bogataj *et al.*, 2005). For example, more than 50,000 reefer trailers used for carrying perishable products and food are registered in Germany (Jedermann *et al.*, 2006). However "value loss" situations are very serious in the case of perishable product transportation. The status of products during transport is usually unknown. In fact there is frequently a loss of value when transported products deteriorate. In North America alone, over $33 billion in losses are incurred annually by the food industry due to the deterioration of goods caused by temperature related issues (Business Wire, 2007). In China, there are serious financial and quality losses during the transportation process of perishable goods. The losses of fruit, vegetables and similar products are usually around 35% in the time between leaving the source and arriving at the destination. There is also a 10% to 15% loss in the meat and seafood industries. The total lost value before arrival may annually reach hundreds of billions CNY (Chinese Yuan) (Gong and Liang, 2006). In cold chains in China, 56 billion CNY is lost annually in the transportation of food

(Zhang, 2006). In addition to the challenge of the transportation of perishable products, the management of perishable product safety is also an issue that needs to be considered.

There is a bond between humans and perishable products that has been in place for as long as mankind has been on the earth. No one can live without food or medicine. If we eat food which is contaminated or spoiled it can make us ill and even cause death. Indeed, the latter has started to become serious and many cases have been reported in the newspapers, statistics and surveys. In 2008, the Chinese milk scandal shocked the world. By November 2008, China reported an estimated 300,000 victims, with 6 infants dying; all caused by melamine contaminated milk. It is estimated that the financial loss could reach CNY¥20 billion (US$3 billion) (Branigan, 2008). In 2011, Taiwan discovered massive amounts of food and beverages contaminated with DEHP (Bis(2-ethylhexyl) phthalate) and DINP (Diisononyl phthalate). Prolonged ingestion of DEHP-contaminated food and beverages can lead to cancer or damage to the reproductive system. It has been reported that DEHP can be particularly damaging to a young male's fertility. Industry sources estimate that the island's retail sales of soft drinks may have fallen by 20% in 2011 compared to 2010, equating to a net loss of US$540 million (Lee, 2011). There are also many other examples, and similar hazards can also be found in numerous reports and studies (Fox News, 2012; Goessl, 2011; New York Times, 2012). These serious food safety scandals make people lose confidence in the products they buy. Though companies can take some action, such as using a monitoring system to control product quality for their reputations, it is hard for them to manage each link in the supply chain, especially delivery. That is because suppliers usually employ the Third-Party Logistics companies

(3PL) to conduct the transportation tasks. The management system for products is hard to continue by a different company. Contamination or spoilage that occurs during transportation is out of their control. Meanwhile, for the 3PL, damage caused by the degeneration of the quality of perishable products is often responsible for great monetary losses, as stated at the beginning of this section. Consequently, whether for financial or human health reasons, it is important to establish effective and professional perishable product safety control measures.

Recently developed technology provides an efficient way to improve this serious situation. Radio Frequency Identification (RFID) is an emerging technology that uses wireless radio to identify objects from a distance without requiring line of sight or physical contact (Borriello, 2005). RFID enables the user to capture real-time information in fast moving and bulky product flows of individual food products with the aim of achieving a high degree of efficiency and assuring high quality. Recently, the lower costs and the increasing capabilities of the RFID technique and the creation of an Electronic Product Code (EPC) have made this technology more useful. An EPC is specially designed to assign a unique identifier to each item. The organisation EPCglobal Inc. oversees the development of the RFID standards (Dolgui and Proth, 2008). Kwok *et al.* (2008b) introduced a new function to EPCglobal. To ensure that different parties would interpret the standard in the same way, EPCglobal proposed the ePedigree, which can help the tracking of products and help the customers better understand their products. An ePedigree is an integral and sole data source containing a series of recorded digital product authentications. It is an assembly of centrally stored and managed data that uses a specifically defined data source. All the entries in the data source are electronically marked with a digital signature, meaning that all entries are validated and do not need to be rechecked. Due to ePedigree, RFID technology also allows users to track items in real-time across the supply chain. User can not only obtain detailed information about the products, but also know through which locations the products have passed, what the storage environment is, whether the products have followed the correct supply chain, and so on, by reading the ePedigree. ePedigree supplies a platform for different parties to share the information on their common products. It is very helpful for the quality monitoring in each link of the entire supply chain. In addition to ePedigree, RFID can also be combined with a sensor technique to develop a real-time monitoring system even when the monitored items are in transportation. Using the RFID-based monitoring system, the operator can take actions to prevent damage when certain products are found to be at risk. For instance, if a shipper determines that his/her goods are heading towards a traffic jam and that the goods will possibly go bad because of the delay, then he/she can quickly change the routing so as to avoid the traffic jam. Additionally, if the owner finds his/her goods have lost all their value, the owner can instruct the driver to dump the goods and thereby save the rest of the transportation fee.

For these reasons, the aim of this research is to find an approach to improve the supply chain management of perishable products: reducing value losses and increasing the safety of perishable products. Due to the limit of time, the major focus of this research is on the distribution of the supply chain. To avoid contamination, decay and spoilage during transportation, the approach combines some existing technologies such as RFID, sensor networks, Global Positioning System (GPS), optimisation algorithms and machine learning methods. The main idea of the approach is to monitor products in each link of the entire supply chain. Based on the monitoring results, an algorithm that combines the *k*-Nearest Neighbour algorithm (*k*-NN) with an Artificial Neural Network (ANN) is developed for product quality evaluation. It is helpful for product quality control and guarantees the product safety. Meanwhile, with the monitoring results and the quality evaluation results, the arrival time of vehicles in distribution can be more accurately forecasted by the proposed fuzzy Case-based Reasoning (CBR), and anything abnormal can be determined in time by a fast Rule-base Reasoning (RBR) method. If something abnormal is discovered or an emergency really occurs, heuristics is applied for dynamic adjustment. For the better management of product distribution, two optimisation algorithms, Improved Quantum-inspired Evolutionary Algorithm (IQEA) and adjusted Genetic Algorithm (GA), are proposed for optimising the vehicle schedule before transportation. Based on the approach, a system called a Monitoring-based Decision Support System (MDSS) is developed. The system has three major functions. The first function is the monitoring of the perishable products during transportation, and sharing information on a platform for assistance on quality control. The second one is warning and forecasting. The third one is vehicle management. The final two functions are for transportation management to improve the distribution of perishable products. It is believed that, with the help of the system, the value loss situation and safety problem of perishable products can be greatly improved.

1.2 Problem Statement

To improve the safety management of perishable products and to reduce the value loss of perishable products during transportation, some approaches, including real-time monitoring and decision support, are considered. A review of the literature shows that some work has already been done on this subject. Jedermann *et al.* (2009) developed a system for monitoring intelligent containers that combines wireless sensor networks and RFID. Tijskens and Polderdijk (1996) proposed a perishable products value loss model. Hsu *et al.* (2007) used a "Time-Oriented Nearest-Neighbour Heuristic" (Solomon, 1983) to solve vehicle routing problems with a time-window (VRPTW) for the delivery of perishable food. Bai *et al.* (2007) discussed food safety assurance systems in China. A number of approaches and systems have been proposed for the assurance of product safety and quality in distribution. However, some existing systems or approaches are practical, mainly focusing on real-time monitoring, while others are academic, mainly focusing on model building and data analysis for the optimisation of value and vehicle route. An integrated system, which has both the functions of real-time monitoring and decision support as well as the functions of scheduling and optimisation, has not yet been developed. There are still some issues to be resolved. These issues are summarised as follows:

- The supply chain of perishable products suffers from a lack of transparency.

  Most food safety problems occurred due to the lack of transparency in the supply chain. Neither companies nor food safety regulators can manage the products effectively, since it is hard to know what the products' real situations are in distribution. Most companies employ 3PL to conduct the product transportation. Suppliers cannot guarantee the product quality during transportation. 3PL are also hard to distinguish which products are easily spoiled, which products are sensitive to changes in temperature and so on. Nor is there a platform for both manufacturers and 3PL to share their information on the products.

- It is difficult to forecast the arrival time of the vehicles.

  Accurate forecasting of vehicle arrival time is important, especially for products that are perishable. Then retailers can prepare in time to receive products. Logistic companies also need accurate arrival time to optimise the vehicle schedule. Much research focused on time forecasting. But the situation always changes during transportation. Events such as traffic jams, horrible weather, traffic accidents and so on are hard to predict. Due to these reasons, the accuracy of most common forecasting approaches is low.

- It is difficult to forecast the quality of perishable products when they arrive at the destination.

  In the past, people mainly judged the quality of perishable products by observation of the product's appearance. This approach is subjective and not scientific. Tijskens and Polderdijk (1996) proposed a perishable product value loss model. Time is the main change in the product quality quantification. However, without the original quality value, the model cannot accurate compute the product quality. Additionally, without an accurate arrival time, the model can only be applied when products really arrive at the destination. At which point any action to save the quality is too late.

- It is difficult to schedule and optimise the delivery of perishable products in a dynamic manner.

  Finding the optimal solution is a hard problem in both mathematics and management, which attracts the interest of many researchers. Most studies focus on finding the optimal solution in a static manner or in a dynamic manner with cyclic changes. But in reality, situations are more complex, especially for the transportation of perishable products. Most 3PL companies choose to develop vehicle schedules just based on the experience. Such companies also lack effective approaches for adjusting the schedule when accidents occur.

Aimed at solving the issues stated above, the following research objectives and scope are expected to be achieved.

1.3 Research Objectives and Scope

The objective of this study is to find an approach to decrease the value loss of products during transportation, and to increase the transparency of the supply chain. For the safety management of perishable products, the approach tries to track, trace and monitor items during transportation through the application of RFID and sensor techniques. Evaluation of the product quality and helpful suggestions for operations and rescheduling when emergencies or accidents occur are other important aspects of the approach. Furthermore, it is based on the monitoring results of products. So, a monitoring-based decision support system is developed to realise the approach. Specifically, based on the idea of the approach, this research attempts to achieve the following for the proposed system:

- To design a RFID and sensor network-based module for real-time monitoring, and an algorithm for the quality evaluation of perishable products.
- To predict the time required for the products arriving at their destination, and to calculate the value of the products when they reach their destination.
- To design a warning module as part of the system to monitor the environmental conditions of the products during transportation.
- To apply optimisation algorithms to create an initial optimal vehicle schedule.
- To develop a dynamic adjustment method to adjust vehicle routing and crew schedules in a short time when emergencies or accidents occur.
- To prove the effectiveness of the proposed system through a case study.

Though the research area is about the improvement of the perishable product situation, the approach can also be expanded to other industries. With only a few changes to the system it is also suitable for other industries to improve their supply chains. Moreover, the idea behind the system, real-time monitoring, a platform for different parties to share common information, initial optimisation, forecasting, timely warning and dynamic adjustment can also be applied to our lives.

1.4 Research Methodology

The methodology of the research framework follows the conventional procedure for most research work. The procedures are mainly divided into three phases. In phase 1 the focus is on the literature review. In phase 2 the main work is system design. In phase 3 a case is examined to test the performance of the system. Figure 1.1 indicates the procedures.

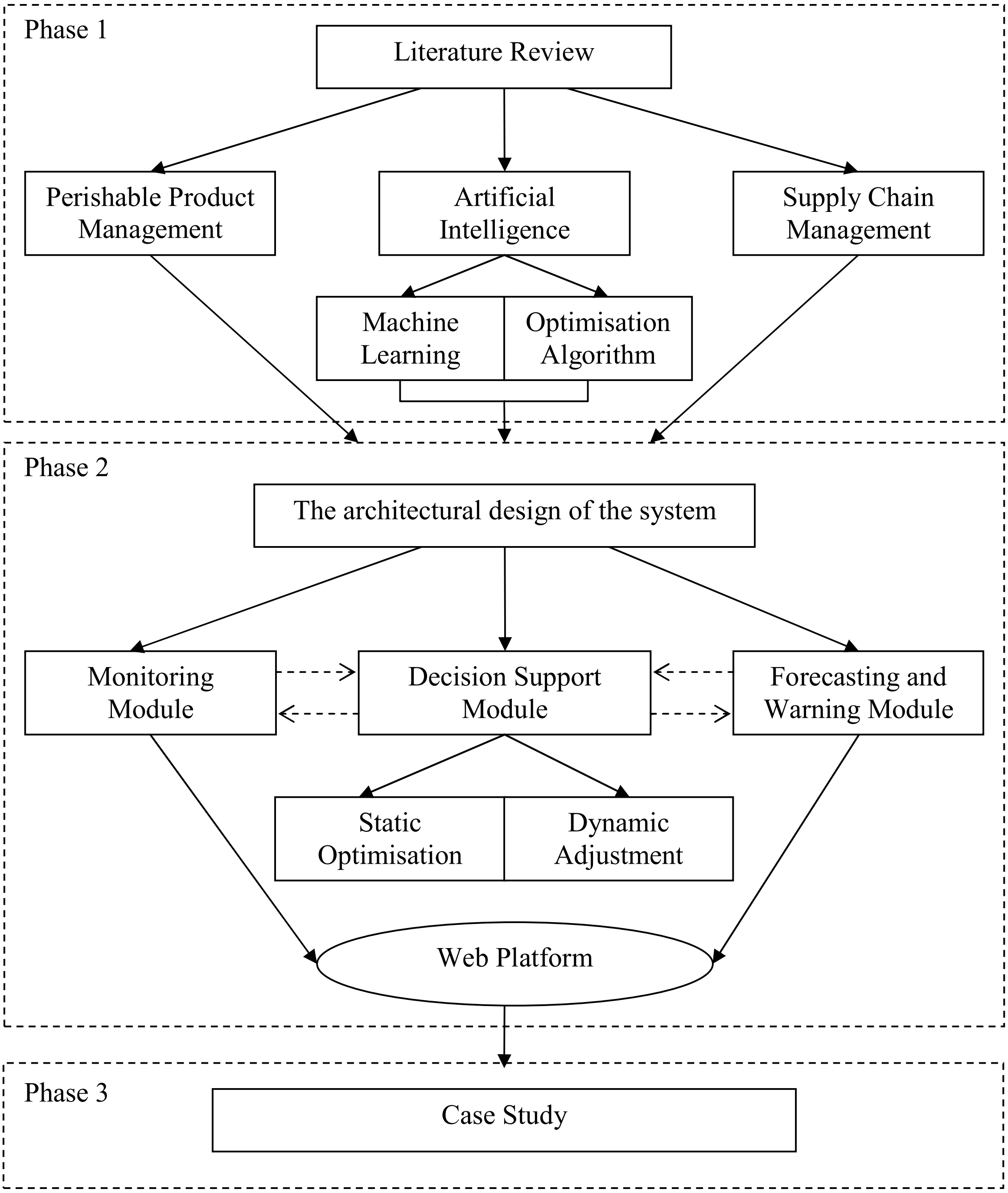


Figure 1.1 Research Procedure

A literature review is the bedrock of a study, which can integrate different opinions, criticise previous scholarly works, build bridges between related topic areas, and identify the central issues in a field (Fellows and Liu, 2003; Naoum, 1998). Based on the above research motivation and objectives, this study first involves a review of existing literature in the area of perishable products, supply chain management and artificial intelligence. The review of perishable products identifies the big challenge being in its supply chain. The poor management of the supply chain causes safety issues and a huge value loss during transportation, and it also implies research opportunities. Through a review of other supply chain management approaches, we try to find an effective approach to improve the current perishable product industry. Based on the approach, it is decided to develop a Monitoring-based Decision Support System (MDSS). Some AI techniques are reviewed for the system design.

To complete MDSS for the objectives mentioned in the last section the following achievements are expected:

- The architecture of the MDSS design:

The system is composed of three modules. One is a Real-time Monitoring Module (RMM). The second is a Forecasting and Warning Module (FWM). They transmit, acquire and share information on a common web platform. The third one is Decision Support Module (DSM). RMM can be used to monitor the manufacturing conditions, the environments in warehouses, the conditions in containers, and the location of vehicles, to evaluate product quality and to manage the transmission of data to the platform. FWM can detect whether the vehicle is in a traffic jam, or whether the container is experiencing abnormal conditions. If something unexpected happens, the system will give a warning to the DSM. DSM optimises the vehicle schedule and adjusts the schedule in a timely manner when accidents or emergencies occur.

- The Real-time Monitoring Module design:

RMM applied RFID and sensor technologies for the real-time monitoring of perishable products during transportation. It can be extended for monitoring products in each link of the supply chain. All the information is shared on a platform. The algorithm for product quality evaluation is designed by integrating the *k*-NN algorithm and ANN. The module aims to improve the transparency of the supply chain of perishable products

- The Forecasting and Warning Module:

There are two functions in the module: forecasting and warning. The forecasting function of the module uses CBR and fuzzy logic to forecast the arrival time of the products. With the transportation time and the original quality value being evaluated in the RMM, a value loss model is applied to forecast the product quality at the time that they arrive at their destination. The model can also be used to calculate the current product quality.

The warning function of the module uses RBR to judge the following conditions: whether the environmental condition of the products is abnormal; whether the container truck is in a traffic jam; whether there is any emergency arising; whether there is enough time for the products to arrive at their destination with acceptable quality, and so on.

- The Decision Support Module design:

The major function of the DSM is to generate a schedule for the minimisation of the transportation costs. It has two parts: one is static optimisation, the other is dynamic adjustment. Two algorithms, an IQEA and a hybrid algorithm combing GA and Heuristics, are applied for static optimisation and a schedule is then generated. These two algorithms aim to solve vehicle scheduling problems at different scales. If the module receives a warning when the schedule generated by the static optimisation module is in operation, the dynamic adjustment will start up to adjust the original plan. The Heuristic of Checking Embedded Strings (HCES) is applied in this part. A relatively optimal schedule will be generated to reduce most of the losses.

A case study on perishable transportation for 3PL is the last part of this research. The data is simulated based on the background of a real company. Questionnaires and interviews are used for data collection. It aims to prove that the proposed system can monitor perishable products in real-time to increase the transparency of its supply chain and that it offers good performance in preventing the decay of perishable products and reducing value loss during transportation.

1.5 Significance of the Research

Perishable products face great challenges with regard to safety issues. The bottleneck is quality control during transportation. It is difficult for suppliers to monitor 3PL vehicles. 3PL also faces huge value losses due to the spoilage of products. This research proposed an approach to improve the current situation. The significance of this research is stated as below:

- With the combination of RFID and sensor networks, the real-time monitoring function can be realised, and accordingly the product status in each link of the supply chain can be recorded. The ePedigree of products can be constructed. It effectively increases the transparency of the supply chain, thereby solving the safety problem of products.
- With the application of the perishable product quality loss model and the proposed quality evaluation algorithm, the arrival remaining value of products can be estimated when the products are transported. Once anything abnormal occurs, timely actions can be taken to avoid losses or to greatly decrease losses.
- A new optimisation algorithm IQEA is proposed for initial vehicle schedule optimisation.
- Based on the monitoring conditions, the vehicle schedule can be adjusted in a short time by the HCES approach.
- Based on the approach, MDSS is developed. The system integrates real-time monitoring and distribution management. A case study proves the system performs well in avoiding accidents and decreasing the value loss of products.

These achievements will certainly be helpful in food safety issues and supply chain management in logistics.

1.6 Organisation of the Thesis

This thesis is divided into nine chapters. Chapter 1 provides the research background, the research problem and the motivation for the research. The methodology of the research is also introduced in this chapter. Chapter 2 contains a literature review on perishable product management, supply chain management, some decision support and machine learning techniques, and research on optimisation algorithms. Finally, this chapter concludes the current state of research through the review of previous relevant works. The opportunities found in Chapter 2 and the motivations stated in Chapter 1 encourage us to develop an approach that integrates real-time monitoring and decision support. Based on this approach, MDSS is proposed. The following chapters introduce the design of this system.

Chapter 3 discusses the methodology for the system design. The framework of MDSS is presented. The system contains three modules: RMM, FWM and DSM. The relationships and data transmission among the three modules are also discussed in this chapter. In Chapter 4 to Chapter 6, the three modules are introduced respectively. Each chapter contains one or two experiments to illustrate the operation of the module and to present the results.

In Chapter 7, a simulated case to test the performance of the system is presented. The result shows that the system is very helpful in perishable product quality control and management during transportation. Discussions on the system, the three modules, and the case study's results are presented in Chapter 8. Finally, conclusions from the work undertaken are given in Chapter 9. In this final chapter, some suggestions for further study are also offered.

CHAPTER 2 LITERATURE REVIEW

2.1 Introduction

This chapter provides a review of the literature relevant to the study. Numerous researchers have proposed systems for perishable product management. A review on some basic concepts and management methods is presented in Section 2.2. To identify potential food safety hazards, an approach called the Hazard Analysis and Critical Control Points (HACCP) is now used at all stages of the food production and preparation processes, including packaging, distribution and so on (Caswell and Hooker, 1996; Mortimore and Wallace, 1998). Much research has been conducted on the improvement of the transportation of perishable products. This is because most of the value of the products may be lost during distribution. Tijskens and Polderdijk (1996) have proposed a value loss model for perishable products. This model can be used to predict the remaining value of products. With the HACCP method to identify potential food safety hazards and the model for product quality quantification, the main challenge is in the management of perishable product supply chains. Some basic knowledge about supply chain management (SCM) is introduced in Section 2.3. In the review of supply chain management some real-time monitoring systems have been proposed for the transportation of perishable products in previous research, which are introduced in Section 2.4. But no system integrates real-time monitoring, arrival time and product quality forecasting, accident warning, and optimisation and emergency management.

The lack of existing systems for perishable product management encourages us to develop a real-time management and decision support system. Section 2.5 and Section 2.6 presents reviews of machine learning methods and usual techniques in decision support systems. The main challenge in the decision support system is the creation of a vehicle schedule. The vehicle schedule problem can be classified as a Vehicle Routing Problem (VRP). VRP is a traditional problem that has been studied for many years. Genetic algorithm (GA) is the most common optimisation approach for solving VRP. The Quantum-inspired Evolutionary Algorithm (QEA) is an emerging optimisation algorithm. It performs well when applied to solving the Travelling Salesman Problem (TSP), or 0/1 Knapsack Problem. Heuristics can be used to come to a rapidly solution that is close to the optimal solution. Every optimisation approach has advantages and disadvantages. A hybrid optimisation algorithm can avoid disadvantages and develop the advantages of different algorithms. Optimisation algorithms are discussed in Section 2.7.

Finally, research opportunities are derived in Section 2.8. And Section 2.9 summarises this chapter.

2.2 Perishable Products Management

A range of terms, including food poisoning, food borne illness and food borne disease are now commonly encountered, reducing the confidence of the public in purchasing food. In Hong Kong, most of the current precautions only emphasise inspections and tests by taking samples at import, wholesale and retail levels (Centre for Food Safety, 2007). With global economic integration, food safety is not only a problem in a one country; it is an increasingly important public health issue in all countries, as highlighted by Dr Margaret Chan, Director-General of the World Health Organization (WHO) (China Daily, 2007). The Australian Academy of Science (1998) reported that every time we eat we have to rely on the links in the entire food supply chain. In other words, we should be aware of the food's traceability before eating. Ensuring food safety is a tremendous global challenge, and has attracted considerable attention in recent years. How to increase the transparency of the supply chain is the main focus of researchers.

2.2.1 Perishable Product Supply Chains

Due to the nature of perishable products, its supply chain is different from non perishable products. Most perishable products are temperature sensitive. Consequently their shelf-life can be expressed as a function of the product's characteristics, the environmental conditions under which the product is stored, and time (Sahin *et al.*, 2007). Wang and Li (2012) found that the major challenge in perishable food management is waste from inappropriate quality control. If we can improve the visibility and traceability in food supply chains by applying tracking and tracing technologies, it will be helpful to increase product quality during transportation.

Beliën and Forcé (2012) presented a literature review on the inventory and supply chain management of blood products. They found that most publications place the focus of research on the entire supply chain. Pierskalla (2004) focused on the supply chain management of blood banks. They gave an outline of the blood banking supply chain and discussed several technical and operational issues faced by this chain. Katsaliaki (2008) evaluated the performance of the entire blood supply chain in the UK. Their study aimed to determine policies. They hoped that the policies would produce a more cost-effective management of the supply chain, while at the same time increasing safety. Xiao *et al.* (2008) focused on the optimisation and coordination of a fresh product supply chain under the Cost Insurance and Freight (CIF) business model, with uncertain long-distance transportation. The researchers were not only concerned with how to manage the supply chain effectively but studied real-time monitoring, which is also important to ensure the stability of perishable products. Bogataj *et al.* (2005) found that "any changes in time-distance or temperature in the chain could cause the net present value of the activities and their added value in the supply chain to be perturbed." Planning decisions is also a research aspect for the improvement of perishable product management. Ahumada and Villalobos (2011) presented an operational model. The model can generate short-term planning decisions for the improvement of the fresh produce industry. Amorim *et al.* (2012) integrated production and distribution planning of perishable products through a multi-objective framework.

Through the literature review on the perishable product supply chain, it is found that product tracking, monitoring and planning were three major research approaches in the perishable product supply chain management. But only managing the supply chains is not enough, the control of product quality and how product quality is quantified will be discussed in the following two sections.

2.2.2 Hazard Analysis and Critical Control Points

Food is the main branch of perishable products. The common approach for food safety management is called Hazard Analysis and Critical Control Points (HACCP). Its main principle is to identify potential food safety hazards. HACCP is now used in all stages of the food production and preparation process, including packaging, distribution and so on (Caswell and Hooker, 1996; Mortimore and Wallace, 1998). It has seven principles, as listed in Table 2.1.

Table 2.1 HACCP Principles (CAC, 2003; Cerf *et al.*, 2011)

Principle 1	Conduct a hazard analysis
Principle 2	Identify critical control points
Principle 3	Establish critical limits for each critical control point
Principle 4	Establish critical control point monitoring requirements
Principle 5	Establish corrective actions
Principle 6	Establish procedures for ensuring the HACCP system is working as intended
Principle 7	Establish record keeping procedures

In the USA, the Food and Drug Administration (FDA) has mandated HACCP for food relevant industries, such as fish and fishery products. And it is also proposing mandating

HACCP for fruit and vegetable juices. The United States Department of Agriculture (USDA) has mandated Pathogen Reduction/HACCP requirements for meat and poultry processing, and the National Marine Fisheries Service Seafood Inspection Program operates a voluntary HACCP program for seafood plants. “Each agency agrees that HACCP is the best food control system of choice and is committed to improve food safety requirements” (Kvenberg *et al.*, 2000).

Hence, the implementation of HACCP involves monitoring, verifying and validating daily work that is compliant with the regulatory requirements, in all stages and all the time (Laturnas, 2008). Even with the advent of globalisation, the food chain is involved with more items from different locations, and the products may also be transported to different countries. It further increases the complexity of the implementation of HACCP, as companies generally have their own systems. It is hard to integrate all the systems. Moreover, some companies may change in the future, and this is hard to forecast. There is a need to build a public platform to which all companies can transmit their data, for manufactures to analyse the data provided, for investigators to test the products, and so on.

Numerous researchers have proposed systems for food safety management and monitoring. Wijtzes *et al.* (1998) proposed a computerised decision support system to simulate the composition, production and distribution of foods. The developed system is helpful for quantifing effective measures on the microbial load of foods. Consequently, for the implementation of the HACCP methodology in food production and distribution chains, this proposed system can be a discussion tool. Bai *et al.* (2007) discussed food safety assurance systems in China, but most systems face challenges in HACCP implementation. Vela and Fernandez (2003) studied the implementation of HACCP in food industries in the District of Alcorcón and in the VII Health Community Area in Madrid (Spain). They discussed and analysed the main difficulties and barriers to developing and implementing HACCP plans. Shih and Wang (2011) investigated potential factors that may influence the implementation of the HACCP system in hospital catering operations in Taiwan. Bertolini *et al.* (2007) helped small/medium enterprises in the implementation of HACCP. The proposed methodology combines a Fault Tree Analysis (FTA) approach, and can be used to analyse the decomposition of the relevant steps in the manufacturing process of a food product. In order to enhance the real-time monitoring and management of food safety, RFID and EPCglobal techniques are proposed to assist in the implementation of HACCP (Folinas *et al.*, 2006).

2.2.3 Perishable Product Value Loss Model

Product quality quantification can help us build a scientific method to manage perishable products. This section introduces a model which is used in the proposed system to compute product value.

In a constant environment, Taoukis and Labuza (1989) introduced four mathematical descriptions to express the decrease in the value of perishable products. These four models are:

- Zero order reactions with linear kinetics;

- Michaelis Menten kinetics;
- First order reactions with exponential kinetics; and
- Autocatalytic reactions with logistic kinetics.

These models can help us build a relationship between time and the quality of perishable products.

A theory finds a relationship between quality and time. For a given value of initial quality and the value of quality limit, Figure 2.1 gives a summary of the behaviour of quality attributes based on these four kinetic mechanisms. The functions of the linear kinetics model and the Michaelis Menten model are nearly the same most of the time. So we just use three functions to represent the four curves.

The four curves have the same initial quality and the same quality limits. Figure 2.1 shows that the effect of the kinetic mechanisms on the keeping quality (KQ) depends on the level of the same quality present and on the same level of acceptance limit. KQ means the length of time from the time of production up to the point when the quality deteriorates beyond an acceptable level. In Figure 2.1, KQ_{ing} is the keeping quality time of the Linear and Michaelis Menten models, KQ_{exp} is the keeping quality time of the Exponential model, and KQ_{log} is the keeping quality time of the Logistics model. We can use these models to calculate the value of the perishable products in real-time.

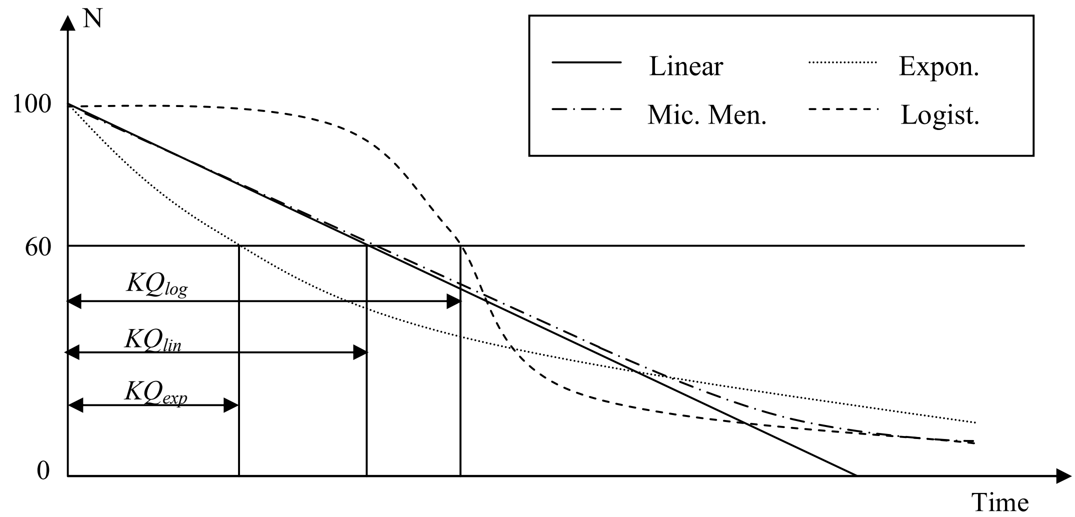


Figure 2.1 Decrease in Quality for sSveral Types of Mechanism

(Tijskens and Polderdijk, 1996)

Linear and Michaelis Menten Kinetics

Although Michaelis Menten and linear kinetics or zero order reactions are relatively rare, this initial part is the most important in quality assessment (see Figure 2.1). Pawsey (1995) proposed a simple linear model to estimate the decrease in the value of fresh vegetables. Osvald and Stirn (2008) extended the model for a vehicle routing algorithm for the distribution of perishable food.

When the quality Q exceeds the quality limit Q_1, the time elapsed is equal to the keeping quality, hence:

$$Q = Q_0 - [(Q_0 - Q_l) \times t] / KQ \tag{2.1}$$

Where, Q_0 is the initial value of Q.

This model is usually used for products that are in the first stage of decay.

Exponential Kinetics

It is commonly found that the first order reactions lead to exponential responses in natural processes. The keeping quality can be derived from the time at which the quality Q reaches the quality limit Q_1:

$$Q = Q_0 \times (Q_0 / Q_1)^{(KQ/t)} \tag{2.2}$$

Where, Q_0 is the initial value of Q.

This model is usually used for products which deteriorate very easily.

Logistic Kinetics

Logistic behaviour is very frequently encountered in natural processes. (Thornley, 1976; Thornley and France, 1984; Tijskens and Evelo, 1993; Tijskens *et al.*, 1994).

The keeping quality can be derived from the time at which quality Q reaches the quality limit Q_1:

$$Q = Q_{\inf} / \{1 + (Q_{\inf} - Q_1) \times [(Q_0 / Q_l)^{(t/K)}] / Q_0\} \tag{2.3}$$

Q_{inf} represents the maximum possible quality at (minus) infinite time.

This model occurs the most frequently. Most perishable products that deteriorate follow this model.

2.3 Supply Chain Management

Supply Chain Management (SCM) is an important area in the field of management. Some approaches for SCM are introduced in this section. It also can help us to propose an approach to improve perishable product supply chains with the knowledge of perishable product management reviewed in the last section.

"SCM is the management of a network of interconnected businesses involved in the ultimate provision of product and service packages required by end customers" (Harland, 1996). It includes the following problems: Distribution Network Configuration, Distribution Strategy, Trade-Offs in Logistical Activities, Information, Inventory Management, and Cash-Flow. SCM has received attention since the early 1980s (Croom *et al.*, 2000). It soon becomes hot subjects in research, due to the expansion of supply chains over national boundaries and into other continents. The globalisation of supply chain management increases the complexity of the problem. For example, Freeman (1990) proposed a four-stage supply chain management model. The necessity of purchasing characteristics in each stage was also described in their research. Eloranta *et al.* (1991) noted that the primary focus of much research began to turn to outbound logistics from inbound logistics. With the development of globalisation, traditional approaches cannot deal with the more complex supply chains. Researches began to focus their vision on emerging techniques.

RFID technologies may improve the potential benefits of supply chain management. According to EPCglobal standards, the chip memory contains an Electronic Product Code

(EPC) which allows the identification of each product in a unique way (Goel, 2007; Brock, 2001). Wal-Mart notified its top suppliers to start using RFID for managing its supplies (RFID, 2003). Sarac *et al.* (2010) reviewed studies about the impact of RFID in supply chain management. It proves that RFID has the potential to improve supply chain management through reduction of inventory losses, increase of the efficiency and speed of processes and improvement of information accuracy. Veronneau and Roy (2009) analyze the economical benefit in global service supply chain for the application of RFID. Thonemann (2002) reported that with the application of RFID technologies, Procter & Gamble and Wal-Mart reduced inventory levels by 70%, and improved service levels from 96% to 99%. The re-engineering of their supply chains also reduced administration costs. Zhou (2009) developed RFID technology in manufacturing. The chosen example was on multiple periods, through the example they analysed the benefit of RFID on the visibility of item-level information. The reduced uncertainty as a key factor to increase the benefit in both static and dynamic conditions is considered. RFID could also be used for the tracking of finished products, work-in-process inventories, and raw materials and so on. Kärkkäinen (2002) developed a Ford's wireless Kanban system based on RFID. The system improved the tracking of parts through the assembly process. RFID could enable quality control to be ensured during production. Nestle used RFID to track product trays in order to prevent poor product quality by ensuring regular cleaning, and Malden Mills used RFID to track imperfections in Polartec fleece fabric (Bear Stearns, 2003).

Through the literature review it can be found that RFID could improve product traceability and visibility through the supply chains. In the next section we will discuss existing systems which have applied RFID.

2.4 Existing RFID-based Systems

With the widespread use of RFID, many researchers have designed systems to enhance food safety management. Applying RFID and sensor technologies, Dupuit *et al.* (2007) presented a decision support system using a rule-based reasoning technology for the management of wastewater treatment plants. This system analysed the dataflow transmitted from sensors, monitored the wastewater, and checked whether the wastewater network was malfunctioning in any observable way. For the purpose of monitoring, Park *et al.* (2006) proposed a Container Yard Management System (CYMS), which aimed to ensure the security of containers, prevent the loss of goods in containers and to track and trace containers. Jedermann *et al.* (2006) developed a real-time autonomous sensor system to monitor products when they are being transported. The backend system can access the on-the-road sensors of this system. The system also separates the sensors and the RFID tags. Therefore the system can be easily expanded to handle special sensor requirements. The use of RFID can also automatically realise task achievement data and information when the products are loaded or unloaded. Woo *et al.* (2009) proposed an activity product state tracking system architecture which is able to track products even when they are in a box or container. Abad *et al.* (2009) developed an RFID-based system for the tracking and cold chain monitoring of food. A RFID-based monitoring system that combines RFID and sensor technologies for monitoring the manufacturing process of wine is proposed. FALKEN Secure Networks (2008) has developed a RFID-based quality tracking system to fulfil the requirements of wine companies from the Bordeaux region in France for ensuring that the quality of wine was preserved during handling, transportation and distribution. The system had four parts. From the vineyard it could track the microclimatic history of the vineyard throughout the growing and harvesting season. During transportation, the environment was monitored, and the locations of the wine could also be viewed. Additionally, it had the function of barrel tracking to manage barrels, which provided winemakers with a complete history of barrel usage and flavour profiles. At the retail level, the system could effectively prevent counterfeit and help restaurants and wine distributors monitor their stocks of wine and manage their inventories.

However, these methods can only provide a partial visualisation of the end-to-end food supply chain. A new data sharing approach, a so-called ePedigree, is advocated in order to gain full supply chain visibility with detailed trace-and-track information. So far only limited work has been published on the topic of verifying food pedigree for food safety. The need for innovative and efficient methods, whereby citizens can be assured that the food quality is satisfactory, is growing because the complexity involved in this issue is enormous. One benefit is that more effective methods with powerful predictions would allow food inspectors to better understand the causes of food safety problems.

2.5 Decision Support Techniques

Three decision support techniques, Fuzzy Logic, Case-based Reasoning and Rule-based Reasoning, are introduced in this section. These techniques will be used in the proposed system.

2.5.1 Fuzzy Logic

Fuzzy logic was first proposed in 1965 by Lotfi Zadeh with the concept of the "fuzzy set" (Biacino and Gerla, 2002; Arabacioglu, 2010). It is a form of many-valued logic. In contrast with traditional logic theory, fuzzy logic deals with reasoning that is approximate rather than fixed and exact. In traditional logic theory, binary sets only have two-value logic: true or false. While in fuzzy logic, it uses degrees of truth to replace absolute statements. "Description in fuzzy logic is closer to human experience and practice" (Ma *et al.*, 2006). The two fuzzy inference techniques are the Mamdani and Sugeno methods. The Mamdani method is widely accepted in fuzzy expert systems for its ability to capture expert knowledge in fuzzy rules (Negnevitsky, 2005).

The main characteristic of a fuzzy expert system is that the expert system uses fuzzy logic instead of Boolean logic (Horstkotte, 2000). Defining fuzzy sets and fuzzy rules, evaluating and then tuning the system to meet the specified requirements are the main events in building a fuzzy expert system (Negnevitsky, 2005). In our research we combined fuzzy logic and CBR for the proposed system. The successful applications of this kind of hybrid system in previous researches will be introduced in the next section.

2.5.2 Case-based Reasoning

Case-based Reasoning (CBR) is a model designed for expert systems (Watson and Marir, 1994). It focuses on the reuse of experience (Aha, 1998). Aamodt and Plaza (1994) describe the traditional CBR model, which defines the problem-solving cycle in four different phases: Retrieval, Reuse, Revise and Return. Figure 2.2 illustrates the cycle.

The traditional life cycle in a CBR system consists four parts:

1. RETRIEVE the most similar case or cases
2. REUSE the information and knowledge in that case to solve the problem
3. REVISE the proposed solution
4. RETAIN the parts of this experience likely to be useful for future problem solving

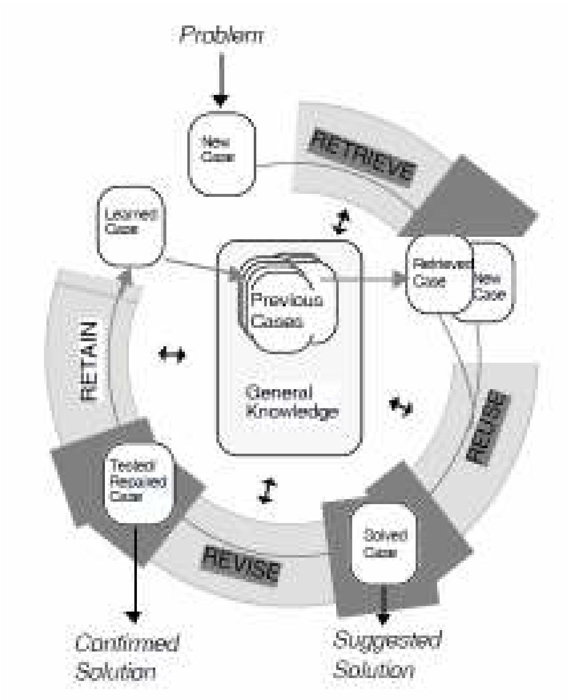


Figure 2.2 Case-based Reasoning Cycle (Aamodt and Plaza, 1994)

The life cycle is described as follows: When there is a new problem to be solved it is first solved by retrieving a previous case, then by reusing the case in one way, and then revising the solution, and finally retaining the new case by adding it into the case base.

Sadek *et al*. (2001) have successfully developed a prototype CBR system for real-time freeway traffic routing. CBR can solve new problems by reusing solutions of similar past problems. The results of their research have demonstrated that the prototype system can run in real-time and produce high quality solutions using case-bases of reasonable size. Shen *et al.* (1994) proposed an approximate CBR model. This model uses neural networks technology to process fuzzy inference with the two dualities of fuzzy logic and approximate reasoning. The self-organising and self-learning procedure can be executed by modifying the weight. Salamo and Lopez-Sanchez (2011) proposed retention and forgetting strategies to maintain the case base of the CBR system a certain scale by adding and removing cases. It has been proven in their research that the model they proposed can effectively maintain the case base. Yeh and Shi (2001) successfully applied a CBR system to handle planning applications in development control. The system helped the planner reuse previous similar cases when making decisions on new applications. Castro *et al.* (2011) developed a fuzzy system to improve the CBR system in solving risk problems. Some rules are developed in the fuzzy system to search for the most suitable cases, not the most similar case. Passone *et al.* (2006) incorporated domain-specific knowledge into a genetic algorithm to implement CBR adaptation. The research improved the adaptation phase in the CBR system. The improved system is suitable for dealing with numerical modelling applications that require the substitution of a large number of parameter values.

2.5.3 Rule-based Reasoning

Rule-based Reasoning (RBR) is a specific type of reasoning which uses "if-then-else" rule statements (Sorli and Stokić, 2009). The reasoning architecture of rule-based systems has two major components: the knowledge base and the inference engine. The knowledge base usually consists of a set of "IF... THEN..." rules, which represent domain knowledge (Dutta and Bonissone, 1993).

The inference engine is the heart of an expert system. There are two types of inference engine for Rule-based expert systems: forward-chaining and backward-chaining. Forward-chaining, also known as data-driven reasoning, starts with data or facts and searches for rules which can be applied to the facts until a goal is reached. Backward-chaining, also known as goal-driven reasoning, starts with a goal and searches for rules which apply to that goal until a conclusion is reached.

This approach has a better explanation than other reasoning methodologies, and since it is relatively simpler it can obtain solutions fast. So it is mainly used in cases that need people to judge and take actions quickly. In this research it is applied in the warning module design.

2.6 Machine Learning

Machine learning is a branch of artificial intelligence. A variety of machine learning methods, such as decision tree learning, ANN, Bayesian networks and so on, are usually used in system design. The proposed approach also applies two of them: *k*-NN and ANN in the product quality evaluation algorithm, and arrival time forecasting.

2.6.1 *k*-Nearest Neighbour Algorithm

k-NN is the simplest method of all machine learning algorithms. It is mostly used for item classification. It has good classification performance on a wide range of real-world data sets (Ghosh *et al.*, 2005).

Unlike other algorithms, a *k*-NN predictor stores all of the training samples. When a new sample needs to be classified it builds a predictor ahead of time. That makes it extremely simple to implement. When a new sample is given to solve, a *k*-NN predictor searches the training space for the closest *k* training samples. And the objective function value of the training sample is assigned to the new sample. Formula 2.4 is used to measure the distances between each two class samples (Liu and Sun, 2011).

$$d(X,Y)=\sqrt{\left(\sum_{i=1}^{n}(X_i-Y_i)^2\right)} \tag{2.4}$$

As *k*-NN is a simple method it is still used in many studies. Lei and Zuo (2009) used a weighted *k*-NN for crack level identification in gears. Yildiz *et al.* (2008) used *k*-NN to determine unwanted e-mails, and a parallelism process was applied to reduce spent time. In most situations, researchers combine it with other algorithms for a new algorithm design. Nasibov and Peker (2011) proposed time series labelling algorithms based on the *k*-NN rule. It can be successfully used in an unsupervised time series labelling process. Fındık *et al.* (2010) used Particle Swarm Optimisation (PSO) and *k*-NN for a novel robust watermarking scheme design. The proposed PSO and *k*-NN hybrid system performs better than many other systems. Jiang *et al.* (2012) combined *k*-NN and fuzzy similarity measures for multi-label document classification. The experimental results showed that the proposed method can work more effectively than other methods. In this research, *k*-NN with ANN is combined for product quality evaluation. ANN will be introduced in the next section.

2.6.2 Artificial Neural Network

An artificial neural network (ANN) can be defined as a mathematical model or computational model that is inspired by the structure and functional aspects of biological neural networks. Simple neural networks are effective in forecasting. It is a model of reasoning based on the human brain (Negnevitsky, 2005). Neural networks can give the best forecasting performance in most time-series investigation, with only one or two hidden nodes. An ANN framework is demonstrated in Figure 2.3. An ANN is composed of a number of very simple and highly interconnected processors. The processors are called neurons. The neurons are connected by weighted links, and the link passes signals from one neuron to another. Each link has a numerical weight associated with it. ANN learns through repeated adjustments of these weights. The simplest form of a neural network is called a perceptron. It can be trained by some learning algorithms. There are usually two phases in the learning algorithm. In the first phase, a pattern is generated from the training input to the input layer. The network repeats the generations from layer to layer until the output layer generates the output pattern. If the output is different from the desired result, an error is calculated and then transferred backwards through the network from the output layer to the input layer. This is the second phase. The weights are modified in this phase (Negnevitsky, 2005).

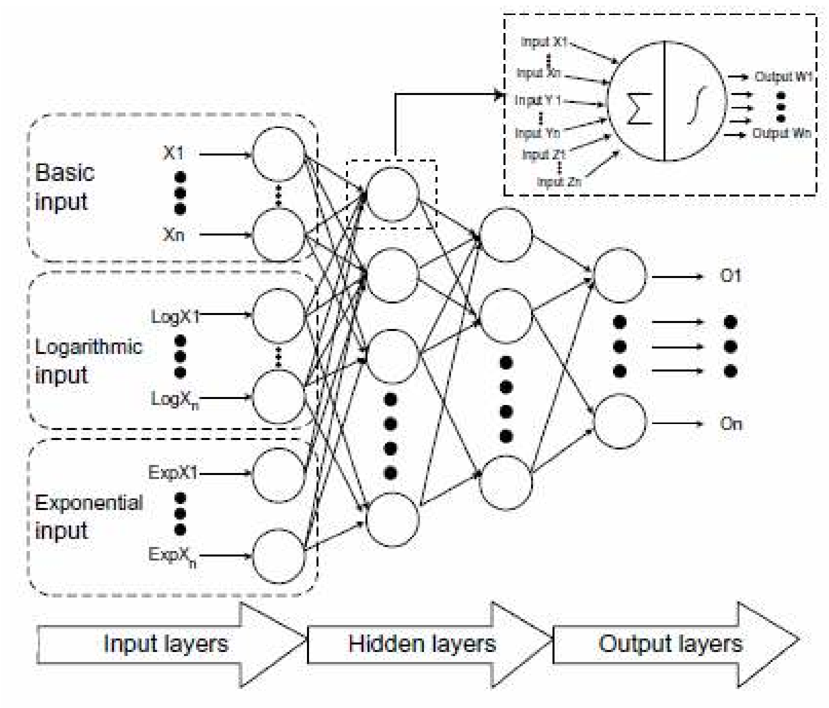


Figure 2.3 ANN framework (Weigend *et al.*, 1991)

Many studies have attempted to apply ANN model to forecast time series. Weigend *et al.* (1991) concluded that the ANN model is better than conventional methods. Chen and Ou (2009) proposed an ANN-based forecasting model for network sales forecasting of perishable food in a convenience store. Taormina *et al.* (2012) presented an application of feedforward ANN for long period simulations of hourly groundwater levels in a coastal unconfined aquifer sited in the Lagoon of Venice, Italy. The results showed that the developed approach can accurately reproduce groundwater depths of the shallow aquifer for several months. Abbass (2002) proposed an evolutionary ANN approach. The approach is based on the pareto-differential evolution algorithm. It aims to predict breast cancer augmented with a local search. Hunt and Deller Jr. (1995) exploited results from matrix perturbation theory and developed a new training method for significant training time improvement.

2.7 Optimisation Algorithms

The main function of the Decision Support Module (DSM) in the proposed system is to help vehicle management. Optimisation of the vehicle schedule is the main challenge. In this section some optimisation approaches, QEA, GA, and some hybrid algorithms are introduced.

2.7.1 Quantum-inspired Evolutionary Algorithm

Quantum computing was firstly proposed by Benioff (1980) and Feynman (1982). It was declared that Quantum Algorithm (QA) could solve many difficult problems in the field of classical computation. The algorithm was based on the concepts and principles of quantum theory, such as superposition of quantum states, entanglement and intervention. There has been a great interest in the application of the QA because of its excellent computational performance (Shor, 1994). Han and Kim (2002) has proposed the

Quantum-inspired Evolutionary Algorithm (QEA), which was inspired by the concept of quantum computing. The new algorithm was successfully applied to solve many difficult problems. The good performance of QEA for finding a global best solution in a short time has attracted the attention of researchers. A lot of research concentrates on quantum-inspired evolutionary computing for classical optimisation problems. The procedure of QEA (Vlachogiannis and Østergaard, 2009) will be introduced first.

In QEA, the smallest unit of information stored in a two-state quantum computer is called a Quantum bit (Q-bit), which is defined as $\begin{bmatrix} \alpha \\ \beta \end{bmatrix}$ (Wang *et al.*, 2007). A Q-bit may be in the "1" state, in the "0" state, or in any superposition of the two (Hey, 1999). The state of a Q-bit as shown in Figure 2.4 can be represented as below:

$$|S\rangle = \alpha\,|0\rangle + \beta\,|1\rangle \tag{2.5}$$

where α and β are complex numbers that specify the probability amplitudes of the corresponding states and therefore are called amplitude amplifications (Hey, 1999).

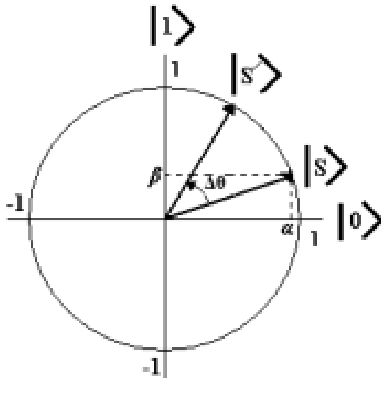


Figure 2.4 Basic Q-bit (Vlachogiannis and Østergaard, 2009)

The Q-bit individual has the advantage that it can probabilistically represent a linear superposition of states in search space (Wang *et al.*, 2005). $|\alpha|^2$ and $|\beta|^2$ are the probabilities that the Q-bit exists in state "0" and state "1", respectively, which satisfy $|\alpha|^2+|\beta|^2=1$. And an *m*-Q-bits is defined as $\left[\begin{array}{c|c|c|c}\alpha_1 & \alpha_2 & \ldots\ldots & \alpha_m \\ \beta_1 & \beta_2 & \ldots\ldots & \beta_m\end{array}\right]$, where $|\alpha_i|^2+|\beta_i|^2=1$ (i=1,2, …, m) and *m* is the number of Q-bits (Han and Kim, 2002).

For example, the state of 3-Q-bits $\left[\begin{array}{c|c|c}1/\sqrt{2} & 1/\sqrt{2} & 1/2 \\ 1/\sqrt{2} & -1/\sqrt{2} & \sqrt{3}/2\end{array}\right]$ can be presented as

$$|S\rangle = \frac{1}{4}|000\rangle + \frac{\sqrt{3}}{4}|001\rangle - \frac{1}{4}|010\rangle - \frac{\sqrt{3}}{4}|011\rangle + \frac{1}{4}|100\rangle + \frac{\sqrt{3}}{4}|101\rangle - \frac{1}{4}|110\rangle - \frac{\sqrt{3}}{4}|111\rangle \tag{2.6}$$

(Han and Kim, 2002)

It means that the probabilities that the *m*-Q-bits exist in state "000", "001", … , "111" are 1/16, 3/16, …… , 3/16. The representation has the advantage of representing a linear superposition of all possible states. It has a better characteristic of population diversity than any other representation (Wang *et al.*, 2005).

The steps of QEA are:

Step 1: Let t=0 and initialise Q(t).

$$Q(t) = \{q_1^t, q_2^t, \ldots, q_n^t\},\ q_j^t = \left[\begin{array}{c|c|c|c}\alpha_1^t & \alpha_2^t & \ldots\ldots & \alpha_m^t \\ \beta_1^t & \beta_2^t & \ldots\ldots & \beta_m^t\end{array}\right] \tag{2.7}$$

Step 2: Make *P(t)* by observing the state of *Q(t)* through comparing with $|\alpha_{ji}^t|^2$ or $|\beta_{ji}^t|^2$ as follows (Han, 2001):

$$p_{ji}^t = \begin{cases} 0........rand[0,1] > |\alpha_{ji}^t|^2 \\ 1....................otherwise \end{cases} \tag{2.8}$$

Step 3: Evaluate population *P(t)* by fitness function, and save the best solution *b.* If stopping condition is satisfied, output results; otherwise, go to next step.

Step 4: Update *Q(t)* with the quantum rotation gate *U(t)*.

The quantum rotation gate is used as the update mechanism, which can help guide the searching direction to the optimal area, and increase the algorithm's convergence speed. It can be chosen according to the problem. A modified rotation gate *U(t)* used in QEA is as follows (Li and Wang, 2007):

$$\begin{bmatrix} \alpha_i' \\ \beta_i' \end{bmatrix} = \begin{bmatrix} \cos(\xi(\Delta\theta_i)) & -\sin(\xi(\Delta\theta_i)) \\ \sin(\xi(\Delta\theta_i)) & \cos(\xi(\Delta\theta_i)) \end{bmatrix} \times \begin{bmatrix} \alpha_i \\ \beta_i \end{bmatrix} \tag{2.9}$$

$$\theta_i = s(\alpha_i, \beta_i) \cdot \Delta\theta_i \tag{2.10}$$

where θ_i is the rotation angle, $s(\alpha_i, \beta_i)$ and $\Delta\theta_i$ represent the sign of θ_i determining the rotation direction and the magnitude of rotation angle respectively.

Step 5: Let *t*=*t*+1, and go back to step 2

The procedure of QEA is described in Figure 2.5 (Xiao *et al.*, 2009).

Han (2002) successfully applied QEA for the 0-1 knapsack problem. Figure 2.6 indicates the results compared with the classical genetic algorithm (CGA). Li and Li (2008) applied the QEA for continuous space optimisation based on the Bloch coordinates of Q-bits. They successfully designed QEA for numerical optimisation.

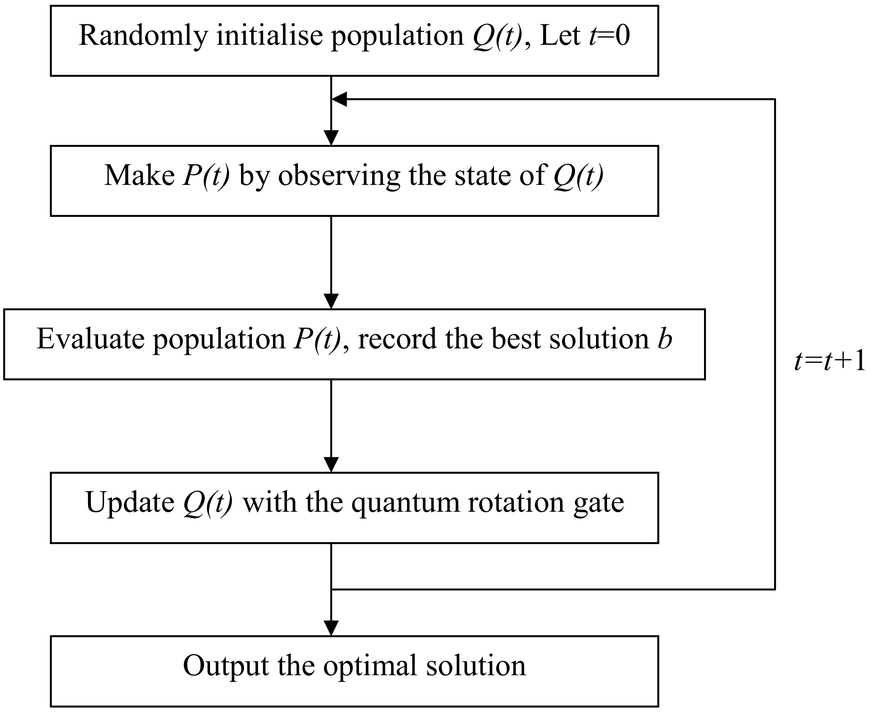
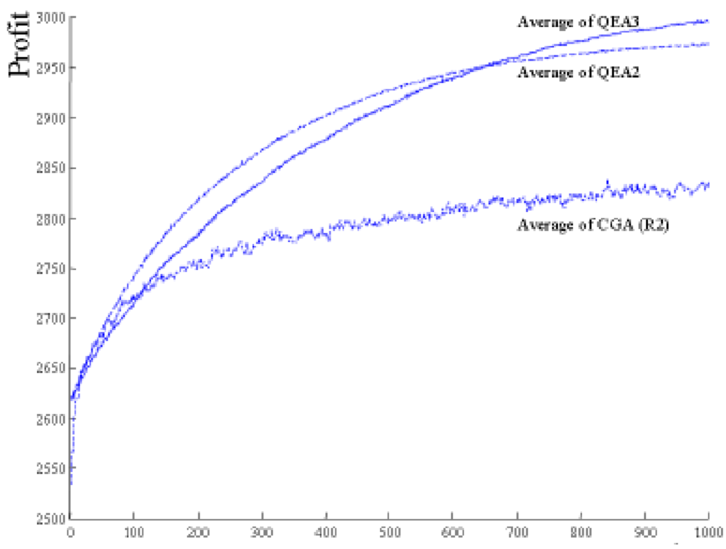


Figure 2.5 Outline of QEA (Xiao *et al*., 2009)



Average profits (500 items)

Figure 2.6 Comparison of QEA and CGA on the Knapsack Problem (Han and Kim, 2002)

These successful applications motivated us to study the improvement and application of QEA for vehicle management in the proposed system.

2.7.2 QEA–based Hybrid Optimisation Algorithm

For the excellent performance of QEA, most researches proposed a hybrid algorithm of QEA and some other traditional optimisation algorithms to get better results. In the field of QEA hybrid algorithms, mainly two quantum inspired algorithms, Quantum Genetic Algorithm (QGA) and Quantum Particle Swarm Optimizer (QPSO), have been proposed recently for solving problems such as the Travelling Salesman Problem (TSP), the knapsack problem, filter design, numerical optimisation problems and so on.

Quantum Particle Swarm Optimizer

Wang *et al.* (2007) applied QPSO to solve TSP. The main characteristic of QPSO is that it uses QPSO to automatically update the Q-bit. The experimental results of the 14 city TSP show QPSO is feasible and effective for small-scale TSP. The successful application of QPSO in solving TSP indicates a promising novel approach.

In QPSO, a quantum angle is defined as an arbitrary angle θ and a Q-bit is represented as [θ], the original Q-bit $\begin{bmatrix}\alpha\\ \beta\end{bmatrix}$ can be replaced by $\begin{bmatrix}\sin(\theta)\\ \cos(\theta)\end{bmatrix}$. The common rotation gate

$$\begin{bmatrix}\alpha_i'\\ \beta_i'\end{bmatrix}=\begin{bmatrix}\cos(\xi(\Delta\theta_i)) & -\sin(\xi(\Delta\theta_i))\\ \sin(\xi(\Delta\theta_i)) & \cos(\xi(\Delta\theta_i))\end{bmatrix}\times\begin{bmatrix}\alpha_i\\ \beta_i\end{bmatrix} \tag{2.11}$$

is replaced by

$$[\theta_i'] = [\theta_i + \xi(\Delta\theta_i)] \tag{2.12}$$

The procedure to update Q(t) is modified with the following improved PSO formula instead of using the traditional Q-gate U(t):

$$v_{ji}^{t+1} = \chi \times (\omega \times v_{ji}^{t} + C_1 \times rand() \times (\theta_{ji}^{t}(pbest) - \theta_{ji}^{t}) + C_2 \times rand() \times (\theta_{i}^{t}(gbest) - \theta_{ji}^{t})) \tag{2.13}$$

$$\theta_{ji}^{t+1} = \theta_{ji}^{t} + v_{ji}^{t+1} \tag{2.14}$$

where $v_{ji}^{t}, \theta_{ji}^{t}, \theta_{ji}^{t}(pbest)$ and $\theta_{i}^{t}(gbest)$ are the velocity, current position, individual best and global best of the *i*th Q-bit of the *j*th m-Q-bits, respectively. In that study, set χ=0:99, *W*=0.7298, *C1*=1.42 and *C2*=1.57, which satisfy the convergence condition of the particles: $W > (C_1 + C_2)/2 - 1$. Since *C2*>*C1*, the particles will converge faster onto the global optimal position of the swarm than the local optimal position of each particle. And the algorithm has global searching properties (Bergh, 2001; Huang *et al.*, 2005).

Quantum Genetic Algorithm

Vlachogiannis and Østergaard (2009) proposed a general quantum genetic algorithm (GQ-GA). The algorithm is applied in the reactive power and voltage control of IEEE 30-bus and 118-bus systems for optimisation. The results of GQ-GA are compared with PSO, classical GA and some other optimisation algorithms. GQ-GA presented a better performance than the others.

In GQ-GA, a one point crossover operator is used. Crossover position (position *i*) is determined randomly, and then the Q-bits of the parents before position *i* are reserved while the Q-bits after position *i* are exchanged.

$$\begin{bmatrix} \alpha_{1,1} \left| \alpha_{1,2} \right| \ldots\ldots \left| \alpha_{1,m} \right. \\ \beta_{1,1} \left| \beta_{1,2} \right| \ldots\ldots \left| \beta_{1,m} \right. \end{bmatrix} \Rightarrow \begin{bmatrix} \alpha_{1,1} \left| \alpha_{2,2} \right| \ldots\ldots \left| \alpha_{1,m} \right. \\ \beta_{1,1} \left| \beta_{2,2} \right| \ldots\ldots \left| \beta_{1,m} \right. \end{bmatrix} \tag{2.15}$$

$$\begin{bmatrix} \alpha_{2,1} \left| \alpha_{2,2} \right| \ldots\ldots \left| \alpha_{2,m} \right. \\ \beta_{2,1} \left| \beta_{2,2} \right| \ldots\ldots \left| \beta_{2,m} \right. \end{bmatrix} \Rightarrow \begin{bmatrix} \alpha_{2,1} \left| \alpha_{1,2} \right| \ldots\ldots \left| \alpha_{2,m} \right. \\ \beta_{2,1} \left| \beta_{1,2} \right| \ldots\ldots \left| \beta_{2,m} \right. \end{bmatrix} \tag{2.16}$$

Mutation is also used for Q-bit. On mutation, the position (position *i*) is also determined randomly, and then the corresponding α_i and β_i are exchanged.

$$\begin{bmatrix} \alpha_{1,1} \left| \alpha_{1,2} \right| \ldots\ldots \left| \alpha_{1,m} \right. \\ \beta_{1,1} \left| \beta_{1,2} \right| \ldots\ldots \left| \beta_{1,m} \right. \end{bmatrix} \Rightarrow \begin{bmatrix} \alpha_{1,1} \left| \beta_{1,2} \right| \ldots\ldots \left| \alpha_{1,m} \right. \\ \beta_{1,1} \left| \alpha_{1,2} \right| \ldots\ldots \left| \beta_{1,m} \right. \end{bmatrix} \tag{2.17}$$

Wang *et al*. (2005) used the Quantum-inspired Genetic Algorithm (QGA) to solve the flow shop scheduling problem. Wang *et al*. (2007) suggested a quantum swarm evolutionary algorithm for a 14 city classical Travelling Salesman Problem and 0-1 knapsack problem. Grigorenko and Garcia (2001) applied QGA to determine the ground-state wave functions of two-particle problems in one and two dimensions. Coelho (Coelho, 2008) introduced the Quantum-behaved PSO (QPSO) approach to find the optimum of a constrained optimisation problem. Vlachogiannis and Otergaard (2009) proposed a QGA for an optimal control problem in a power system and presented a new quantum computing inspired genetic algorithm GQ-GA for the optimal steady-state performance of power systems. Its results proved that GQ-GA has a superior performance to GA, EA and PSO through the testing of the algorithm on an IEEE 118-bus system and 30-bus system. Xiao *et al.* (2009) proposed a hybrid quantum chaotic swarm evolutionary algorithm for DNA coding.

2.7.3 Genetic Algorithm

Genetic algorithm (GA) is the most commonly used algorithm. It has been proven in a variety of optimisation problems. GA applies search mechanisms that are developed to simulate the biological processes of natural selection and natural evolution (Mitchell, 1996; Coley, 1999). The standard GA starts with an initial set of random solutions. The solutions are analogous to chromosomes in biological systems. Each chromosome is composed of genes, and is usually binary. In each generation, also known as an iteration, the chromosomes are evaluated according to a fitness function. The chromosome that has a better performance has a high probability to be chosen as the parent for generating new chromosomes using a crossover operator. The new chromosome may be changed slightly using a mutation operator.

In summary, the GA has three main operators: reproduction, crossover and mutation. These operators are applied in GA for new individuals.

The basic steps of the developed GA are described as follows (Harper *et al.*, 2005):

Step 1: Randomly generate a population of chromosomes,

Step 2: Calculate the results of each chromosome by the fitness function, Step 3: Select two parent chromosomes from the population. Russian roulette is the usual operator,

Step 4: Generate a child chromosome from the two parent chromosomes using a crossover operation,

Step 5: Mutate the new chromosome,

Step 6: Calculate the result of the child chromosome by the fitness function,

Step 7: Replace the worst chromosome with the new one based on the calculation result,

Step 8: Stop if the stop condition is satisfied, otherwise go to step 3.

2.7.4 Optimisation Algorithm for Vehicle Routing Problems with Time Windows

The vehicle management we want to solve in the proposed MDSS can be classified as the Vehicle Routing Problem with Time Windows (VRPTW). VRPTW is a generation of the Vehicle Routing Problem (VRP). In this section, some hybrid optimisation algorithms for solving VRPTW are discussed.

VRP concerns developing a plan for vehicles to deliver and collect goods or people. The classical VRP is defined with a single depot and route length constraints. Several variants of the classical problem have also been proposed for study because real-life cases are much more complex, such as VRP with time windows. VRPTW defines that the transportation must start and end within a given time window [a, b]. The vehicle is allowed to arrive before a. But it needs to wait until the time is a. Arrivals after b are forbidden. VRPTW is a Non-Polynomial (NP) problem. Consequently, most research about VRPTW has concentrated on heuristics. Nevertheless, mathematical programming techniques can help optimally solve realistic size instances when the problem is sufficiently constrained. The methods for VRPTW usually consider a hierarchical objective which first minimises the number of vehicles used and then the distance.

Various VRP have been studied by a number of researchers. Hwang (2002) developed a GA-TSP (Genetic Algorithm-Travelling Salesmen Problem) model by improving the GA to solve the typical VRPTW. However in this research all the vehicles are considered to be of the same type. Ho and Haugland (2004) described a Tabu search heuristics method for the Vehicle Routing Problem with the Time Windows and Split Deliveries problem (VRPTWSD). This research considered that a customer can be serviced by more than one vehicle, but again all the vehicles are of the same type. Alba and Dorronsoro (2006) used cellular GA hybridised with a specialised local search method to solve the classical VRP. Tarantilis and Kiranoudis (2007) used a new two-phase construction heuristics, called Generalised Route Construction to solve two practical planning problems, the distribution of perishable products and the distribution of ready concrete for a construction company. But the problems are just capacitated vehicle routing problems (CVRP) without time windows. Zapfel and Bogl (2008) have proposed a hybrid metaheuristic combined with a construction heuristic for a real-life case of an Austrian postal company. The case considered includes all the constraints of real-life, such as each customer has a time window, vehicles have varying capacities, and workers' working hours vary and so on. The method has four steps to solve the problem: 1. Using the Solomon heuristic for an initialisation solution. 2. Using Tabu search and the GA for the General Vehicle Routing Problem with Time Windows (GVRPTW). 3. Using a simple heuristic for crew scheduling to ensure the satisfaction of relevant constraints. 4. Using GA and Tabu Search to evaluate the quality of the solution. In addition, Tavakkoli-Moghaddam *et al*. (2006) developed a hybrid simulated annealing system for capacitated vehicle routing problems with independent route length. They used a nearest neighbour based heuristic for VRP with independent route length for generating initial solutions, and then simulated annealing was used for evaluating the quality of the solution. Battarra *et al*. (2009) proposed a two-phase heuristics method for real-world application. The research considered different kinds of products. Prisinger and Ropke (2007) applied the Adaptive Large Neighbourhood Search (ALNS) to solve all variants of the VRP problem, including VRPTW, CVRP, the multi-depot vehicle routing problem (MDVRP), the site-dependent vehicle routing problem (SDVRP) and the open vehicle routing problem (OVRP). Cheung *et al.* (2008) developed a mathematical model that can be used in this monitoring system for dynamic fleet management. The model takes into consideration dynamic data such as vehicle locations, travelling time and incoming customer orders.

2.8 Research Opportunities

Although many approaches have been proposed to improve product safety, monitor perishable products and reduce losses from the deterioration of perishable products during transportation, a system that integrates both real-time monitoring and management functions together with an optimisation function has not yet been proposed. The most important things for a company are product quality and operational costs, as for the logistics company. To save transportation costs, optimisation is necessary. To guarantee the product quality, real-time monitoring is also necessary. Moreover, due to the characteristics of perishable products, temperature sensitivity and short shelf-life, timely warning, positioning and arrival time forecasting are also important. Consequently we compare systems or models with these five aspects: real-time monitoring, optimisation, positioning, forecasting and warning.

Beliën and Forcé (2012) reviewed the publications over time for blood supply chain management. They found nearly all the papers were at individual hospital level and regional blood centre level. While there were very few studies about blood management at the supply chain level prior to 2000. However, during the last decade the number of publications on the supply chain level has increased quickly. It has caught up with the number of publications on the individual hospital and regional blood centre levels. Similarly to blood management, most studies on other perishable products at the supply chain level have also come out after 2000. We compare some of the highly citated papers on perishable product management systems published after 2000 from academic article databases. The main objective of the selected researches and this research are the same. The comparison of the results is summarised in Table 2.2. In the first column, the researchers and publication year are given. In the second column, the name of the system or approach that was discussed in the publication is given. Below its name, the five functions that are considered as important to the perishable product supply chain management are listed. If the discussed system has the particular function, a tick is given in the block, under the corresponding function.

Table 2.2 Major Studies on Perishable Products Management Systems

Articles (2000-2012)	System/Approach				
	Monitoring	Optimisation	Positioning	Forecasting	Warning
Hewett (2003)	SCM for perishable horticultural crops				
Bogataj *et al.* (2005)	Material requirements planning model for the evaluation of the stability of perishable goods in cold logistic chains				
			√	√	√
				Forecast the product quality	
Li *et al.* (2006)	Two dynamic models for perishable food supply chain planning				
	√	√		√	√
		Maximise the product quality value when they arrived		Forecast the product quality	
Liu and Ma (2008)	Quality flexibility contract model for perishable product supply chain coordination				
		√		√	
		The Best Decision		Forecast the product quality	

Articles (2000-2012)	System/Approach				
	Monitoring	Optimisation	Positioning	Forecasting	Warning
Jedermann *et al*. (2009)	Semi-passive RFID loggers for perishable food transportation				
	√		√		√
Feng (2009)	Multi-agent based simulation model of a three-echelon supply chain				
	√	√	√		
	Monitor the vehicle location	Minimise the travelling distances			
Wang *et al.* (2009)	An integrated optimisation model for perishable food production				
		√		√	
		Maximise the product quality value when they arrived		Forecast the product quality	
Cai *et al.* (2010)	A model for optimal decisions in decentralised and centralised systems to preserve the freshness of the product				
		√		√	√
		Maximise the product quality value when they arrived		Forecast the product quality	

Articles (2000-2012)	System/Approach				
	Monitoring	Optimisation	Positioning	Forecasting	Warning
Kuo and Chen (2010)	An advanced multi-temperature joint distribution system for a food cold chain				
	√				√
Wang *et al.* (2010)	An integrated production planning model to improve traceability and manufacturing performance of perishable food				
		√		√	
		Maximise the product quality value when they arrived		Forecast the product quality	
Ghandforoush and Sen (2010)	A prototype DSS for platelet production and blood mobile scheduling for a regional blood centre				
		√			
Ahumada and Villalobos (2011)	An operational model for planning the harvest and distribution of perishable agricultural products				
		√			
Delen *et al.* (2011)	Applications of RFID-based environmental sensors in a perishable product supply chain				
	√				√
Hong *et al.* (2011)	A financially viable business model for a food traceability system in a chain of convenience stores				
	√				

Articles (2000-2012)	System/Approach				
	Monitoring	Optimisation	Positioning	Forecasting	Warning
Wang (2011)	A system dynamics model to analyse the causes of the bullwhip effects in a perishable product supply chain				
		√			
Rong *et al.* (2011)	A mixed-integer linear programming model for the planning of fresh food throughout the supply chain with a focus on product quality				
		√		√	√
				Forecast the product quality	
Santa *et al.* (2012)	A Telematic platform for the integral management of agricultural and perishable goods in terrestrial logistics				
	√		√		√
White and Cheong (2012)	A computationally practical approach for single vehicle transport of a perishable product based on partially observed Markov decision process				
	√	√			

From the review of the existing systems/models for perishable products in logistics, the systems/models can be basically classified into two groups: practical systems and academic models. The researchers of practical systems focus on the hardware development to realise real-time monitoring, and usually their backend systems are weak. Most can only record data and perform some simple judgments. The researchers of the academic models focus on data analysis. The approaches about real-time information achievement and avoidance of value losses during transportation are usually ignored.

Additionally, since perishable product quality changes quickly, most optimisation objectives in these studies are the maximisation of product values. Few studies consider saving transportation costs for logistics companies.

In summary, there is no system/model that presently has all five functions. It provides us with research opportunities to propose an approach to guarantee perishable product quality for customers and to save operational costs for companies through real-time monitoring, optimisation, timely warning, positioning and forecasting. A system can be developed based on the approach.

2.9 Summary

In this chapter, some relevant works about perishable product management are reviewed.

Firstly, the general condition of perishable product management is discussed. The management of perishable product supply chains is important. The previous studies mainly focus on quality control for food safety management. Though the implementation of HACCP is still a challenge, it is still the most common method. The quantification of product value is an approach to make HACCP more scientific. Tijskens *et al.* (1996) proposed a value loss model for perishable products. On the assumption that the keeping quality time (the period during which the product will not have deteriorated) is equal to the guarantee date, the curve of the reduction in value of the perishable products can be determined for product quality estimation.

The management of perishable product supply chains is a branch of SCM. A review of techniques for SCM is conducted. The emerging technology RFID is a good tool to improve the currently complex SCM due to globalisation. The existing RFID-based systems are also reviewed. The review shows that the RFID-based system has a good performance in real-time monitoring. Based on these literature reviews, a real-time monitoring and decision support system is considered for development. Some Artificial Intelligence (AI) techniques are applied in the proposed system for decision supports. So the techniques of fuzzy logic, RBR, CBR, k-NN and ANN are reviewed.

We also note that most monitoring systems lack consideration on vehicle schedule optimisation. This vehicle schedule problem can be classified as VRP. Approaches to solve VRP for the improvement of vehicle management are introduced. In the early 21^{st} Century, Han (2002) proposed QEA. The results show that QEA has a better performance in searching for the global optimisation solution than other traditional optimisation algorithms in the TSP and 0/1 knapsack problem. There is still not enough research about this algorithm. No one has used this algorithm to solve VRP, because this kind of problem has so many constraints. GA and heuristics are considered for hybridisation with QEA for solving VRP and the dynamic adjusting of schedules when abnormal situations occur.

From a review of the existing systems for perishable product management in logistics, it is clear that there is a need for the development of a system that integrates real-time monitoring, accident warning, quality evaluation and forecasting, positioning and optimisation. This research aims to find an approach for the development of such an integrated system. The basic idea of this research is to use RFID to get real-time information about products, including dynamic data on the position of the vehicle, load level, travelling time, status of the customer orders, the environment outside the products, and the status of the products being transported. After obtaining the real-time information, the management part is to evaluate the product quality, to optimise the vehicle schedule, to judge whether there is anything abnormal, to offer some suggestions for coping with emergencies or accidents, and to adjust plans once emergencies or accidents occur. The next four chapters will introduce the approach and the proposed system in detail.

CHAPTER 3 THEORITICAL FRAMEWORK AND SYSTEM ARCHITECTURE

3.1 Introduction

As stated in the first two chapters, it is necessary to improve the supply chain management of perishable products, especially in distribution. And presently there is not a satisfactory system or model. An approach, including real-time monitoring, optimisation, positioning, timely warning and forecasting, is proposed for filling the research gap.

In this chapter, the theoretical framework of the proposed approach is firstly introduced in Section 3.2. Based on the approach, a system called MDSS is developed. The architecture of the system in presented in Section 3.3. MDSS contains three modules. The general discussion on the three modules is also conducted in this section. The discussion is focused on the relationships of the modules. The algorithm and approaches applied in the three modules are discussed in Chapter 4, Chapter 5 and Chapter 6 respectively. Finally, Section 3.4 provides a summary of this chapter.

3.2 Theoretical Framework

The review of existing systems for perishable product management in distribution shows that there is no system or model that integrates real-time monitoring, optimisation, positioning, timely warning and forecasting together. The approach for improving perishable product management is considered from five aspects. The theoretical framework is illustrated in Figure 3.1.

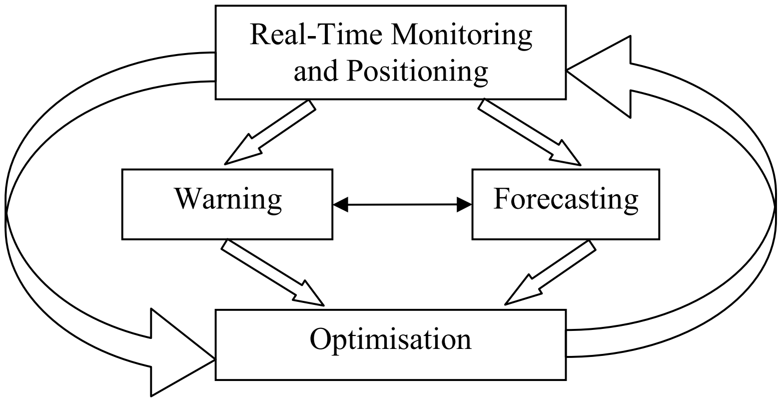


Figure 3.1 Theoretical Framework

As shown in Figure 3.1, there are three main stages in this approach. Stage 1 is monitoring and positioning. It is used to collect real-time information on products, locations and on the environmental conditions in which the products are stored. RFID, GPS and sensor techniques are considered in this stage to identify the products and monitor them in real-time. The real-time monitoring of the entire supply chain can help the implementation of HACCP for quality control. In this stage, all the relevant information on the products in each link of the supply chain is recorded. For a scientific evaluation of the products, a *k*-NN and ANN hybrid algorithm is proposed based on the records. All information is transmitted to a web platform, such as EPCglobal, for sharing among the cooperating companies in the supply chain. The second stage plays the role of assistance, which includes warning and forecasting. The stage acquires the required data from stage 1 and transmits the results to stage 3. For forecasting, a value loss model introduced in Section 2.2.3 is applied to calculate and to estimate the product value. A CBR hybrid with fuzzy logic is proposed to forecast the arrival time of vehicles. ANN is used to train the similar weightings of CBR. For warning, RBR is applied because of its fast response and explanation characteristics. The third stage is optimisation. It is designed for 3PL. GA and a proposed IQEA are used to develop a vehicle schedule for minimising transportation costs. If there is anything abnormal or an emergency occurs, a heuristic approach, called HCES, is applied for vehicle schedule adjustment to help users cope with accidents and emergencies.

Based on the approach, MDSS is developed. This system aims to improve the current situation of perishable product supply chains in distribution. Corresponding to the three stages of the approach, the system contains three modules: a Real-time Monitoring Module (RMM) in stage 1 for real-time monitoring and positioning, a Forecasting and Warning Module (FWM) in stage 2 for forecasting and warning, and a Decision Support Module (DSM) in stage 3 for optimisation.

3.3 System Architecture

MDSS integrates the functions of the three modules together and shares their respective information on a platform for the better management of perishable products. General discussion about the system is conducted in this section.

Figure 3.2 illustrates the operating procedure of the system. As shown, the entire system comprises of three modules; RMM, FWM and DSM. RMM uses RFID, sensors and GPS. In addition to real-time monitoring in distribution, it can also be extended to monitor products at each link of the entire supply chain. After processing the data, the system transmits the useful information to a platform. Users can access information from the platform. FWM also selects information from the platform. The module has two main functions: arrival time forecasting and accident warning. If there is anything abnormal, FWM will transmit relevant information to DSM. DSM also has two functions: static optimisation and dynamic adjustment. Static optimisation optimises the schedules of the vehicles that carry out distribution tasks, based on the information from the platform. When FWM gives a warning to DSM, dynamic adjustment will re-arrange the vehicle schedule and help users cope with accidents. In summary, RMM monitors product conditions and collects data. FWM and DSM get data from it. FWM helps users find out whether there is anything abnormal occurring. And DSM adjusts their decisions in time to avoid major problems. Meanwhile, DSM arranges the vehicle schedule conducting RMM.

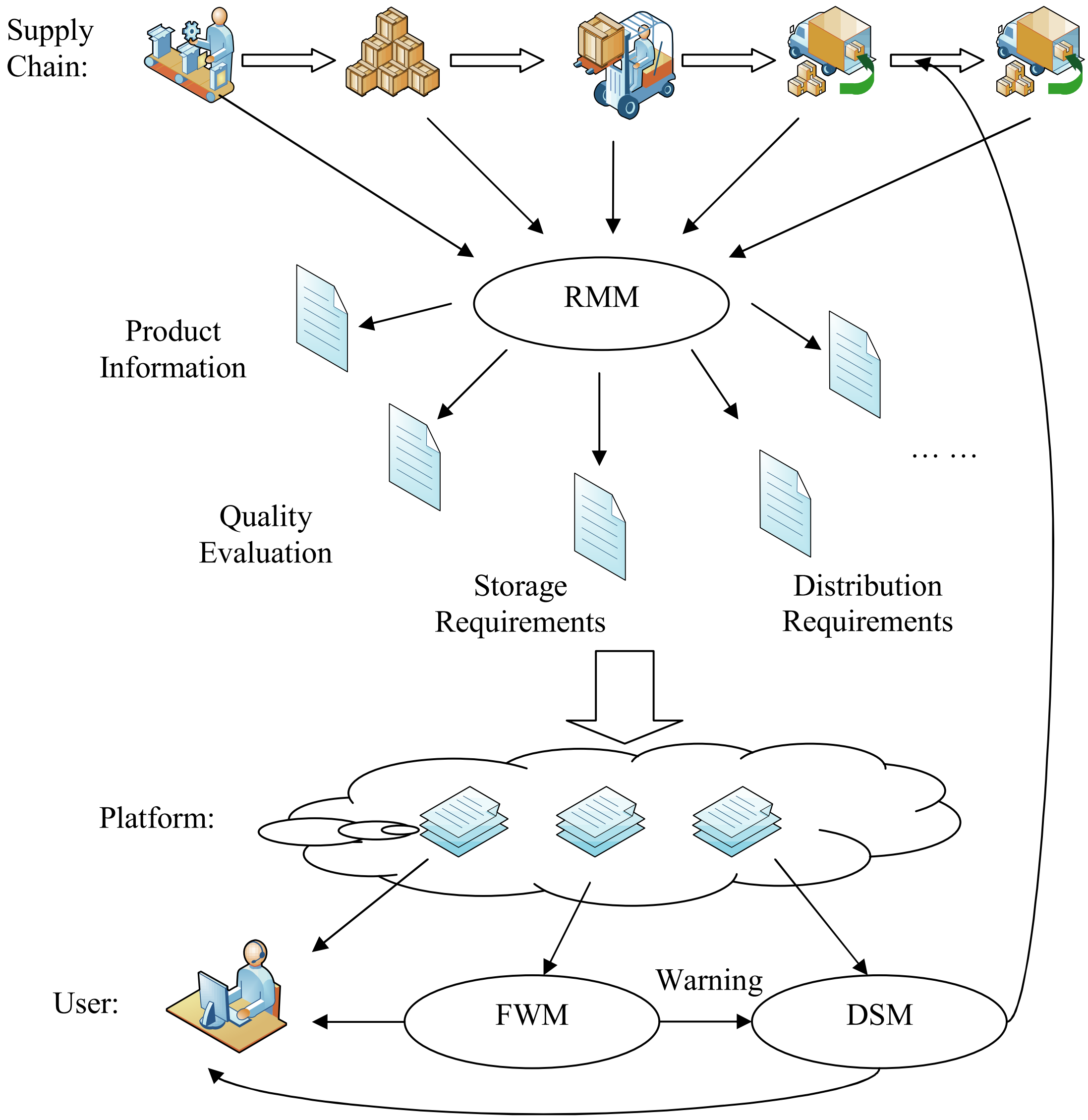


Figure 3.2 System Architecture

Figure 3.2 presents the architecture of the entire system. It illustrates the relationships between the three modules. Next, there are some general introductions to the three modules. Chapter 4, Chapter 5 and Chapter 6 will discuss these modules in detail.

3.2.1 Real-time Monitoring Module

RMM aims to collect real-time information of products to increase the transparency of the entire supply chain. The data collection is similar in each link. As shown in Figure 3.3 there are two parts main of the module involved in collecting the real-time data, RFID and RFID and Sensors parts. The RFID part is composed of RFID tags and RFID readers. This part can transmit product information, storage information and distribution information to a platform, such as EPCglobal, which supplies the network platform sharing the RFID information, and to the backend system including the evaluation algorithm, FWM and DSM, at any time. The RFID & Sensors part can monitor the status of the products and the environment. A sensor network is composed of RFID and several sensor nodes connecting different kinds of sensor according to the needs of the shippers and customers. A sensor transmits information to the backend system through a communication module. The signal of the communication module can be designed using GPRS (General Packet Radio Service), CDMA (Code Division Multiple Access), LTE (Long Term Evolution) or any other communication methods based on the real situation. There is an additional GPS part designed for distribution. The EPCglobal and GPS can visualise the locations that the products past. In addition to the real-time positioning of products, this information also helps customers check whether their products are following the right logistics flow. If some part of the transportation chain is lost or disrupted, the products may encounter problems. The location information will also be transmitted to the backend system in real-time. FWM can judge whether the vehicle is trapped in a traffic jam.

There are four data sources from which the module gets information. One is the customer; the module will record the time the customer's order is placed. The suppliers' delivery order will also be recorded. The dispatcher should provide information about the truck and the driver. The module will also send and get information from EPCglobal for the ePedigree of the products. The RFID & Sensor will give the status of all perishable products in real-time. After getting the data RMM firstly cleans it, this includes identifying outliers and smoothing out noisy data, removing inconsistent data, and so on. Secondly it integrates the data that has been collected. Data comes into the warning module after it has been processed.

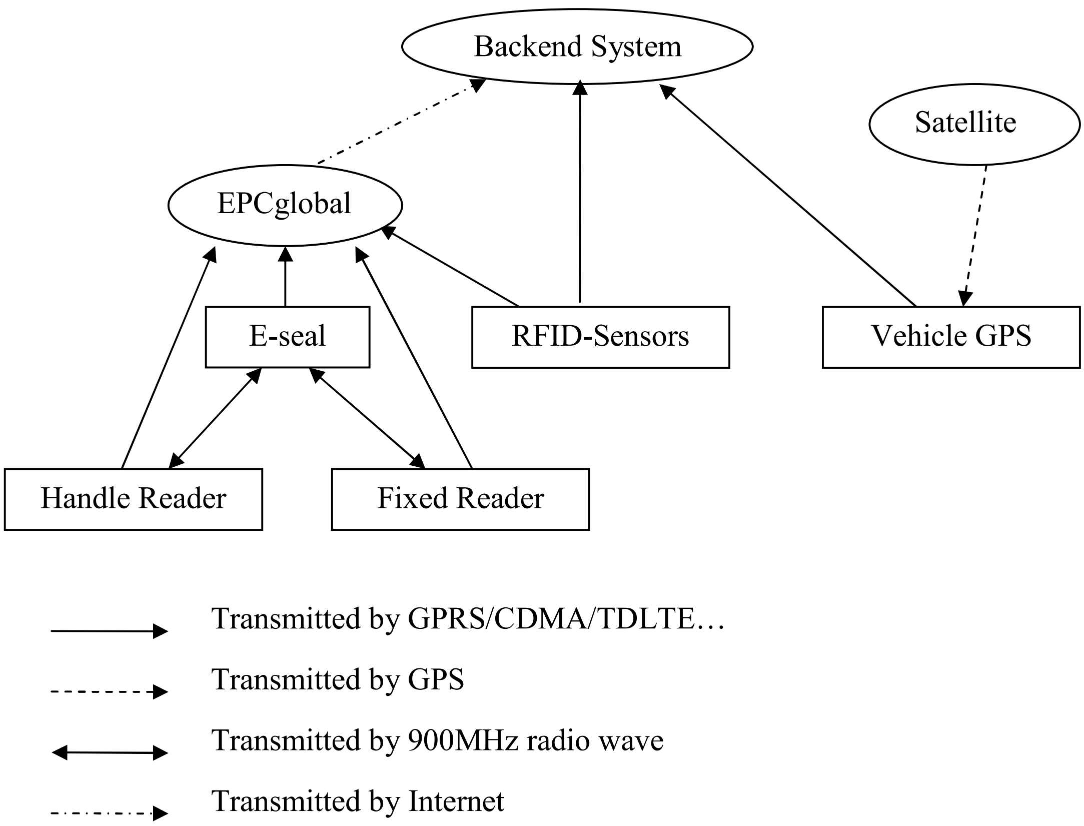


Figure 3.3 The Real-time Data Acqisition of the RMM

With the collected data, a quality evaluation algorithm is applied to evaluate the product value. The results will also be transmitted to the platform for reference for the other two modules.

The main role of the module in this system is to collect information on the real-time conditions of perishable products. In the past, the information has been hard to obtain, since the product is hard to distinguish and the amount of the data is huge. However, with the application of RFID, real-time monitoring can be realised; even when the products are in transportation. In addition to real-time monitoring, the module provides quality evaluation results for the reference of other modules to make decisions about the products. More details about this module can be found in Chapter 4.

3.2.2 Forecasting and Warning Module

As Figure 3.4 shows, this module has two functions: forecasting and warning. The warning function uses RBR to judge whether the environmental conditions inside the container are abnormal, whether the transport is fast enough and check whether there are any emergencies. The forecasting function forecasts the arrival time and the product quality. CBR, ANN and fuzzy logic are used in it.

FWM gets useful information from the platform to which RMM transmits data. Firstly the module judges whether to give customers a warning based on the data transmitted to the module. For example, if the observed temperature is higher than the upper limit, warnings will be given. The module will also check whether there is enough time left for the vehicle to complete all its consignments. All the consignments have a time window, which sets the earliest and latest arrival times, FWM will compute the latest starting time of each vehicle. If it finds the present time is later that the latest starting time of any consignment assigned to the vehicle, warnings will be given. Since FWM needs to provide some suggestions to cope with emergencies if an incident occurs, the responding speed of the online decision support system is very important. The users need to get a solution as soon as possible. Additionally, the module needs the capability to provide a very good explanation. The situations in a real emergency are very complex; when FWM suggests a decision for a warning it is better to tell users how the decisions have been made and explain the reasoning behind the decisions. Considering these reasons, RBR is applied in the warning function design.

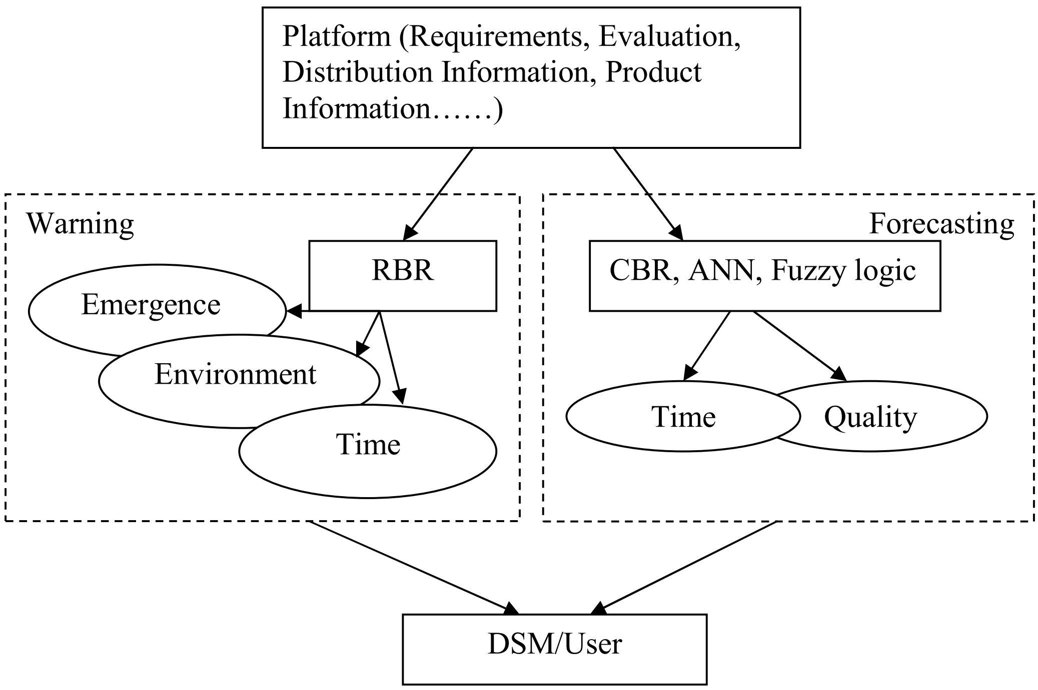


Figure 3.4 Input and Output of the FWM

For the forecasting function, a value loss model of perishable products is applied for the quality control of the products. Due to the application of this model, the remaining time for the products with the required quality can be calculated. Meanwhile, the module also forecasts the arrival time of the vehicle. A hybrid approach including CBR, ANN and fuzzy logic techniques is used. If the module forecasts that the current consignment cannot arrive before the required time, a warning will be given to DSM. With the predicted arrival time and the quality evaluation result given by RMM, the value loss model can also forecast the product quality arriving at the destination.

The role of the module in this system is assistance. It aims to avoid accidents. When accidents or emergencies really occur, FWM deals with the data from RMM and selects the emergency conditions to transmit to DSM. The details of the module design can be found in Chapter 5.

3.2.3 Decision Support Module

DSM is designed for 3PL. It focuses on vehicle management. The main challenge of vehicle management is how to optimise the schedule. The general optimisation approaches cannot usually obtain a solution within a reasonable time. The vehicle schedule problem can be classified as VRPTW. VRPTW is a generation of VRP. VRP is a classical combinational optimisation problem; many researchers have studied it. However it usually takes a long time to achieve the optimal solution and it is hard to get global optimisation. In this research, an emerging algorithm QEA and traditional GA are improved to obtain better performance in solving this kind of problem. They target problems at different scales. GA is for large scale problems, while the proposed IQEA is for small scale problems. When a schedule is made, the vehicles carry consignments following the schedule. And RMM starts the real-time monitoring of these consignments.

If DSM receives warnings from FWM, the dynamic adjustment will change the schedule. It is designed using a heuristic method, HCES, for a quick relative optimal solution. Though the adjusted schedule may not be the best one, the time for coping with emergencies is the first consideration. Figure 3.5 gives a general description of this module.

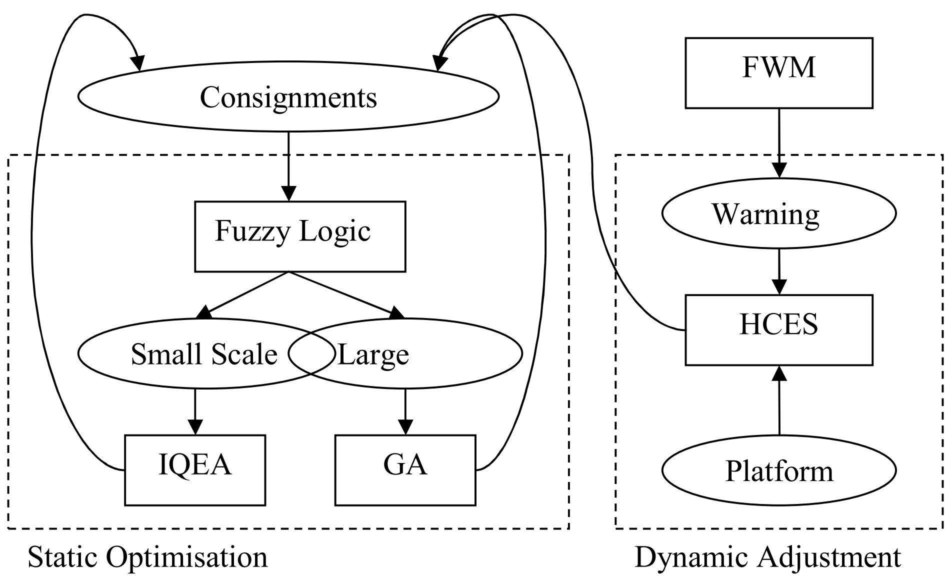


Figure 3.5 Input and Output of the DSM

The role of this module in the system is decision support. It is designed for 3PL. Its main function is to help the Logistics Company manage distributions, minimise the transportation costs and deal with accidents or emergencies. Chapter 6 will offer more information about DSM.

3.3 Summary

This chapter conducts an introduction on the theoretical framework and a general discussion of the entire system. The proposed approach for the improvement of perishable product management is considered in five aspects: real-time monitoring, positioning, timely warning, forecasting and optimisation. Based on the approach, MDSS is proposed. The system aims to improve perishable product safety issues and save transportation costs for 3PL.

The discussions on the system focus on the relationships of the modules and how the system operates. The system contains three modules: RMM, FWM and DSM. RMM monitors products and the environment of the containers. And it can be extended to monitor products at each link of the supply chain in real-time. The module collects all relevant information and transmits it to a web platform for the different parties joined in the supply chain to share. In addition to real-time monitoring, this module also evaluates product quality based on this information using an algorithm designed by ANN and k-NN. The results are also transmitted to the platform. FWM and DSM focus on the management of distribution. FWM is a connection between RMM and DSM. It selects useful information from the platform and uses CBR, fuzzy logic and ANN to forecast the arrival time. A value loss model is applied to predict the product quality at the destination. The module also uses RBR to judge whether the transportation satisfies the distribution requirements, whether the products can arrive at the destination on time, whether the vehicle is trapped in a traffic jam and offers some simple suggestions. If there is anything abnormal, a warning signal will be transmitted to DSM. DSM has two functions. One is static optimisation; it uses GA and IQEA for optimising the vehicle schedule. GA is for large scale problems, while IQEA is for small scale problems. Its other function is dynamic adjustment. If DSM receives warnings, it uses a heuristic approach called HCES to adjust the original schedule for the optimal reduction of the value loss.

In summary, to guarantee product quality and to save the costs for logistics companies, one approach is proposed. Based on the approach, MDSS is developed. The system can improve the SCM of perishable products, especially for distribution, and increase the transparency of the supply chain for safety management. Moreover, it optimises and adjusts the vehicle schedule to save transportation costs and to reduce the losses.

CHAPTER 4 REAL-TIME MONITORING MODULE

4.1 Introduction

Real-time monitoring is the foundation of the proposed approach for the improvement of perishable product management. It helps collect data and analyse product quality. It can also help in the implementation of HACCP and visualisation of the food supply chain, which is undoubtedly a good method in ensuring food quality. Consequently, a Real-time Monitoring Module (RMM) is included in the developed system for real-time monitoring and positioning, which also improves the current real-time monitoring.

This chapter firstly introduces the architecture of the module and then discusses the designed algorithm for quality evaluation. Finally, in the experiment design, the characteristics of a wine industry are considered as a representation of the perishable products. Because of the variety of perishable products it is hard to summarise a common work flow for all products. The experiment mainly focuses on the wine industry. Strictly wine is not a perishable product, but it is a kind of temperature-sensitive product. Sudden changes in environment can greatly affect its quality. Consequently, the approach for monitoring and quality evaluation in the wine industry is also suitable for other perishable product industries after some slight adjustments.

In summary, RMM has provided an effective tool to monitor perishable products. The chapter reports on the design and use of RMM to monitor the entire wine supply chain. With the application of this module in the experiment, all relevant information about the wine before they are put on the market for sale can be recorded, processed and managed. As a consequence, HACCP can be easily implemented and food safety can be enhanced with this highly interactive perishable product supply chain information. A method that combines a *k*-NN algorithm and a simple ANN technique to provide an evaluation of the final wine quality is also proposed. The module with FWM can determine accidents in time to reduce losses and prevent counterfeiting.

4.2 Architecture

The architecture of the module will be introduced first. The module contains three main parts: the monitoring hardware which can be installed in the manufacturing equipment, warehouse and vehicles, the database and the quality evaluation algorithm. Each product has a RFID tag, which records its ePedigree. The ePedigree changes in each link of the supply chain. The proposed algorithm computes the evaluation result based on the ePedigree. All the information in the database, the product ePedigree and evaluation results will be transmitted to the web platform. Users and organisations can access the data they want. The work flow and architecture of this module is shown in Figure 4.1.

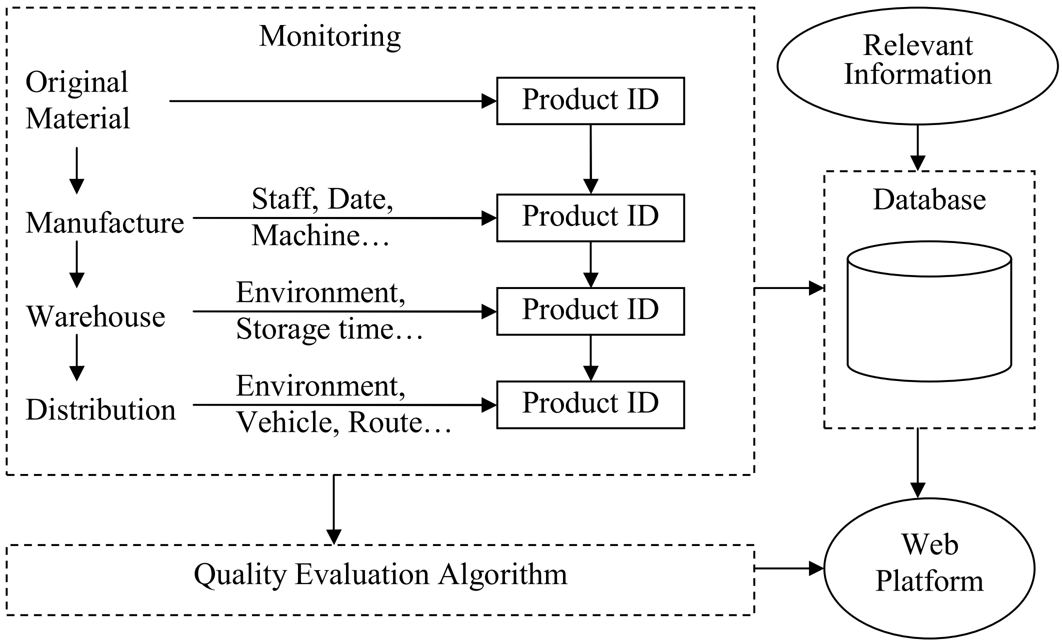


Figure 4.1 RMM Architecture and Workflow

4.3 RFID-based Monitoring Module

The module applied a RFID technique for monitoring. The following sub-sections describe the applications of the module for manufacturing, warehousing and distribution.

4.3.1 Application in Manufacturing

In manufacturing each product has a RFID tag which records the ePedigree. Information can be found in the database about the material, producer, machine used, date, time and so on of the product by searching the ePedigree. RFID readers are also installed at the gateway. When the products are finished and transported to the warehouse the information will be automatically produced.

4.3.2 Application in Warehouses

Sensors with RFID tags are installed in the warehouses. The sensors monitor the environment in the warehouses. If anything abnormal occurs it is able to distinguish which location in the warehouse has problems due to the warning sensor ID. There are also readers installed at the gateway and on forklifts (See Figure 4.2). When the products are picked up, the reader will inform the system. If someone selects the wrong products there will be a warning.

Figure 4.2 Application in Warehouse (Kwok, 2008a)

4.3.3 Application in Distribution

When products are distributed, the RMM is designed to monitor the environmental conditions in the vehicles. As shown in Figure 4.3, the system consists of two parts: RFID and RFID & Sensors. The RFID part is composed of RFID tags and RFID readers. This part can protect the security of the products and transmit product information and distribution information to EPCglobal, which supplies the network platform sharing

RFID information, and to the backend system, at any time. The EPCglobal and GPS can visualise and track the different locations that the products have past. The information helps customers check whether their products are following the right logistics flow. If some parts of the transportation chain during distribution are lost there may be some problems with the products. The RFID & Sensors part can also monitor the environment in the vehicles. A sensor network is composed of a RFID and several sensor nodes connecting the temperature, vibration and humidity sensors or other sensors according to the needs of the shippers and customers. A sensor transmits information to the backend system through GPRS, CDMA or LTE. When the containers are loaded onto the trucks the vehicle GPS can also track the location of the products in the containers. The location information will then be transmitted to the backend system in real-time. After data processing, information will be transmitted to the FWM introduced in Chapter 5. The FWM can inform users of the environment in the container when the products are transported.

Finally, when the products are on sale, by reading the RFID tag on the product packages the final ePedigree can be retrieved from the web platform like EPCglobal. The marks of each link are evaluated by the quality evaluation algorithm, which will be introduced next.

4.4 Design of the Algorithm for Quality Evaluation

The principle of the algorithm is to evaluate the product quality at each link of the supply chain, based on relevant factors set as the vectors. Then set the evaluation results of each link as the vectors. These vectors are used to evaluate the final product quality.

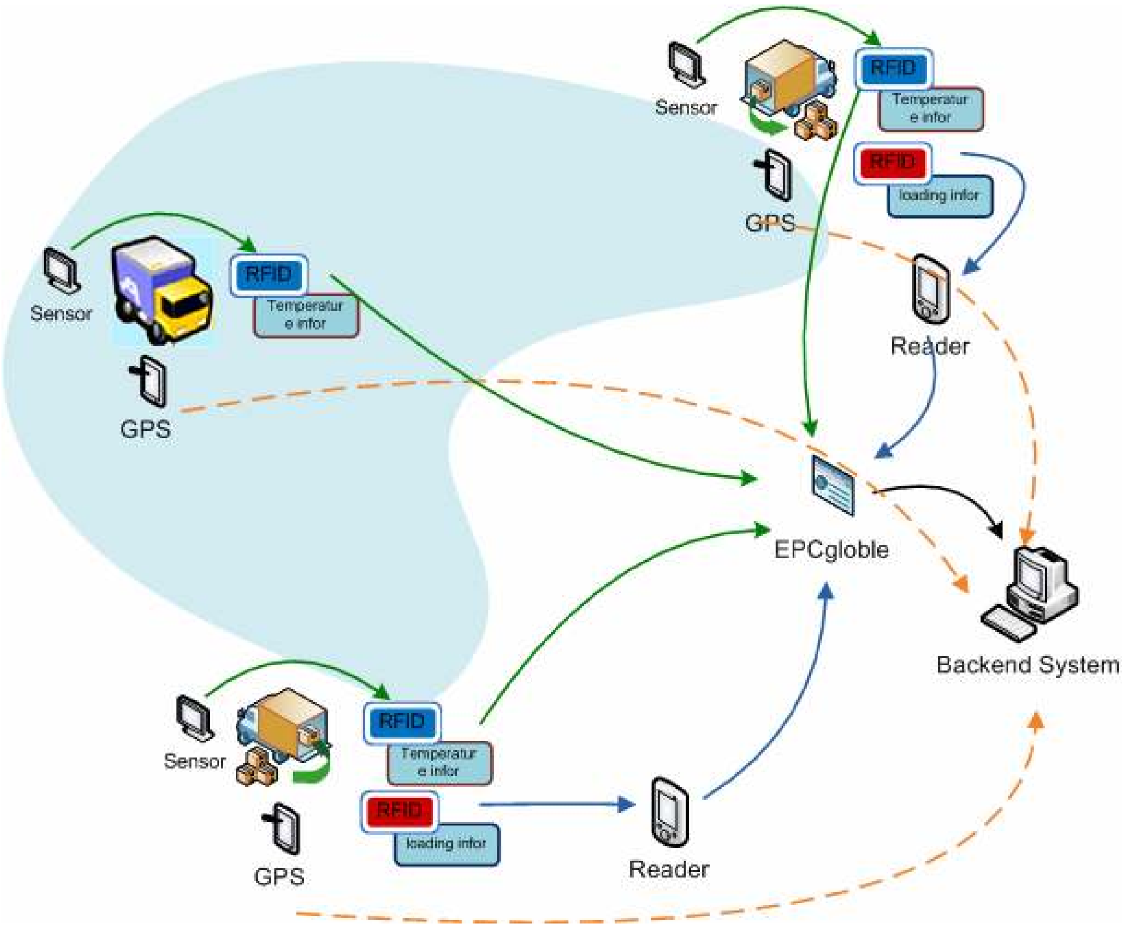


Figure 4.3 RFID-based Tracking and Monitoring System

The *k*-NN algorithm is used to estimate the quality of each link in the supply chain. Firstly, some standard products are chosen. The Information on the standard products is predefined as standard data. The algorithm calculates data distances between the products that the estimation requires for all standard products. The quality of the closest standard product is considered as the estimation result. The algorithm is stated in previous research work (Keller *et al.*, 1985). ANN is also applied to make this algorithm more suitable for the aforementioned problem.

Let $W = \{x_1, x_2, ..., x_n\}$ be a set of n vectors, where the components of each vector represent qualitative measurements of input z_i, which means $x_i = (w_1 \cdot z_{1i}, w_2 \cdot z_{2i}, ..., w_n \cdot z_{ni})$, $w_i \cdot z_{ij}$ denotes the value of one coordinate axis, and w_i is the coefficient whose value is determined based on specific problems. A simple single layer neural network is used to train their values (Negnevitsky, 2005).

Step 1: Initialisation

Set initial weights w_i and threshold θ to random numbers.

Step 2: Activation

Activate the perceptron by applying inputs $z_i(p)$ and the desired output $Y_d(p)$. Calculate the actual output at iteration p=1

$$Y(p) = step[\sum_{i=1}^{n} x_i(p) w_i(p) - \theta] \tag{4.1}$$

where n is the number of the perceptron inputs, and step is a step activation function.

Step 3: Weight training

Update the weights of the perceptron

$$w_i(p+1) = w_i(p) + \Delta w_i(p) \tag{4.2}$$

where $\Delta w_i(p)$ is the weight correction at iteration p.

The weight correction is computed by the delta rule:

$$\Delta w_i(p) = \alpha \times x_i(p) \times e(p) \tag{4.3}$$

$$e(p) = Y_d(p) - Y(p) \tag{4.4}$$

Step 4: Iteration

Increase iteration p by one; go back to step 2 and repeat the process until convergence is obtained. Then w_i can be determined.

Let $u_i(x)$ be the assigned membership of the unclassified x, and u_{ij} be the membership in the ith class of the jth vector of the set. The inputs to the fuzzy classifier are the set W along with the memberships u_{ij}, the number of k-NN and the unknown sample classification x. The output of the fuzzy classifier is the assigned membership $u_i(x)$, where $\sum_{i=1}^{C} u_i(x) = 1$, for a given number of classes, C.

The fuzzy algorithm is described as follows:

Step 1: Choose k, $l \le k \le n$

Input of the unknown x

Initialise i=1

DO UNTIL k-NN to x found

FOR j=1,2,…,n

Step 2: Compute the distance from x to x_j:

$$d^2(x_j, y) = (x_j - x)^T M(x_j - x) \tag{4.5}$$

M is a $p \times p$ positive definite matrix, p is the dimension of the vectors x_j (j=1,2,…,n). When M is the identity matrix I_p, d is the Euclidean distance.

Step 3: IF ($i \leq k$) THEN

include x_j in the set of k-NN.

ELSE IF x_j is closer to x than any previous nearest neighbour

THEN

Delete farthest in the set of k-NN

Include x_j in the set of k-NN.

ENDIF

Step 4: i=i+1

NEXT j

Step 5: Initialise i=1

DO UNTIL (x assigned membership in all classes)

FOR j=1,2,…,n

Step 6: Compute

$$u_i(x) = \frac{\sum_{j=1}^{k} u_{ij} \left(\frac{1}{d^2(x, x_j)^{\frac{1}{(m-1)}}} \right)}{\sum_{j=1}^{k} \left(\frac{1}{d^2(x, x_j)^{\frac{1}{(m-1)}}} \right)} \tag{4.6}$$

Step 7: i=i+1

NEXT j

END

4.5 Simulation Test and Results Analysis

A simulated experiment on a wine company is used to demonstrate the operation of this module. Though wine can be preserved for a long time its quality is affected by temperature, humidity and many other factors in production and delivery. Consequently, the approach for guaranteeing the wine quality is also suitable for other perishable products.

The wine industry is an old industry that began hundreds of years ago. In a study of it, Charters and Pettigrew (2007) used qualitative methods to examine Australian wine drinkers' perceptions of wine quality to provide a comprehensive, consumer-focused description of the complexity of the wine quality concept. The complexity comes from the shortage of information on the wine in a bottle. Ferrer *et al*. (2008) focused on wine grape harvest operations and proposed that the quality of wine grapes had a huge effect on wine quality. Wine was categorised into quality groups starting at the premium level. A quality loss function is also used to represent wine quality reduction at each vineyard block due to premature or deferred harvest, with respect to an optimal date in their paper. Raptis *et al*. (2000) studied the classification of aged wine distillates using fuzzy and neural networks, and found that barrels were the main factor, and that the aroma and taste of wine were the main considerations when judging wine quality.

Due to a lack of transparency in the supply chain, how to evaluate the quality of wine in objective ways has always been a difficult problem. Since the production of wine usually takes several years, the data collected in real life is not enough for the system analysis. This experiment is used to describe the operating procedure of the module.

CLR (alias) is a chateau in the Bordeaux region. The chateau produces large amount of wine each year. In the past, the chateau expended energy and money on distinguishing wine quality. The traditional method they used is to employ experts to taste the wine, and the experts would give a mark to the wine. The average marks would help the chateau compare different batches of wine. However, the method is subjective, and it is hard to compare the wine evaluated from different experts. The chateau wanted an objective method to evaluate the wine quality. RMM can solve this problem, and the operating procedure of the module is described in the following paragraph.

Figure 4.4 shows the basic features of the RMM in the company. The manufacturing processes of the wine can be divided into four parts: growing grapes in the vineyard, brewing in the winery, aging in the cellar and distribution. Different RFID-based monitoring systems are designed for each part. Finally, the information recorded comprises the "ePedigree" of a bottle of wine. The information is also used for quality analysis. The RFID-based monitoring system for each part will be described next.

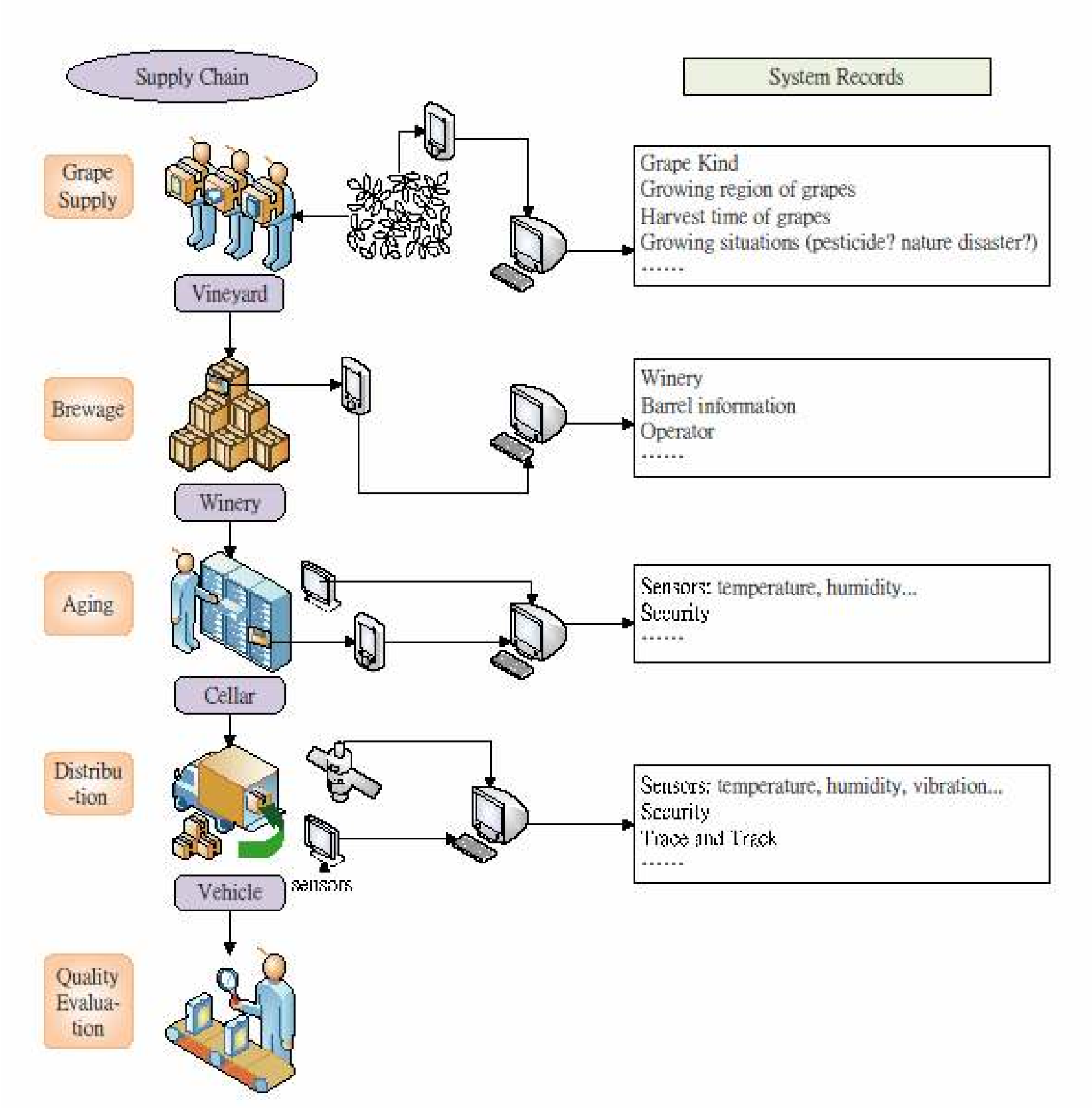


Figure 4.4 Monitoring Design in Wine Industry

Quality tracking in vineyard

Undoubtedly, the grape is the main factor affecting the wine quality. If possible it is better to set the RFID system in the vineyard to record the time of sunshine, humidity and the difference in temperature between the day and the night. However this step is not obligatory. In order to save costs, when the grape producer supplies grapes to the chateau, he/she can inform the staff of the location of their vineyard is, the time he/she planted and harvested, and so on, and the module will record the weather information during this period for the pedigree of this batch of grapes. Grape varieties, producers' information and the conditions of spreading insecticide are also included in the pedigree.

After obtaining the above information, the module of the quality evaluation algorithm, introduced in section 4.4, will assign a mark to this batch of grapes.

The chateau does not force the farmers to install RFID-based monitoring systems in their vineyards. However, when they sell grapes to the chateau the farmers will need to fill in a form as shown in table 4.1.

Quality tracking in brewing

Distillation is a very important chain in the production of wine. The quality of distillates also affects the final wine quality. Fresh distillates usually have pungent, unpleasant odours and a sharp taste. Storage in oak barrels for several years is necessary to improve the aroma and taste of the distillates (Thoukis, 1974; Nishimura, 1989). During maturation, barrels are the main factor affecting the quality of distillates, and an important and costly winery asset. Consequently, the RFID is applied to record a complete history of each barrel, including its flavour profiles and age. The age of the distillates can be recorded and tracked in the module when the RFID tags on the barrels are read. These two types of information are used to evaluate the mark of the distillates using the quality evaluation algorithm introduced in Section 4.4. The other function of the RFID quality tracking function is barrel tracking. As all the barrels look the same, the module can also help workers avoid selecting the wrong barrels.

Table 4.1 Grape Information

Vineyard Serial Number	
Grape Variety	
Planting Date	
Harvesting Date	
Quantity	
Insecticide	
Time of Spreading of Insecticide	
Remarks	

In this experiment, the RFID-based system is mainly used to manage barrels. A D2B™ device, as shown in Figure 4.5, is installed on the exterior of each barrel. The D2B™ device is composed of active RFID tags and wireless communication stations. The frequency of the RFID tags is 433 MHz, and the device operates at a distance of approximately 40–60m (Kwok, 2008a). When a worker uses a RFID reader to read the tag, he/she can find the current and historic information of the barrel as shown in Table

4.2. Moreover, when the worker wants to select some barrels, he/she can simply click on the mobile terminal of the required barrels and a wireless message will be sent out to the barrels. Then, the selected D2B™ devices on these barrels will flash and beep to get the attention of the worker.

Figure 4.5 D2B™ Device (Kwok, 2008a)

Quality tracking in cellar

After distillation, wine is stored in a cellar for aging. The temperature and humidity need to be monitored. The application of RFID to assist the monitoring of cellars and warehouses is an effective method. The system can help monitor the humidity and the temperature in the cellar. Since cellars are usually very large, only one temperature or humidity sensor is not enough. 20 temperature and humidity sensors are installed in this case. Each sensor is connected to a RFID tag. The tag can help people identify the locations of the sensors. In this case the safety temperature is set from 13°C to 17°C, and the safety humidity is set from 70% to75%. Data about environmental factors can be transmitted to the module in real-time. FWM helps judge whether a warning should be given. If the temperature or humidity is out of the range, the occurrence will be recorded. Finally, a record as shown in Table 4.3 can be obtained.

Table 4.2 Barrel Information

Barrel Serial Number	
Age	
Material	
Current Wine Flavour	
Distillate Age	
Flavour Profiles (last 10 times)	1
	2
	… …
	10

Table 4.3 Cellar Environment

Barrel Serial Number	
Storage Time	
Abnormal Temperature	
Lasting Time	
Abnormal Humidity	
Lasting Time	

Quality tracking in distribution

In the transportation process, the RFID-based monitoring system is installed in the vehicle as shown in Figure 4.6. The system can supply real-time vehicle location information. Moreover, the system can record the environmental factors in the vehicle during transportation to help people analysis the effect on the wine quality during transportation. Finally, a table as shown in Table 4.4 can be obtained.

Table 4.4 Transportation Information

Wine Serial Number	
Transportation Time	
Transportation Distance	
Vibration	
Humidity	
Temperature	

When the wine is delivered to the destination for sale, their ePedigree can be checked. Figure 4.7 shows an example of the pedigree of a bottle of wine and the application of the proposed algorithm for quality evaluation. The quality evaluation algorithm is divided into five parts. These are grape quality evaluation, distillate quality evaluation, quality evaluation in aging, quality evaluation in wine distribution and wine quality evaluation. For the grape quality evaluation the inputs are {longitude of the region, latitude of the region, time of sunshine, disaster, pesticide, and flaws}. The output is {grape quality evaluation mark}. For the distillate quality evaluation, the inputs are {distillate age, barrel usage, and barrel age}. The output is {distillate quality evaluation mark}. For the quality evaluation in aging the inputs are {abnormal temperature, and abnormal humidity}. The output is {quality evaluation mark}. For the quality evaluation in wine distribution the inputs are {transportation time, transportation distance, abnormal vibration degree, abnormal temperature, and abnormal humidity}. The output is {quality evaluation mark}. For wine quality evaluation the inputs are {grape mark, distillate mark, aging mark, and distribution mark}. The output is {Wine quality mark}. The scale of the mark system ranges from 0 to 10 with a step of 1 in ascending quality order.

Figure 4.6 Deployment of RFID-based Tracking and Monitoring System

Each factor in the four tables has a weighting, and a neural network is used to train the weightings. The wine should be marked by experts, the marks given are used to train the weighting. After trainings a certain number of times, the value of the weightings will not be adjusted and there no longer a need to employ experts. Formula 4.6 is applied to compute the degree into which the wine will be classified.

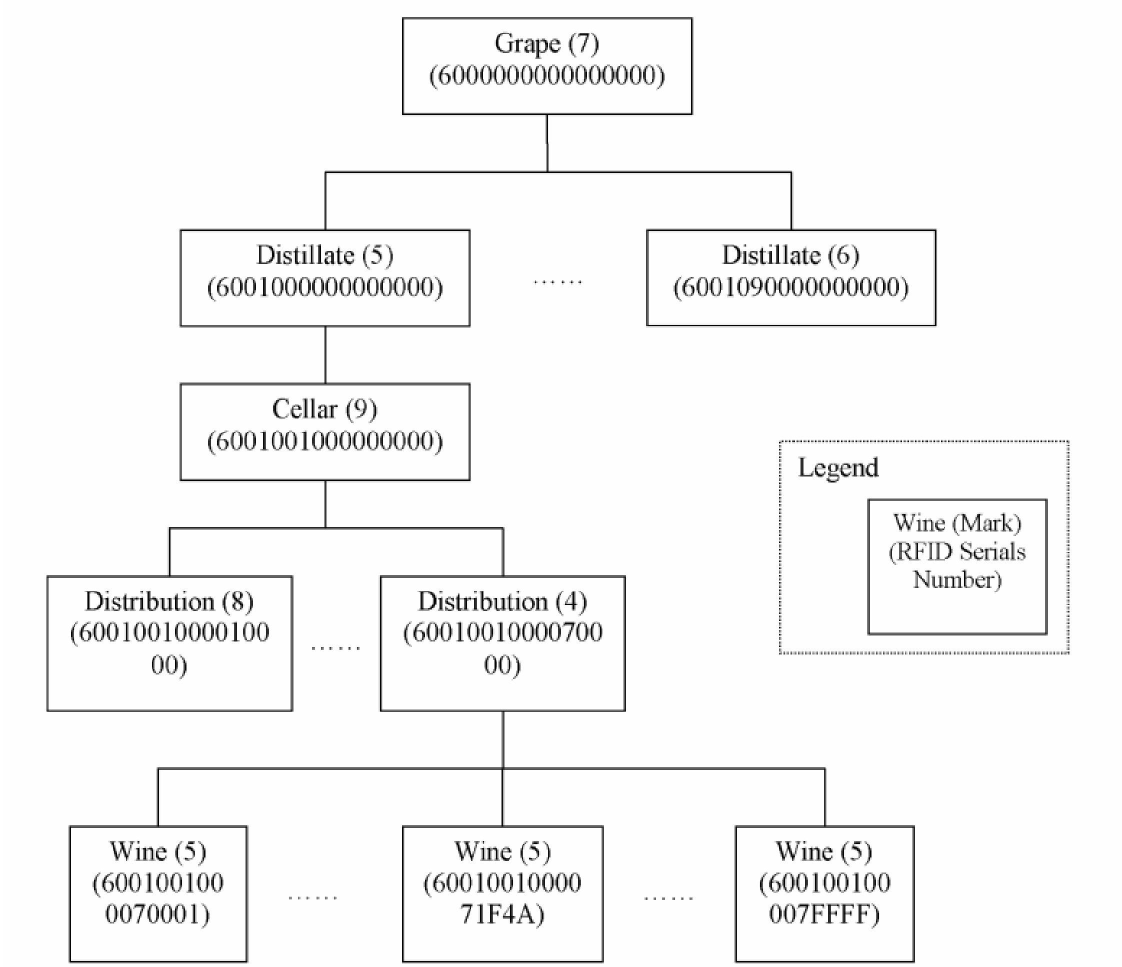


Figure 4.7 ePedigree of Wine

Finally, when a customer wants to buy a bottle of wine they can just put the wine on the counter on which a RFID reader and a monitor is installed and he/she can read the mark and the pedigree of the bottle of wine. With the application of RFID, the module can also effectively counteract counterfeiting.

4.6 Summary

RMM is developed for realising the function of real-time monitoring and positioning of the proposed approach. Through real-time monitoring, the module can improve product quality control. It has two functions: quality tracking and quality evaluation. The quality tracking function is to monitor and manage the entire supply chain of perishable products. The quality evaluation function is to estimate the product quality of each link. The quality evaluation algorithm applies the *k*-NN algorithm and ANN for processing the data from the real-time monitoring.

A simulated experiment about wine industry is used to demonstrate RMM. The module begins to work when grapes are delivered to the winery. The quality evaluation algorithm marks the levels of the grapes based on the weather and region information of the grapes. The wine producers can estimate the quality levels of wine by identifying the quality of the bulk of grapes, since the quality of grapes is the main factor affecting wine quality. With this information, producers can decide how much resources to use and costs to pay for the wine making. During brewing, the quality tracking system can manage the barrels to avoid human errors. The environmental factors in the cellars are also monitored. If any accident occurs, the system can give timely warnings. After brewing, the quality of distillate will be estimated by the evaluation algorithm. If the mark of the distillate is high, the producer should pay more attention to aging and distribution. The marks of the RFID tags will be attached to the wine when they are marketed. Consumers can select the wine with consideration of the marks from the module. Additionally, the RFID tag on the wine bottle provides an effective tool for counterfeit identification.

Using the RFID technique, the quality evaluation function of RMM can help improve the quality control of perishable products. And it can replace the current subjective and ineffective wine evaluation method. It helps consumers understand their products before they consume them. Moreover, in the wine industry different regions currently have different evaluation rules. The approach can combine hundreds of rules into one for all the wine around the world. It can also help people with little knowledge of wine to better understand the quality of the products they have bought.

CHAPTER 5 FORECASTING AND WARNING MODULE

5.1 Introduction

Warning and forecasting in the proposed approach aims to assist the management of perishable products in logistics. FWM is designed for this objective. With the data acquired by RMM, FWM has two functions as suggested by its name; one is forecasting and the other is warning. The module is designed for the distribution link in the supply chain. It helps predict the arrival time of vehicles and the product quality. It also detects whether there is anything abnormal happening.

This chapter firstly introduces the architecture of the module in Section 5.2. Then, the two functions are discussed respectively in Section 5.3 and Section 5.4. Finally, in Section 5.5, an experiment is used to show the operation of this module.

5.2 Architecture

Figure 5.1 illustrates the system architecture designed in this study. The forecasting function of the module includes two parts. One part separates the planned route of the vehicle into several segments. It helps find the same route from the case base. If the same route does not exists, a similar route will be selected using fuzzy logic and CBR. The other part of the module uses CBR to calculate the time of each segment of the planned route. The weightings of the CBR are trained using neural network theory. And the case base is updated using some rule-based strategies. The value loss model introduced in Section 2.2.3 uses the predicted time to estimate the product quality at the time the vehicle arrives at the destination. The outputs of arrival time and product quality are both transmitted to a RBR system designed for a warning function. Then the module can judge whether the time is sufficient for the vehicle to deliver the products to the destination with an acceptable quality.

5.3 Forecasting Function

5.3.1 Route Division

Firstly, the route division part of the module will be introduced. When the user inputs the start location and the destination into the module, several routes will be generated. The user can choose one as the planned route. Then the module can help the user estimate the time needed for the vehicle from the start point to the destination. The first step is to divide the planned route of the vehicle into several segments using important traffic cross points. Figure 5.2 shows the route segments of an example. If the vehicle is transported from point 1 to point 9, the planned route is 1-2-8-9. The system divides the route into three parts: 1-2, 2-8, 8-9. Then, it searches the case base for those segments.

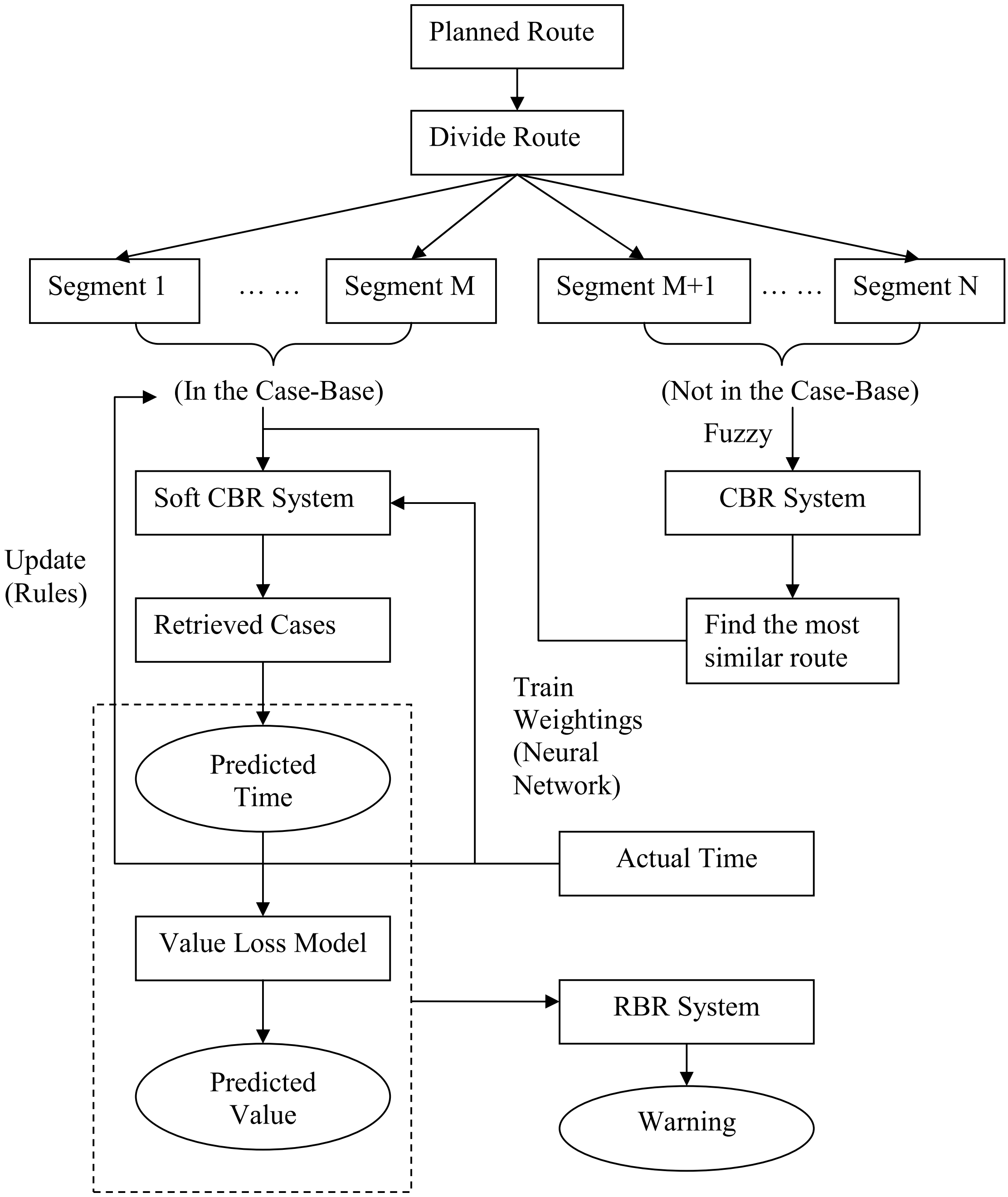


Figure 5.1 Module Architecture and Work Flow

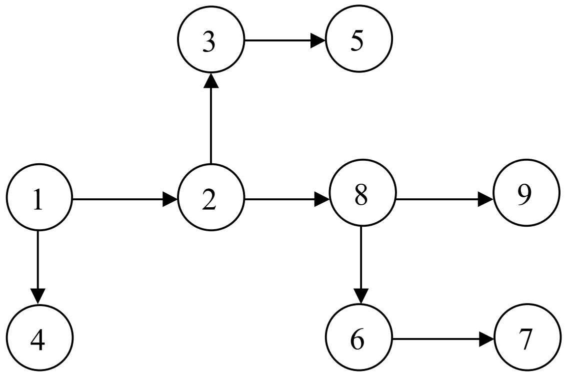


Figure 5.2 Example of Route Separation

If the module cannot find the same route segment from the case base, the most similar route will be selected using fuzzy logic. Since road grade and city scale are two main factors affecting vehicle speed, the fuzzy sets in this system include road grade (1, 2, 3 and 4), which indicates the designed vehicle speed on that road and city scale (super, large, mid and small), which indicates the population in that city. Figure 5.3 shows the membership functions. The sum of each similarity measure is the finally similarities of the route. The route with the biggest value is the most similar route.

There are two reasons for dividing a route into several segments. One is that the short route segments have relatively more similar routes than long route segments, which can reduce the scale of the case base so the search speed can also be increased. The other reason is that the number of same routes will be increased. Two vehicles may start from different places and also arrive at different places, but part of their routes may be the same.

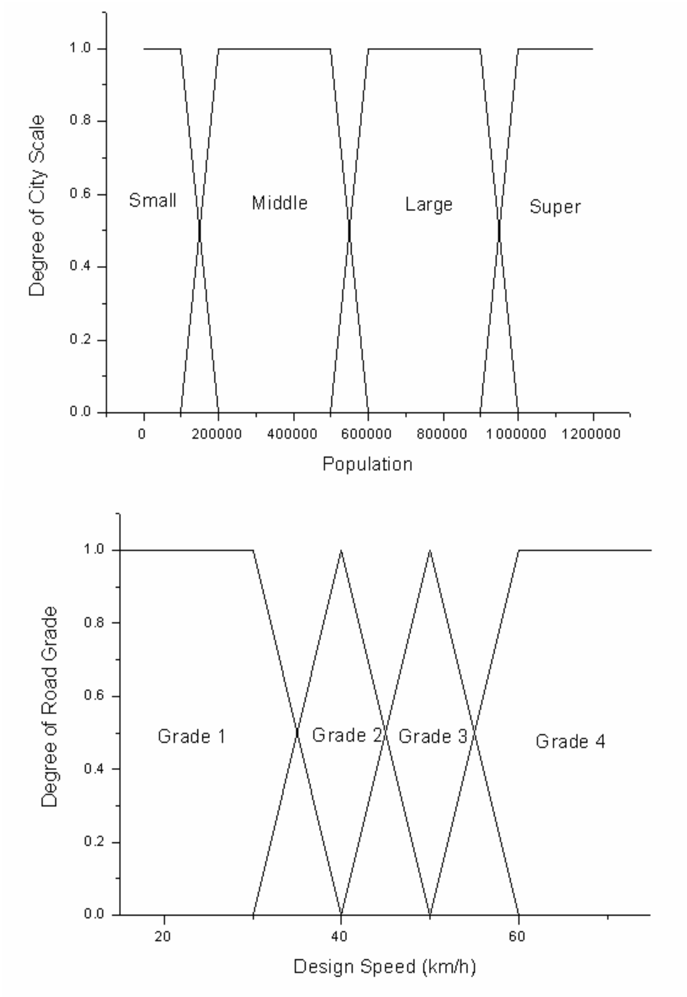


Figure 5.3 Membership Functions

5.3.2 Design of the Case-based Reasoning Algorithm

The forecasting function of the module is designed using CBR. The weight coefficients of all factors which affect the process of degeneration are saved in a database. The design of the database is shown in Table 5.1

Table 5.1 Weighting Coefficients Database

Weighting (w_i)	Factor	Match_Degree (x_i)
w_1	Weather	1/0
w_2	Workday/Holiday	1/0
w_3	Time_Period	1/0
w_4	Vehicle_Type	1/0
w_5	Driver	1/0
w_6	Products Weight	1/0
… …	… …	1/0
w_n	Fuel_level	1/0
	Sum	$\sum w_i x_i$

Different kinds of data have different weightings (w_i). The weightings need to satisfy the constraints:

$$\sum_{i=1}^{n} w_i = 1 \qquad (5.1)$$

where, $0 \le w_i \le 1$ $(i = 1, 2\ldots \ldots n)$

When the vehicles finish their transportation tasks, they will provide the information listed in the table to the backend system. FWM will store the data in the case base and produce a new case_id for it. The case base is shown in Table 5.2.

Table 5.2 The Case Base for Monitored Containers

Case_ID	Time_Consumed (min)	Match_Degree
A01A0201	36	0.5
A02B0301	44	0.7
B03B0501	15	0.9
A02C0801	24	0.3
C08C0901	17	0.5
C08C0601	32	0.7

When the system starts to estimate the travelling time, it firstly searches for the case base. If one kind of data of the vehicle matches the same kind of data of a case, the system will record 1 as the value of x_i in the blank space of match_degree. Then, it multiplies the weighting of this kind of data by the match_degree ($w_i \times x_i$) to produce the result. After calculating all the types of data belonging to the case, the system adds all the results together. The sum (M) is the degree to which the case matches the problem that needs to be solved.

$$x_i = \begin{cases} 0, & \text{not match,} \\ 1, & \text{match,} \end{cases} \qquad (5.2)$$

$i = 1, 2……n$,

$$M = \sum_{i=1}^{n} w_i x_i \qquad (5.3)$$

where M indicates the degree to which the case matches the problem.

After calculating all the cases of the same route, the module chooses the best match in the database and then uses the time consumed on this case as the predicted result of this segment. All the time needed by each segment added together is the time for the vehicle to arrive at the destination.

On the other hand, if all the degrees to which the case matches the problem are less than 0.7 (the value is a coefficient and users can adjust it based on real conditions), the module will compute the deviation of the most existing similar route segments under the condition of the best match case and the condition of the unsolved problem. The deviation ratio will be set as the deviation ratio of this unsolved problem and the best match case. Then the travelling time can be computed.

Finally, the total time spent for each segment is the time needed for the consignment's delivery.

In CBR, w_i is used to represent the weighting of each factor in a case for calculating the travelling time. Sometimes the weightings in the database are not accurate and need to be adjusted. The situations in which the system needs to be adjusted will be introduced in Section 5.3.3, but first the adjustment methodology will be discussed. ANN is applied to train these weightings. The details will be introduced as follows.

Let $X = \{x_1, x_2, ..., x_n\}$ be a set of n vectors, where the components of each vector represent the match degree of Case j, and w_i is the coefficient. The value is decided by specific segments. Different segments have different sets of w_i. A simple single layer neural network is used to train the values (Negnevitsky, 2005).

Step 1: Initialisation

Set initial weights w_i and threshold θ to random numbers.

Step 2: Activation

Activate the perceptron by applying inputs $x_i(p)$ and desired output $Y_d(p)$, which means the actual travelling time. Calculate the actual output at iteration p=1

$$Y(p) = step[\sum_{i=1}^{n} x_i(p)w_i(p) - \theta] \tag{5.4}$$

where n is the number of the perceptron inputs, and formula 5.4 is a step activation function.

Step 3: Weight training

Update the weights of the perceptron

$$w_i(p+1) = w_i(p) + \Delta w_i(p) \tag{5.5}$$

where $\Delta w_i(p)$ is the weight correction at iteration p.

The weight correction is computed by the delta rule:

$$\Delta w_i(p) = \alpha \times x_i(p) \times e(p) \tag{5.6}$$

$$e(p) = Y_d(p) - Y(p) \tag{5.7}$$

Step 4: Iteration

Increase iteration p by one, go back to step 2 and repeat the process until convergence. Then w_i can be determined.

5.3.3 Design of the Case Base Updating

Everything is in the course of continuous movement change and development in the world. With the development of vehicles and cities, the travelling time needed from the same start location and destination under the same conditions will be different. The old cases in the database will be unsuitable for newly arriving cases. Consequently it is necessary to update the old case base, when the value of deviation is too large. The case base is updated using the rules listed below. Firstly, the module will check whether the segment calculated is the same route with the unsolved problem. If it is the most similar route the actual segment and its result will be set as a new case in the case base. For the same route segment, if the new case can find a previous case from the case base in which $M = 1$, the old case will be replaced by the new case. If the results are different, the weighting of the case will be trained again. If $M \neq 1$, the case will also be added to the case base.

Rule 1: If the segment is the same as the actual segment and the match degree is not less than 0.7 then go to Rule 3;

Rule 2: If the segment is the same as the actual segment and the match degree is less than 0.7 then train the weighting and add the case to the case base.

Rule 3: If $M = 1$ then go to Rule 5

Rule 4: If $M \neq 1$ then train the weighting using the neural network and add the case to the case base.

Rule 5: If (Result_New-Result_Old) / Resul_Old >5% or (Result_New-Result_Old) / Resul_Old < -5%, then train the weighting of this segment and add the case to the case base.

5.4 Warning Function

The warning function uses rule-based reasoning to judge the environmental conditions inside the container and forecast the quality of the perishable products. The module selects useful information from RMM and the predicted time and product quality from the forecasting function. Based on the information, the warning module will decide whether to give the customer warnings. For example, if the present observed temperature is higher than the upper limit, the module will give a warning. The module will also use the existing quality loss model to estimate the present value of the products. Based on the kind of the perishable product that is being transported, the module will chose a quality loss model for it. The manufacturer can also choose a model thought to be the most suitable. Having established the given initial value, limit value and guarantee date, it will report to the module how much time is left until the value of the perishable product will fall below the quality limit. The module can judge whether the time is adequate for the container to arrive at the destination, because the forecasting function can inform the warning function how much time needed. If the time left is less than the remaining time calculated by the quality loss curve or if the present value is lower than the limit value, the module will also give a warning. Additionally, the warning can forecast the exact value of the perishable products. If the user thinks the profit is too low, the transportation of the perishable products can be cancelled. If there are no accidents, the module will give "No Warning" information. The user will see a user interface similar to that shown in Figure 5.4

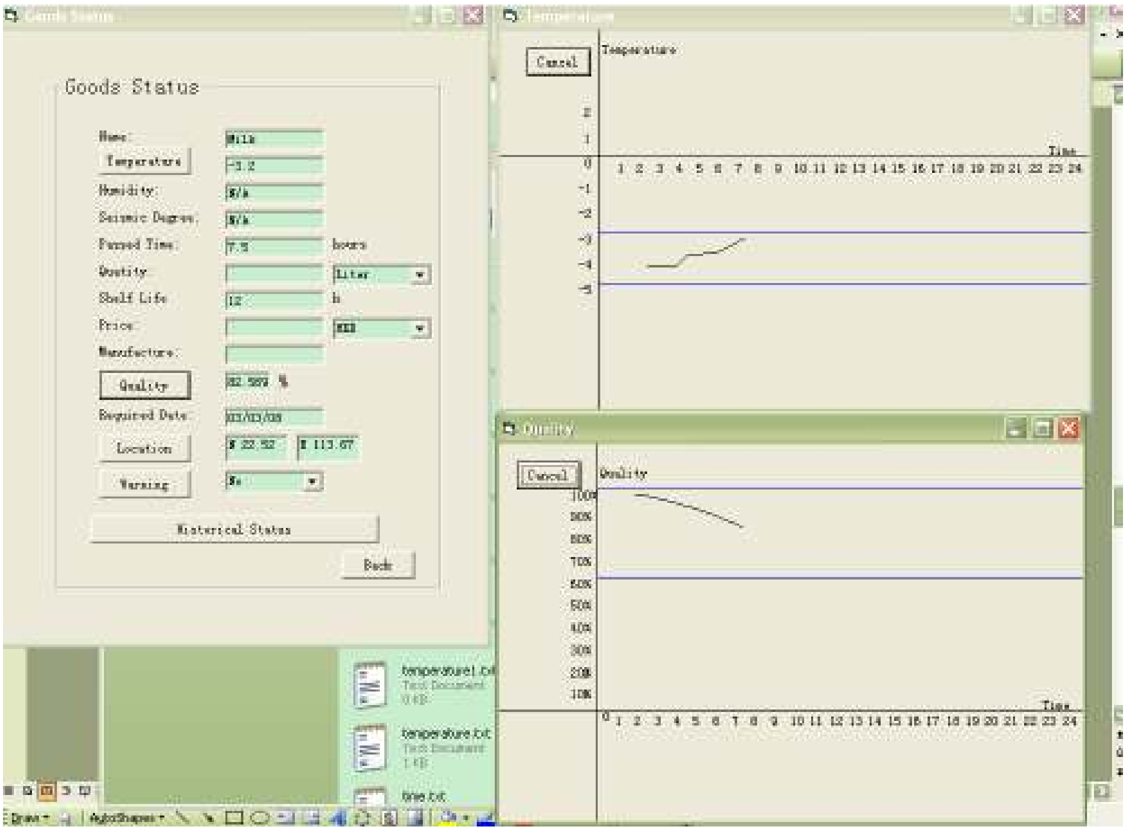


Figure 5.4 User Interface of the Warning Module

The sensors on the containers can transmit information to the backend system through the communication module. People can see the real-time environmental factors in the containers in the user interface, such as temperature, humidity and so on. If some unexpected events occur, FWM will give "warning" information to DSM, which is introduced in the next chapter. At the same time, the users can see the warning and the reasons for them in the user interface. Figure 5.5 indicates the following situation: when the perishable products arrive at the destination, the receivers want to know what the received perishable products have experienced during transportation. They can input the delivery list number, and then click the "historical status" button in Figure 5.4 and Figure 5.5. The module will show information on the products, such as whether the temperature exceeded the safety range or if there was severe vibration in the truck and so on. It is very easy for customers to judge whose fault it was if an accident has occurred.

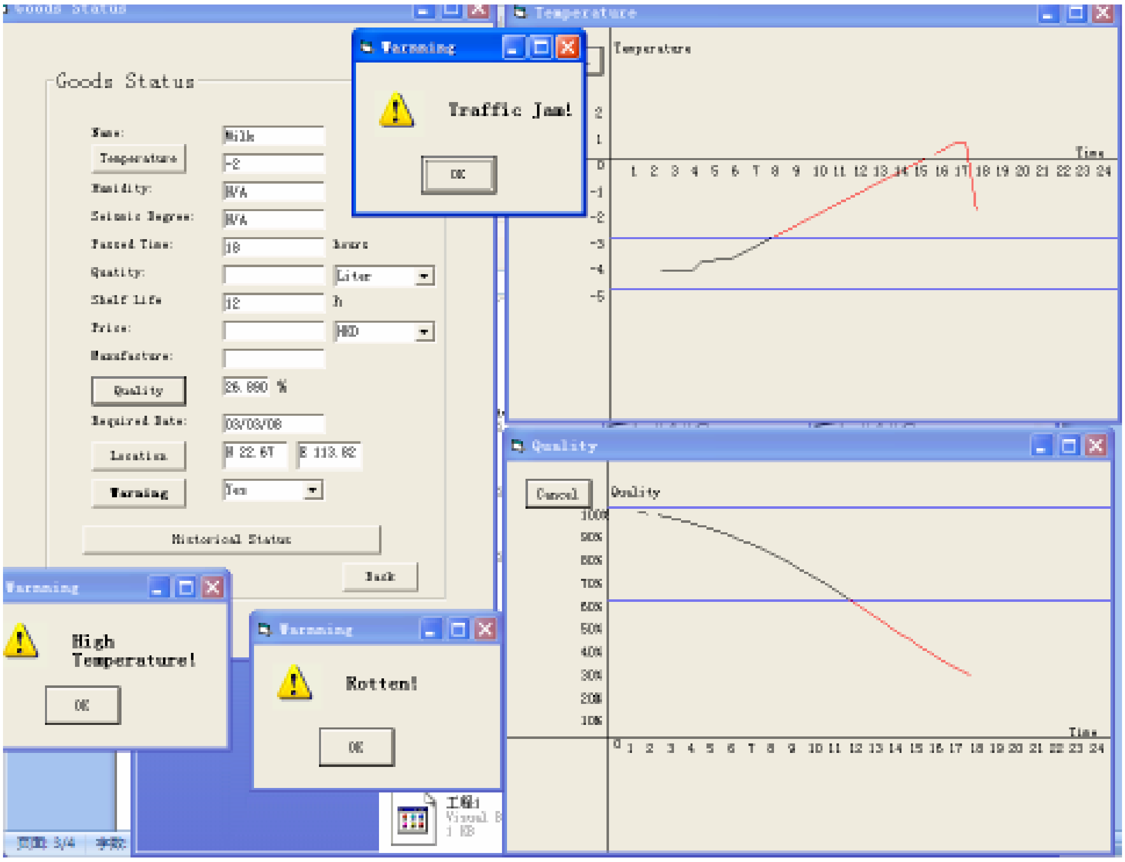


Figure 5.5 User Interface of a "Warning" Situation

This part is designed using RBR and the following sections will give further details about it.

5.4.1 Knowledge Database

The decision rule database is composed of some rules. It is designed as shown in Table 5.3.

Table 5.3 Knowledge Database

Rule_ID	001
Rule_Name	AccidentReason1
Rule_Status	1
If	temperature(current(T))$\leq$temperature(lowlimit(T))
Or	temperature(current(T))$\geq$temperature(uplimit(T))
……	… ….
Then	Environmental_Factor_Comtainer=1
Instruction	None

Its attribute fields include Rule ID, Rule Name, Rule Status, **If** sentences, **And** sentences, **Then** sentences (i.e. Conclusion) and Instruction. The rule status denotes whether a rule is available for the case. If the status is available, the rule will be shown in the user interface. **If** and **And** sentences all have certainty factors. Instruction is used to inform the user of the rule in a direct way or give some supplementary information.

5.4.2 Inference Chain

The method of the inference chain uses forwarding chaining. Figure 5.6 indicates the flow. The inference engine calls out the *i*-th rule of the knowledge database. We use the certainty factor to judge whether the rule is applicable to the reason. The certainty factor of the conclusion can be calculated as below:

$$CFQ = CF(Rule) \times CF(\mathrm{Re}ason), \tag{5.8}$$

where *CFQ* represents the certainty factor of the conclusion, *CF(Rule)* represents the certainty factor of the rules, and *CF(Reason)* represents the certainty factor of the reason.

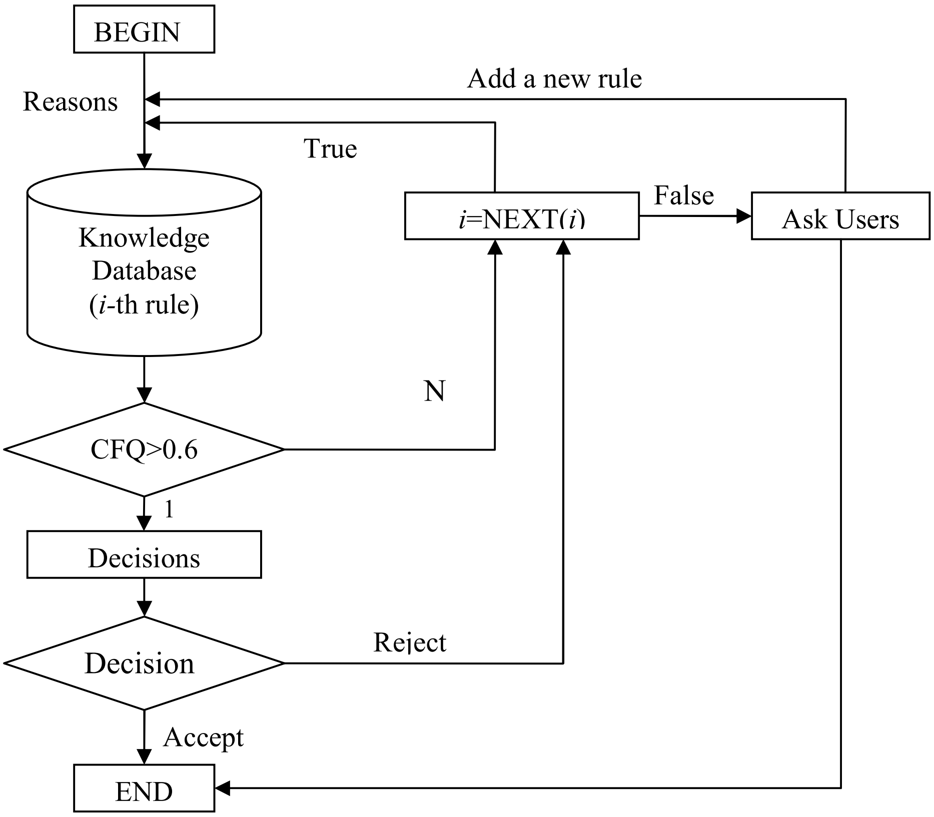


Figure 5.6 Flowchart of the Reasoning Process

If *CFQ* is more then 0.6 the conclusion of the rule will be input into the decision part, then the inference engine will re-search the database to find out whether there is a more suitable rule for this case. If *CFQ* is not greater than 0.6, the inference engine will try to search the knowledge database for a suitable rule. If none of the rules in the database are available, the system will ask the user how to cope with the situation. Then the user can define a new rule and input it into the knowledge database. Additionally, all suitable conclusions are displaced on the user interface. They will be ordered based on the number of the certainty factor. If the user does not want to apply any of them, he/she can also input a new rule into the decision rule database.

5.4.3 Rule-based Approaches

For the warning function, FWM applies RBR to judge the environmental conditions inside the container and forecast the quality of the perishable products. An example is given below to illustrate the design. The sensors in the containers are set to monitor the temperature, humidity and degree of vibration conditions.

If an abnormal situation occurs, the warning module will give warning information to the decision part. The warning part is designed as described below. It firstly determines what the warning reasons are. There are two main reasons for this case, environmental factors and value loss. Then, the module considers the problem based on the information concerning the warning; is the error to do with the container or with the vehicle; is the present situation causing the problem or is the forecasting the problem? Next, the module judges the feasibility of all the solutions. It will choose some simple and quick actions to cope with the accident. Figure 5.7 presents the flowchart of the RBR of the module (Wang *et al.*, 2010).

```
start(warning(X)) :- temperature(current(T))>=temperature(uplimit(T))

start(warning(X)) :- temperature(current(T))<=temperature(lowlimit(T))

start(warning(Y)) :- humidity(current(H))>=humidity(uplimit(H))

start(warning(Y)) :- humidity(current(H))<=humidity(lowlimit(H))

start(warning(Z)) :- seismic(slope(S))>=seismic(uplimit(S))

?-warnning(_)

Print_instructions :- nl, write('No warning.')


askuser(Initial_quality[], Limit_quality[], Guaratee_time[])

askuser(Model_no.[])

use(Model_no.[4]) :- askuser(Model_no.[]) is void

solve((Initial_quality[], Limit_quality[], Guaratee_time[]), Model_no.[])

value(current(Q)) = solve(_)

Start(warning(Q)) :- value(current(q))<=value(lowlimit(Q))
```

Some rules from experienced operators are collected for this case:

Rule 1: If the current temperature is over the lower or upper thresholds, then set the environmental factor of the container to 1, and both the environmental factor of the vehicle and the value factor to 0. The formula for the rule is:

IF temperature(current(T)) ≤ temperature(lowlimit(T))

OR temperature(current(T)) ≥ temperature(uplimit(T))

THEN Environmental_Factor_Comtainer=1, Environmental_Factor_Vehicle=0,

Value_Factor=0

Rule 2: If the current humidity is over the lower or upper thresholds, then set the environmental factor of the container to 1, and both the environmental factor of the vehicle and the value factor to 0. The formula for the rule is:

IF humidity(current(H)) $\leq$ humidity(lowlimit(H))

OR humidity(current(T)) $\geq$ humidity(uplimit(H))

THEN Environmental_Factor_Container=1, Environmental_Factor_Vehicle=0,

Value_Factor=0

Rule 3: If the vibration degree is over the threshold, then set the environmental factor of the vehicle to 1, and both the environmental factor of the container and the value factor to 0. The formula for the rule is:

IF vibration(degree(S)) $\geq$ vibration(uplimit(S))

THEN Environmental_Factor_Vehicle=1, Environmental_Factor_Container=0,

Value_Factor=0

Rule 4: If the current value is over the threshold, then set both the environmental factor of the container and the vehicle to 1, and the value factor to 0. The formula for the rule is:

IF value(current(Q)) $\leq$ value(lowlimit(Q))

THEN Environmental_Factor_Vehicle=1, Environmental_Factor_Container=1,

Value_Factor=0

Rule 5: If the environmental factor of the vehicle is 1, then make the system search for the nearest vehicle and loading station. The formula for the rule is:

IF Environmental_Factor_Vehicler=1

THEN search the nearest vehicle and the loading station

Rule 6: If the environmental factor of the container is 1, make the system search for the nearest empty container. The formula for the rule is:

IF Environmental_Factor_Container=1

THEN search the nearest empty container

… …

5.5 Simulation Test and Results Analysis

Since it is difficult to collect adequate data from a real transportation system, a simulated experiment is studied to describe the operating procedure of the module. It is used to illustrate how to apply this module to calculate the travel time and to cope with accidents.

YT (alias) is a logistics company in mainland China. The company plans to transport consignments from Shanghai to Beijing. A suggested route can be generated by the system based on Google Maps. The routes include: 311 Guangfu Road in Shanghai to G2 Highway, G2 Highway, S29 Highway, G25 Highway, G18 Highway, G3 Highway, S30 Highway, Jingjing Highway, Jingjing Highway to 14 Hepingli in Beijing. All the route

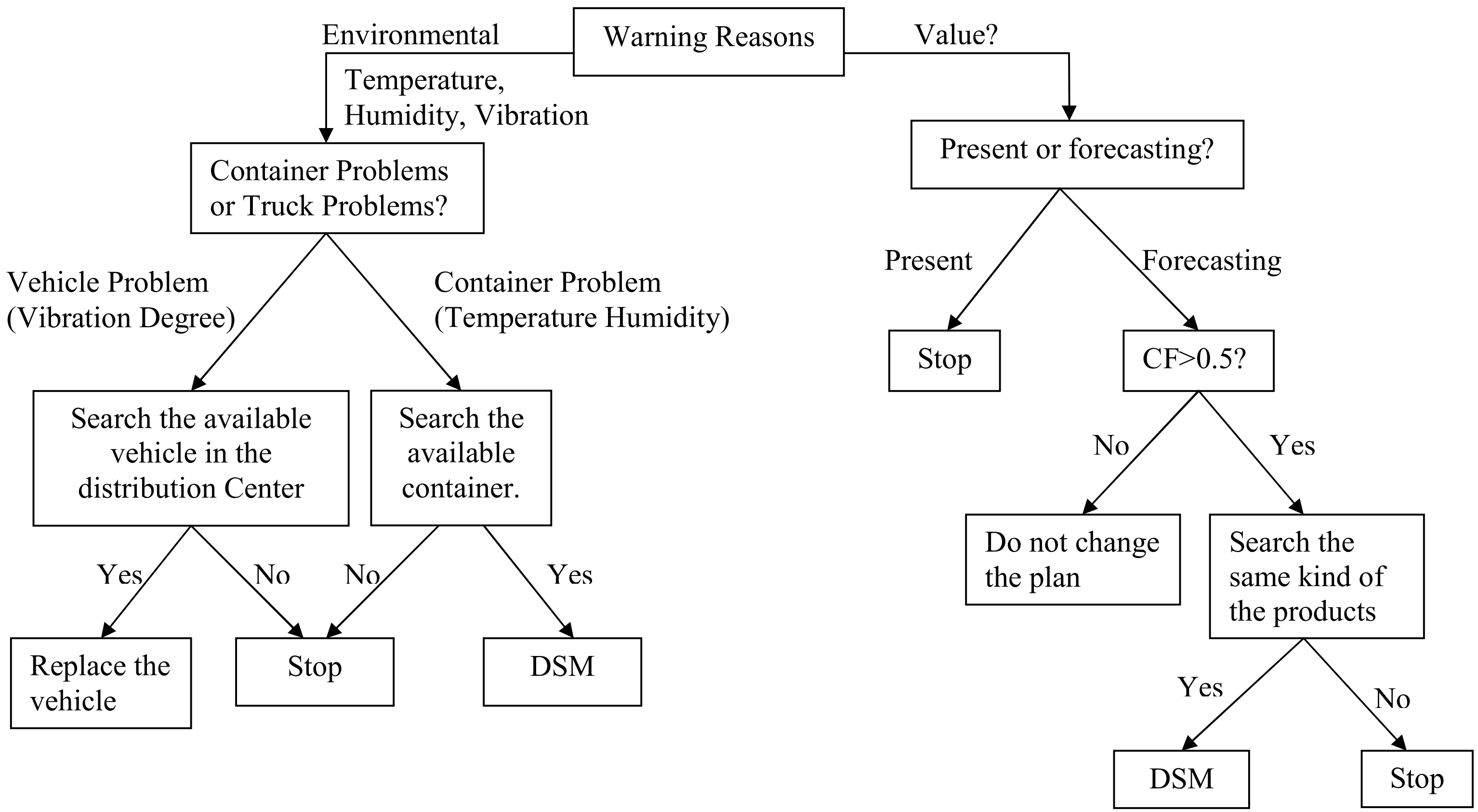


Figure 5.7 The Flowchart of the RBR Process

segments can be found in the case base, except for the first one and the last one. The first route, that from 311 Guangfu Road in Shanghai to G2 Highway, will be used to illustrate the operation of the fuzzy part of the module. Another route G2 Highway, which can be found from the case base, will be used to illustrate the neural network part of the module as an example.

How the module calculates the time spent in the first route segment will now be introduced. The fuzzy sets of this case are city scale and road grade. The city scale is measured by the population, which is more than 10 million, and the designed road grade is grade 2. Through computing by fuzzy logic, the most similar route segment is found. Then the system sets the most similar route segment as the unsolved new case and inputs it into the CBR system. Considering the weather, driver and other factors listed in Table 5.1, the most similar case can be found. Then, formula 5.9 can be used to estimate the travel time of this route segment. The method is the same as the calculation of the travel time for the G2 Highway segment.

$$t = t_s \cdot \frac{L}{L_s} \tag{5.9}$$

where t_s is the travel time of the similar case, L_s is the route length of the similar case, t is the travel time of the unsolved route segment, and L is the route length of the unsolved route segment.

G2 Highway is used to illustrate a route segment found in the case base. G2 Highway in this case is shown in Table 5.4. Table 5.5 shows the details of the most similar case where $M = 1$. Since $M = 1$, the travel time of this similar case is regarded as the estimated time of this route segment. When all the segments are calculated, the time added together will be the total estimated time. After simulation, the division of real travel time and the estimated result is greater than 5%. Consequently, the weightings of this case need to be adjusted and the neural network is applied. After adjustment, the case base is updated using the new result for the G2 Highway.

Table 5.4 Case Information 1

Weather	Sunny
Workday/Holiday	Workday
Time_Period	8:45
Vehicle_Type	Truck_JF_15T
Driver	00012
Products Weight	15T

Table 5.5 Case Information 2

Weighting (w_i)	Case_2314	Match_Degree (x_i)
0.20	Weather	1
0.30	Workday/Holiday	1
0.30	Time_Period	1
0.05	Vehicle_Type	1
0.05	Driver	1
0.10	Products Weight	1
	Sum	1

During transportation, the warning part found the detected temperature supplied by RMM is under the low limit of the temperature rule. It gave warnings to the system. Table 5.6 shows the abnormal information

Table 5.6 Information About the Abnormal Container

Container	Running Time	Required Date	Required Time	Estimated time of arrival	CF	Location
sh005	4:17:08	04/03/ 2009	14:00	04/03/2009 12:57	0.63	N121.8 E31.1

Destina-tion	Products	Quantity	Estimated quality of arrival	Tempera -ture	Humidity	Vibration Degree
N121.5 E31.2	Fish	1	68%	-9	59%	Normal

When FWM receives the warnings, the module firstly judges what the reason for the warning is. The reasons are divided into two kinds, those concerned with economic value and those concerned with environmental factors. The factor monitored by the sensors all belong to the environmental factors. The environmental factors are also divided into two kinds, container problems and vehicle problems. In this case, temperature and humidity both belong to container problems; while the degree of vibration belongs to vehicle problems.

When a vehicle problem occurs, the module will search, using GPS, for the nearest available truck to the container truck that is experiencing the problem. Then the module will ask the nearest available truck to take the place of the abnormal one. When a container has a problem, the decision module will search for the nearest distribution centre with available containers from the database, and will determine whether there is such a distribution centre. If there is one, the module will ask the container truck which has the problem to go to the distribution centre so that the container can be replaced. If there are no empty containers, the module will also search for the nearest container truck that currently has no transportation duties, via GPS. Then the module will ask the nearest truck to drive to the nearest distribution centre.

In this experiment, the module judges that sh005 has a problem with the container, and it will ask the driver of the truck sh005 to go to the nearest distribution centre C. At the same time, the module searches for empty containers and finds there is an empty container at distribution centre C. Finally the container will be changed, but the driver and the truck will not be changed.

The module will add the time for changing the container to the estimated time of arrival, and then a new warning concerning sh005 pops up. The quality of the perishable products being transported cannot meet the demand of customer A when they arrive at their destination. The warning information is shown in Table 5.7.

In the case of value problems, the module decides whether or not to dispose of the perishable products. The decisions are based on the degree of certainty of whether it is possible to save the rest of the transportation fee, or whether it is more economical to transport the perishable goods to another nearer customer who has requested the same kind of product. In this case, the module finds another customer near the distribution center that needs half a container of fish on 04/03/2009. After changing the destination, the truck will transport the products to this new customer, and the products originally planned for delivery to this customer will be sent to the customer who originally was to have received the goods carried in sh005.

Table 5.7 Warning Information About the Abnormal Container

Container	Running Time	Required Date	Required Time	Estimated time of arrival	CF
sh005	4:17:08	04/03/2009	14:00	04/03/2009 13:57	0.66
Location	Destination	Products	Quantity	Estimated quality of arrival	
N121.8 E31.1	N121.5 E31.2	Fish	1	59%	
Temperature	Humidity	Vibration Degree	Truck	Driver	
-15	50%	Normal	AK 7332	3513	

In this experiment, without this module the company would have lost the whole container of products. Fortunately the loss in this case was able to be reduced by half.

5.6 Summary

FWM aims to realise warning and forecasting functions for the proposed approach for the management of perishable products in logistics. It has two contributions. A soft case-based reasoning method is proposed to estimate the travelling time of vehicles, and a

RBR method is applied to give warnings and to avoid losses. The soft CBR method is developed based on the traditional CBR system. It integrates fuzzy logic and neural network techniques. Consequently, the method has a machine learning function and it can update itself automatically. The method firstly divides the planned route into several segments. Then it helps users search for the most similar case for each segment. If the deviation of the estimated time and real travel time is huge, the weightings will be trained using the neural network and old case will also be replaced. In summary, the method combines soft computing and CBR techniques to estimate travel time. With its help, the arrival time can be predicted more accurately. With the forecasting of the arrival time, the warning part applying the RBR method can judge whether there is anything wrong about the vehicle, the container or the products. It aims to help the user adjust their decisions in time to avoid value loss during the transportation of perishable products. It can advise the user of the best action to take, and give customers suggestions on how to deal with critical situations.

A simulated experiment is used to test the module. The results showed that FWM can be applied to estimate the travel time. The accuracy increased with the help of the eural network and fuzzy logic after some training. It also proves that the module offers a good performance in coping with accidents. In that case, FWM uses the rules set for that case to reschedule the vehicles and the containers. The new plan successfully reduced the loss by 50% following a particular incident.

CHAPTER 6 DECISION SUPPORT MODULE

6.1 Introduction

Optimisation in the proposed approach is the biggest challenge in this research. How to obtain the optimal solution within a reasonable time attracts the attention of many researchers. DSM is designed to make and adjust vehicle schedules for the minimisation of transportation costs and losses. The module is discussed in this chapter. The architecture is firstly presented in Section 6.2. The module has two functions: one is static optimisation for making schedules. In Section 6.3.1 the algorithm for static optimisation will be discussed, this section also contains a test of the proposed optimisation algorithm IQEA. The other function concerns dynamic adjustment, and it will be discussed in Section 6.3.2. Finally, a simulation about a case that may occur in real life is used to test the performance of the proposed optimisation algorithm and dynamic adjustment approach, which is described in Section 6.4.

6.2 Architecture

Figure 6.1 illustrates the architecture of the module. It is designed to manage vehicles in the distribution link. At the start of a workday the module helps the company to develop an optimal vehicle schedule. When the vehicles are carrying the consignments, RMM monitors the situations in real-time. If there is anything abnormal, FWM will report the situations to DSM, and DSM will take the necessary actions to deal with these emergences.

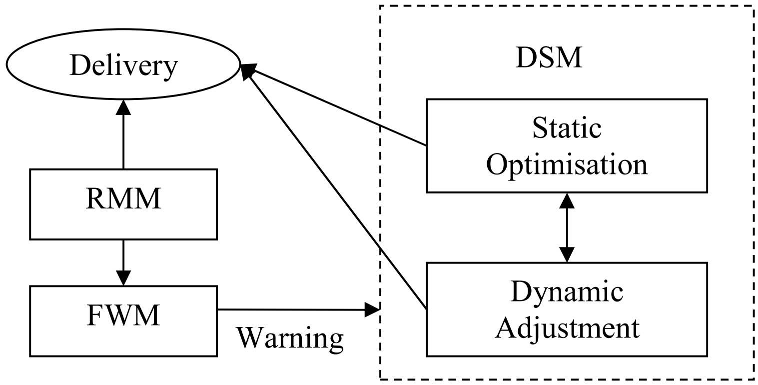


Figure 6.1 Module Architecture

6.3 Vehicle Management

6.3.1 Static Optimisation

Before starting the day's work, DSM will make an optimal initial schedule for the company. In Section 6.3.1.1, the proposed IQEA is introduced for the static optimisation of problems at small scale. In Section 6.3.1.2, the hybrid algorithm, combining GA and heuristics, is applied for designing this static optimisation for problems at large scale.

6.3.1.1 Improved Quantum-Inspired Evolutionary Algorithm (IQEA)

IQEA is improved based on the QEA for the real-time vehicle routing problem combined with the crew schedule. This work includes the algorithm design principles, Q-bit based encoding and decoding scheme, the design of a quantum rotation gate, selection of evolutionary and survival strategies and so on. Firstly, IQEA will be designed for TSP. The result will be compared with results achieved by other algorithms. IQEA is used to develop a schedule for the delivery of perishable products and to optimise the route. The procedure of IQEA for solving the problem can be summarised as follows.

Step1: Produce an Initial Solution.

An example of initial solution is given below:

31, 32, 5, 6 - 23, 24 - 39, 40……27, 28, 13, 14

where, "-" means the consignment before it and the consignment after it are in different trucks.

Consignment $2n$-1 and consignment $2n$ are a pair. They represent two different operations (collection and delivery) of the same container. The two consignments are relevant and they must be finished sequentially. So we just consider one of the pairs to simplify the problem. The steps for producing the initial solution are described as below.

(1) Produce a random sequence of consignment numbers.

(2) Assign the consignments to the trucks satisfying the constraints of time window and vehicle capacity.

(3) Evaluate the initial solution by fitness function

Step 2: Optimisation

The connection of neighbouring consignments is set as a quantum bit *Q(t).* A Q-bit may be state 1 or state 0 according to the probability of the quantum state. When a Q-bit is 1, a cutting point is set between the two corresponding consignments. When a Q-bit is 0, the two corresponding consignments will keep the connection.

(1) Let t=0 and initialise *Q(t)*.

$Q(t) = \{q_1^t, q_2^t, ..., q_n^t\}$, where q_1^t means the probability of the quantum state, being state 1 or state 0.

(2) Make $P(t) = \{p_1^t, p_2^t, ..., p_n^t\}$ by observing the state of *Q(t)* through comparison with q_i^t as follows:

$$p_i^t = \begin{cases} 0.........rand[0,1] > q_i^t & \text{keep the connection} \\ 1................otherwise & \text{divide the connection} \end{cases} \tag{6.1}$$

(3) Produce a new sequence of consignment numbers.

i) Compute each segment:

Ready Time: R=max{r_1, r_2-s_1, r_3-s_1-s_2,……}

Due Time: D=min{d_1,d_2-s_1, d_3-s_1-s_2,……}

Total weight of the segment: $W = \sum w_i$ (6.2)

Total service time of the segment: $S = \sum s_i$ (6.3)

Read Time in reverse order:

R'=max{r_n, r_{n-1}-s_n, r_{n-2}-s_n-s_{n-1},……}

Due Time in reverse order:

D'=min{d_n,d_{n-1}-s_n, d_{n-2}-s_n-s_{n-1},……}

where r represents ready time, d represents due time, w represents the weight of a consignment, and s represents service time.

ii) Feasibility Study of each segment

If $w_i > C$, the segment is unfeasible. Where C denotes the capacity of the vehicles

If $D<R$ and $D'<R'$, the segment is unfeasible

If all the segments are feasible go to next step, otherwise go back to substep (2)

iii) Select candidate segments

If $t \le D$ and $U + W \le C$, then the segments is chosen as the candidate segment.

If none segments satisfy these two conditions, then let t=0, U=0.

iv) Arrange the sequence of combined segments

If $L_{ij}^{t} = \min\{L_{ij}^{1}, L_{ij}^{2}, L_{ij}^{3} ... L_{ij}^{n}\}$, then Segment t is chosen to be the next segment, $t = t + S$, $U=U+W$, go back to Sub-Step iii).

If all the segments have been chosen, go to the next step.

where L_{ij} means the distance between consignment i and consignment j, i means the last consignment number of the last segment has been chosen, and j means the first consignment number of the candidate segments.

(4) Evaluate the solution by fitness function, and save the best solution b. If the stopping condition is satisfied, go to (8); otherwise go to the next step.

(5) Update *Q(t)* with the quantum rotation gate *U(t)*.

$$U(t) = \{\Delta\theta_1^t, \Delta\theta_2^t, ..., \Delta\theta_n^t\} \tag{6.4}$$

The change of $\Delta\theta_t$ is described in Table 3, where *f( )* is the result of the *i*-th iteration and b is the best solution recorded. In this problem, θ_1=0, θ_2=0, θ_3=0.01 π , θ_4=0, θ_5=-0.01 π , θ_6=0, θ_7=0 and θ_8=0

Table 6.1 Change of $\Delta\theta_t$

x_t	b_t	$f(x) \geq f(b)$	$\Delta\theta_t$
0	0	False	θ_1
0	0	True	θ_2
0	1	False	θ_3
0	1	True	θ_4
1	0	False	θ_5
1	0	True	θ_6
1	1	False	θ_7
1	1	True	θ_8

$$q'^t_i = \cos^2(\arccos q_i^{0.5t} + \Delta\theta_i) \tag{6.5}$$

(6) Let *t*=*t*+1, and go back to Sub-step (2).

(7) If the stopping condition is satisfied, output the results; otherwise go to the next step.

(8) Let i=i+1, and go back to Step 1

The procedure is illustrated in Figure 6.2.

6.3.1.2 Genetic Algorithm (GA)

In this section, a GA combined with heuristics is described. It is applied to minimise the transportation costs. Chromosome design, evaluation, selection and crossover strategies are introduced as follows.

A. Chromosome Representation

The chromosome is designed as follows. Where a gene represents a consignment number. The chromosome string means the arrangement order of the consignments. The consignment at the beginning of the chromosome will be arranged first.

31	32	5	6	…..	27	28	13	14

B. Evaluation Strategies

The first step in the evaluation process is to arrange the consignments in each vehicle. Finally a schedule can be produced, as follows:

3, 1, 5, 6 - 2, 4 – 9 - 7, 8

where, "-" means the consignment before it and the consignment after it are in different trucks.

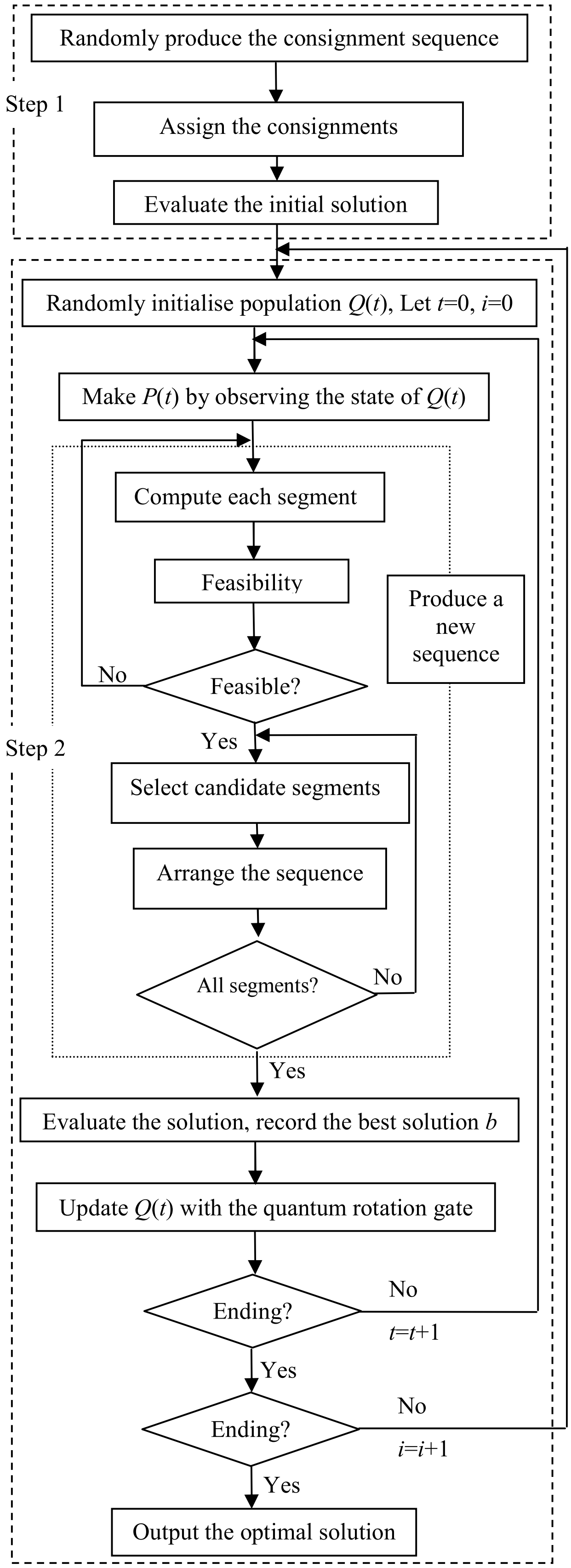


Figure 6.2 Outline of IQEA optimisation

Figure 6.2 Outline of IQEA Optimisation

Transportation cost is used for the evaluation, because each behaviour in logistics can be measured by cost. The formula is designed as follows, and the operation cost, drivers' salary and petrol cost all need to be considered. These values can be changed with respect to market prices.

$$T = \sum (T_{v_i} + T_{d_i} + P_{v_i} \cdot \sum_{v_i} D_{mn}) \tag{6.6}$$

where, T: Transportation Fee

T_{v_i} : Daily Operation Cost of Vehicle i

T_{d_i} : Daily Salary of Driver i

P_{v_i} : Petrol Cost of Vehicle i per kilometre

D_{mn} : Total distance Vehicle i is planned to go

The aim of the algorithm is to determine a vehicle schedule using the least transportation cost.

C. Initial Population

Initial population is produced randomly. Some random orders of numbers can be achieved. However, if the scale is large, some heuristics, which will be introduced in the next chapter, can be used for producing relatively optimal solutions.

D. Selection Strategy

Parents are selected using the roulette wheel, which is the most commonly used method in ordinary GA. A selection factor is also set for this strategy. First a random number is generated. If the random number is bigger than the selection factor, the chromosome with the best solution will be chosen as the parent; otherwise another random number will be generated. The roulette wheel uses this random number to select the parent from all the chromosomes.

E. Reproduction: Crossover Strategy

A simple example is used to illustrate this strategy. Assuming two parents are chosen for reproduction then:

e.g.

P1:

3	5	7	2	1	9	6	4	8

P2:

4	7	9	1	6	8	3	5	2

Step 1 generates a random cut point.

P1:

3	5	7	2	1	9	6	4	8

P2

4	7	9	1	6	8	3	5	2

Step 2 removes Genes “3, 5 and 2” from P1. Then Genes “1, 9, 6, 4 and 8” are removed from P2. Two new chromosomes are generated.

P1’:

7	1	9	6	4	8		3	5	2

P2':

7	3	5	2		1	9	6	4	8

Step 3 inserts the genes which have been removed into the new two chromosomes. Firstly a random gene is chosen from the removed genes. The heuristics, which will be discussed in the next section, will be used for choosing the most suitable location for inserting this gene. If there are no feasible locations in which it can be inserted, the gene will be placed at the end of the chromosome. This step will be repeated until all the removed genes are inserted into new chromosomes. Two children as follows have been generated:

Ch1

7	2	3	1	9	5	6	4	8

Ch2

1	7	6	4	8	3	5	2	9

F. Reproduction: Mutation Operation

The mutation operation helps prevent the population from becoming trapped in the local optimisation. Firstly a random number is generated, if it is smaller than the mutation probability set by considering specific problems, the mutation operation will be carried out. The simple example below illustrates how the mutation operates:

Two genes are selected randomly when there is a need for mutation.

Ch

7	2	***3***	1	9	***5***	6	4	8

Then, the locations of these two genes are exchanged.

Ch

7	2	***5***	1	9	***3***	6	4	8

After these mutation operations, a new generation is produced. The algorithm will go back to perform the evaluation operation and the entire process will be repeated. The best solution of each generation will be recorded. After a given number of iterations or after a set period of time, the best solution will become the final vehicle schedule, as follows:

Final Schedule:

Vehicle A

7	2	3

Vehicle B

1	9	5	6

Vehicle C

4	8

The logistics team will arrange consignments using this schedule at the beginning of a working day. If the RFID-based monitoring system gives a warning to the backend system, the schedule has to be adjusted. In the next section the method to find the most appropriate adjustment which can reduce the losses the most will be discussed.

6.3.1.3 Experiments and Results

The GA algorithm is designed based on the Route Crossover by Ombuki *et al.* (2006). The method has been proven to perform well in solving Solomon's VRPTW benchmark problems (Ombuki *et al.*, 2006). Consequently, the main objective of the test described in this section is to prove the performance of the proposed IQEA. Firstly the problem is described.

Travelling Salesman Problem (TSP)

The basic idea of the proposed IQEA is to embed a greed heuristic method into the standard QEA for the optimal recombination of the city subsequences. The city subsequences are generated by cutting a whole city sequence of a tour according to the values of the quantum bits.

The first step for solving the TSP is to randomly produce a city sequence of the travelling tour. The connection of a neighbouring city pair is set as a Q-bit. A Q-bit may be state 1 or state 0 according to the probability of the quantum state. When a Q-bit is 1, a cutting point is set between the two corresponding cities. When a Q-bit is 0, the two corresponding cities will maintain a connection. It is clear that a Q-bit string with m bits equal to 1 will cut the city tour into m subsequences of cities. Then, these subsequences are recombined by a well-designed greed heuristic. The algorithm can obtain a better city tour with a shorter total path length. Q-bits are updated by the rotation of quantum gates, which can guide the search direction to the optimal area.

In the TSP, a salesman has to visit all the cities and returns to the starting city. The problem aims to find the shortest route for all the cities in the map, and each city must be visited at least and only once. It is often modelled as a graph; a set of vertices indicates the cities and edges connecting vertices indicate the travelling routes. The objective is to find a route that visits all the vertices in the map where each vertex is visited only once. Consequently, the input of the problem is City Labelled Number and their locations. The output is the feasible travelling route and the total distance. An example is given as follows.

Burma 14 is one instance of a TSP. Figure 6.3 indicates its map with the route：

1→2→3→4→5→6→7→8→9→10→11→12→13→14→1.

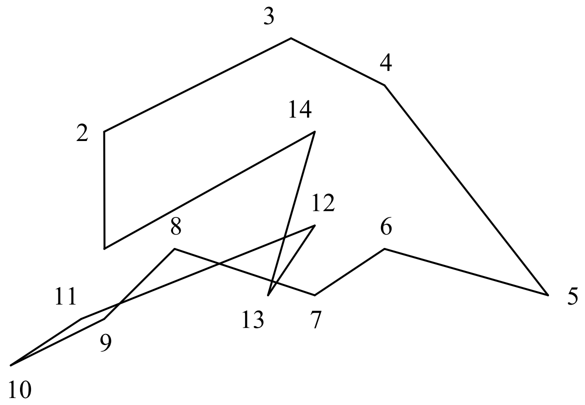


Figure 6.3 Map of Burma 14

The input of Burma 14 is described in Table 6.2.

The output of Burma 14 is the travelling route and its corresponding travelling distance.

The procedure of IQEA for solving the TSP can be summarised as follows (Wang *et al.*, 2011).

Step 1: Produce an Initial Solution. For example,

7→2→5→4→14→11→3→1→12→6→13→9→8→10

(1) Calculate the distance between any two vertices.

(2) Produce two random numbers *m* and *n*; exchange the tour order of the *m*-th visited city and the *n*-th visited city. Replace the operation for hundreds time, then a random tour order of the cities can be achieved. Set it as the initial solution.

Table 6.2 City Information

City Number	Location	
	X.	Y.
1	16.47	96.10
2	16.47	94.44
3	20.09	92.54
… …	……	……
14	20.09	94.551

(3) Evaluate the initial solution by the fitness function.

$$D = \sum d_{ij} \tag{6.7}$$

where *D* represents the total distance the salesman needs to travel, and d_{ij} represents the distance between City i and City j.

Step 2: Optimisation

(1) Let *t*=0 and initialise *Q(t)*.

$Q(t) = \{q_1^t, q_2^t, ..., q_n^t\}$, where q_1^t denotes the probability of the quantum state, being state 1 or state 0.

(2) Make $P(t) = \{p_1^t, p_2^t, ..., p_n^t\}$ by observing the state of *Q(t)* through comparison with q_i^t as follows:

$$p_i^t = \begin{cases} 0.........rand[0,1] > q_i^t & \text{keep the connection} \\ 1................otherwise & \text{divide the connection} \end{cases} \tag{6.8}$$

(3) Produce a new sequence of the tour.

i) Produce the subsequences.

The city subsequences are generated by cutting the whole city sequence according to the values of the quantum bits. A Q-bit string with m bits equal to 1 will cut the city tour into m subsequences of cities.

ii) Arrange the sequence of combined subsequences

A random segment is chosen as the first segment of the new sequence.

If

$$d_{ij}^{t} = \min\{d_{ij}^{1}, d_{ij}^{2}, d_{ij}^{3} ... d_{ij}^{n}\} \tag{6.9}$$

then subsequence t is chosen as the next segment.

where d_{ij} means the distance between City *i* and City *j*, *i* means the last City of the last segment has been chosen, and *j* means the first City of the candidate segments.

Repeat this operation until all segments have been chosen, go to the next step.

(4) Evaluate the solution by fitness function, and save the best solution *b*. If the stopping condition is satisfied, go to (7); otherwise go to the next step.

(5) Update *Q(t)* with the quantum rotation gate *U(t)*.

$$U(t) = \{\Delta\theta_1^t, \Delta\theta_2^t, ..., \Delta\theta_n^t\} \tag{6.10}$$

The change of $\Delta\theta_i$ is described in Table 6.3, where *f( )* is the result of the *i*-th iteration and *b* is the best recorded solution. In the TSPs, θ_1=0, θ_2=0, θ_3=0.01π, θ_4=0, θ_5=-0.01π, θ_6=0, θ_7=0 and θ_8=0

Table 6.3 The Change of $\Delta\theta_i$

x_i	b_t	$f(x) \geq f(b)$	$\Delta\theta_t$
0	0	False	θ_1
0	0	True	θ_2
0	1	False	θ_3
0	1	True	θ_4
1	0	False	θ_5
1	0	True	θ_6
1	1	False	θ_7
1	1	True	θ_8

$$q'^t_i = \cos^2(\arccos\sqrt{q^t_i} + \Delta\theta_i) \tag{6.11}$$

(6) Let t=t+1, and go back to Substep (2).

(7) If the stopping condition is satisfied output the results; otherwise go to the next step.

(8) Let i=i+1, and go back to 1

6.3.1.4 Discussion

Four instances of the TSPs obtained from the standard TSPLIB (1995) are chosen to test the proposed algorithm. This section gives the results of the problems "Burma14", "Gr17", "Gr21" and "Gr24" applying the IQEA. The results are presented in Table 6.4

below. The initial solution and the best solution of the first test of Burma14 are shown in Figures 6.4 and 6.5.

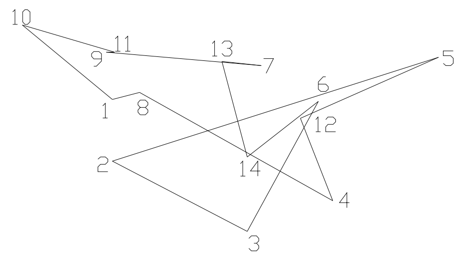


Figure 6.4 Initial Solution

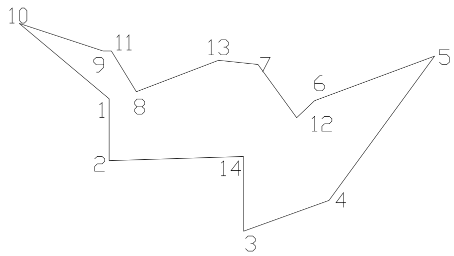


Figure 6.5 Best Solution

As the table shows the computational results are very good. Compared with the standard GA, the population and the iteration of the proposed algorithm are both less than the GA. In fact, the population of IQEA has only one individual. The results proved that global optimisation can be achieved, even with only one quantum. The good characteristic of population diversity is the main advantage of quantum encoding. It can also be observed in Table 6.4, where in most cases the optimal solution can be achieved in less or around 1000 iterations. GA usually needed thousands of iterations to obtain a result for the same problem. Compared with the standard QEA (Feng *et al.*, 2006), the scale of the problems that IQEA solved is greater. Limited to the requirements of quantum encoding, the standard QEA just solved the 14 cities TSP. Compared with QGA (Talbi *et al.*, 2004), IQEA has a smaller searched space. The searched space for the standard QEA is around 0.072% of the solution space (Feng *et al.*, 2006). The searched space of QGA is less than 5.14×10^{-7} of the solution space (Talbi *et al.*, 2004). However the population size of QGA is four. The number of iterations of IQEA is nearly the same as QGA, but the population size of IQEA is one. Consequently, the searched space of IQEA is only one quarter of QGA.

Table 6.4 Experimental Results

Test	Burma14		
	Result	Max. Iter.	Deviation
1	30.8785	328	0%
2	30.8785	322	0%
3	30.8785	512	0%
4	30.8785	664	0%
5	30.8785	813	0%
6	31.4536	1000	1.86%
7	31.4536	1000	1.86%
8	30.8785	111	0%
9	31.87911	1000	3.24%
10	30.8785	418	0%
Optimal Solution	30.8785		
Test	Gr17		
	Result	Max. Iter	Deviation
1	2178	5000	4.46%
2	2085	622	0%
3	2178	5000	4.46%
4	2178	5000	4.46%
5	2085	595	0%

6	2085	1027	0%
7	2178	5000	4.46%
8	2149	5000	3.07%
9	2085	326	0%
10	2178	5000	4.46%
Optimal Solution	2085		
Test	Gr21		
	Result	Max. Iter.	Deviation
1	2707	1064	0%
2	2998	7000	10.75%
3	2707	1229	0%
4	2707	529	0%
5	2707	3112	0%
6	2707	844	0%
7	2707	1473	0%
8	2707	1010	0%
9	2707	532	0%
10	2707	914	0%
Optimal Solution	2707		
Test	Gr24		
	Result	Max. Iter.	Deviation
1	1272	3015	0%
2	1272	2425	0%
3	1272	2409	0%

4	1272	4623	0%
5	1272	1004	0%
6	1272	2189	0%
7	1272	1036	0%
8	1272	3685	0%
9	1272	4336	0%
10	1272	3031	0%
Optimal Solution	1272		
Max. Iter.: Number of maximum iterations			

There are still many limitations of IQEA. Though IQEA can achieve an optimal solution very fast, it is also easily trapped in the local optimisation. It takes a very long time for IQEA to jump out of this. For example, in the 7th experiment of Gr17 it needs ten thousand iterations to jump out of a local optimum and achieve the optimal solution. This is also the biggest obstacle for applying IQEA to large scale TSPs. We ascribed the problem to the population size. In the next phase of our research, more than one quantum will be applied in the IQEA.

6.3.2 Dynamic Adjustment

In this section, the method for dynamic adjustment is described. When some urgent consignments need to be inserted into the present schedule, an accident occurs or the schedule has to be adjusted, the method will play a key role. The method is called Heuristics of Checking Embedded Strings (HCES). Heuristics is a general way of solving a problem. It uses experience-based techniques that help in problem solving, learning and discovery. The advantage of heuristics is that it can come to a solution rapidly. However the result may not be the best solution and it is just hoped to be close to the best possible answer.

Three situations which need dynamic adjustment will be introduced first, then HCES will be described. Finally, a simple example is used to illustrate the method.

A. Situations of dynamic adjustment

i. Traffic Jam

Traffic situations are hard to forecast. Though FWM applies case-based reasoning to estimate the arrival time, it is hard to foresee an accident on the road. If RMM finds the truck trapped in a traffic jam, it will send a warning to FWM. The module will check whether the current time will exceed the latest starting time of the consignments which may be affected by the traffic jam. If the module finds some consignments that cannot be delivered within their given time windows, it transmits the information to DSM. And the consignments will be removed from the original schedule and they will need to be reassigned by DSM.

ii. Environmental Effects

Some products are sensitive to some environmental factors, such as temperature, humidity, concentration of dangerous gas and so on. These environmental factors strongly affect the quality of products and their expired date. In RMM, these factors can be monitored by sensors, and the monitoring data can also be transmitted FWM system through moble communication techniques. If there are any problems with respect to environmental factors in the containers, the time for the products staying in a acceptable quality will be adjusted. Then these consignments are removed from the original schedule, and they will need to be inserted into the schedule again.

iii. Urgent Consignments

If some consignments are urgent to be delivered and they are accepted after the static optimisation of the schedule, a dynamic adjustment is needed so that these consignments can be inserted into the original schedule.

All these three situations, and some other situations, can be changed by inserting consignments into a schedule, while some parameters of the problem need to change. The method is the same as the insertion method in the hybrid algorithm for static optimisation. After which a new schedule will be generated. The procedure of the method, Heuristics of Checking Embedded Strings, will be described next.

B. Heuristics of Checking Embedded Strings

The procedure of the method Heuristics of Checking Embedded Strings is illustrated in Figure 6.6. It can be summarised as follows:

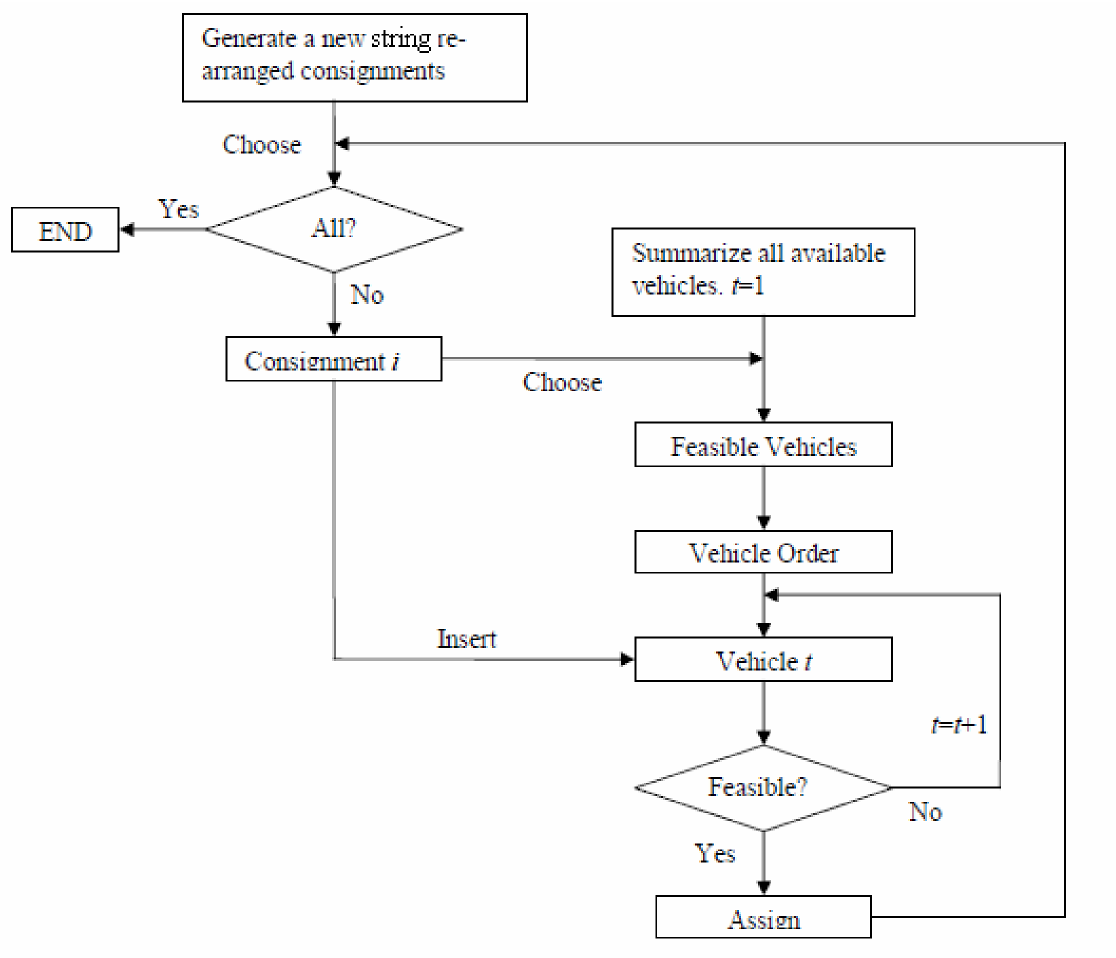


Figure 6.6 Procedure of Heuristics of Checking Embedded Strings

Step 1: Summarise all the products that need to be re-arranged.

The consignments that need to be re-arranged are removed from the original schedule. They compose a new string.

Step 2: Summarise all available vehicles.

Vehicles that still have time spaces available after removing re-arranged consignments and vehicles that have not yet been used are chosen. These vehicles may carry re-arranged consignments for dynamic adjustment. If there are not enough vehicles for the new schedule, some consignments may have to be dropped based on their value.

Step 3: Randomly choose a consignment of the new string.

The order in which the consignments are chosen can affect the new schedule. However, the string is usually very short. It is almost impossible that three or more consignments would need to be re-assigned at one time. So the method described in this paper just randomly chooses the consignments.

Step 4: Generate an order for the available vehicles.

The vehicles with feasible capacities are chosen. The order of the vehicles is from small capacity to large capacity. The order of vehicles also affects the schedule that is generated. In this step the working hours of each driver are considered. Vehicles of the same type are ordered in accordance with the time that drivers have worked. A vehicle with a driver who has worked for a short time will be in front of the vehicle with a driver who has worked for a long time.

Step 5: Feasibility Analysis

The algorithm tries to insert the randomly chosen consignment in all locations of available vehicles. Judgments mainly consider the given time window of the consignment and the forecast travel time. The consignment will be inserted into the first feasible location. If there are no suitable locations, the consignment will be assigned to a new vehicle. After this step the algorithm will go back to Step 3. The algorithm will stop when all consignments have been allocated to vehicles.

Next, a simple example will be used to illustrate the method and the rules.

C. Example

It is assumed there is an original schedule that has been optimised using the hybrid GA algorithm introduced in Section 6.3.1.2. As the schedule in the previous section shows, the consignments are assigned to three vehicles. Assuming consignment 1 and consignment 4 have been successfully delivered, Vehicle A gets trapped in a traffic jam while transporting consignment 7. After computation, the current time exceeds the latest starting time of consignment 2 and consignment 3. Therefore they need to be re-assigned. At the same time, FWM gives a warning to the backend system: the temperature in the container of consignment 5 is abnormal, and the product in consignment 5 is fish which easily goes bad in a high temperature environment. So consignment 5 also needs to be reassigned. There was also a new urgent consignment that needs to be delivered at the same time. How the optimisation will be worked out is introduced next.

Schedule:

Vehicle A

7	*2*	*3*

Vehicle B

1	9	*5*	6

Vehicle C

4	8

First the consignments that need to be reassigned and the consignments that have been transported or are being transporting are removed from the original schedule. A string needs to be inserted is designed, composed of the consignments that need to be reassigned together with incoming new urgent consignments. The schedule, shown below, has been changed.

Schedule:

Vehicle A

Vehicle B

9	6

Vehicle C

8

String:

2	3	5	10

On the assumption that consignment 5 is chosen, Vehicle A and Vehicle B are suitable vehicles. Then the algorithm computes the time needed to complete the current plan of each vehicle and checks whether consignment 5 can be inserted into these vehicles whilst still satisfying its time window. As Figure 6.7 shows, no feasible locations can be found for consignment 5 to be inserted. In which case it will be assigned to a new vehicle and will be transported at once. If it is also too late, the consignment will not be transported in order to save the transportation fee.

After this consignment 2 is chosen. There are four available vehicles for its transportation. As Figure 6.8 shows, the algorithm finds that it can be inserted before consignment 9. The algorithm will stop. A new plan for vehicle B is produced. Which is 2-9-6.

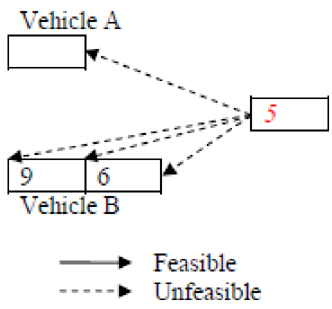


Figure 6.7 Inserting Consignment 5

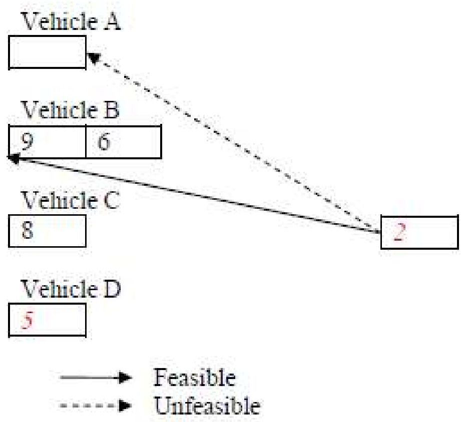


Figure 6.8 Inserting Consignment 2

The algorithm continues trying to insert other consignments into the current plan until all the consignments of the string have been chosen. Finally, a new schedule can be achieved as follows and Dynamic Adjustment is completed.

Vehicle A

10

Vehicle B

2	9	6

Vehicle C

8	*3*

Vehicle D

5

The result of dynamic adjustment may not be the best result. If other dynamic methods are applied to solve this kind of problem, the final result may be better. However those algorithms all need a long time to obtain the optimal solution. The biggest advantage of this proposed algorithm is that it only takes a short time to produce a relatively optimal solution. This is highly effective as decisions can be adjusted during transportation. Consequently this dynamic adjustment method is very suitable for the proposed system.

6.4 Simulation Test and Results Analysis

The schedule problem can be classified as VRPTW. As denoted in Figure 6.9, it is defined in a direct graph G=(V, A), where V={1,2,…,v} is the set of distribution centre locations, and A is the set of arcs.

For any $i \rightarrow j \in A$, let t_{ij} denote the normal travel time from distribution centre i to distribution centre j. There are m identical vehicles available, where each has a capacity C. Set p_k as the price of vehicle k running 1 unit. All the vehicles start from the same distribution centre called the depot. There are 2n consignments, where each two is a pair. One is the consignment that needs to be picked up, and the other is the consignment that needs to be delivered. In the problem, a vehicle is only allowed to deliver or pick up consignment i within a given time window [a_i, b_i], which means that the distribution centre only deals with the consignment after a_i and before b_i. A vehicle is allowed to arrive at the distribution centre before a_i and can wait until the consignment becomes available, but arrivals after b_i are forbidden. Let s_i denote the service time of consignment *i*. Let w denote the weight of consignment *i*. The opening time of distribution centres is defined as [*a, b*]. The lunchtime for drivers is set as l. The problem can be stated as follows:

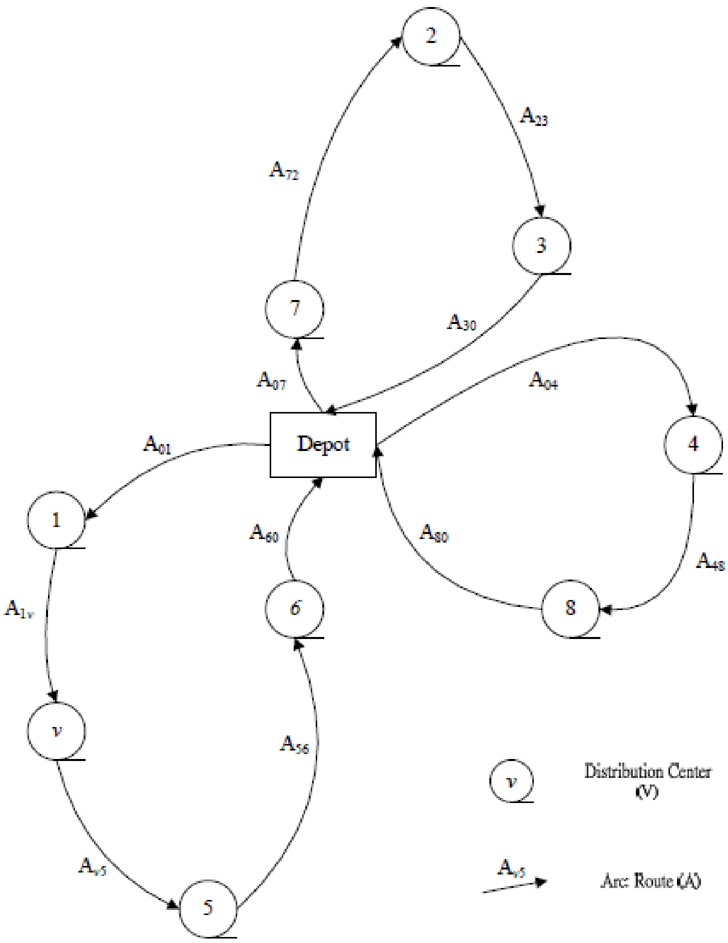


Figure 6.9 Definition Graph of VRPTW

Minimise $\sum_{m \in K} (p_m \sum_{(i,j) \in A} d_{ij} + f_m)$ (6.12)

where f_m represents the fee for using vehicle *m*, such as the driver salary and depreciation cost of vehicle *m*.

The schedule of each vehicle is subject to:

$$t + t_{ij} <= b_m \tag{6.13}$$

where b_m denotes the latest time for the consignment m.

$$t = \max(t, a_m) + s_m \tag{6.14}$$

$$\sum W_k \leq C_m \tag{6.15}$$

where W_k denotes the weight of consignment k in vehicle m.

Lunchtime and opening time are both considered in this model. When t satisfies some conditions, a lunchtime will be added to it. When t is greater than the closing time of the distribution centres, that means the consignment listed last cannot be assigned to this vehicle. A new vehicle will be used for that consignment.

Based on the problem model, the input is described as below. It includes three parts Vehicle information, Consignment Information and Distribution Centre Information.

Vehicle Information: Number of vehicles, Vehicle Capacity

Consignment Information: Time Window (Start Time, Due Time), Location, Weight, Service Time

Distribution Information: Distance, Travel Time

An example of the input is given as follows:

Table 6.5 Vehicle Information (*M*=20)

Vehicle	Capacity
A	75
B	67
…	…
T	79

Table 6.6 Consignment Information

Con.	Lo.	Wt. (Unit)	Time Window		
			R.T.	D.T	S.T
1	KB	75	9:00	10:00	35
2	MF	-75	9:30	11:30	35
… …	……	……			
80	KT	-57	16:00	17:30	60

Table 6.7 Distribution Centre Information (Distance: km)

	CSW	HMT	KB	…	MF
CSW	1	3.8	6.9		2.5
HMT	3.8	1	4.2		4.3
…					…
MF	2.5	4.3	5.2	…	1

Table 6.8 Distribution Centre Information (Time: Min.)

	CSW	HMT	KB	…	MF
CSW	10	50	50		20
HMT	50	10	39		25
KB	50	39	10		60
…					…
MF	20	25	60	…	10

The output of the problem is the schedule of each vehicle.

In the initial solution, it costs 44157.06 in fees for the company to complete the transportation of all the consignments. But after optimisation the transportation cost can be reduced to 35408.84. The detailed information of the results is shown in Figure 6.10 and Figure 6.11. The final schedule is shown in Table 6.9.

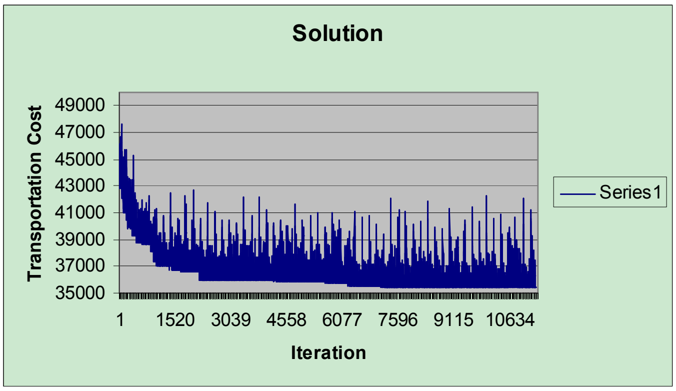


Figure 6.10 Experimental Result

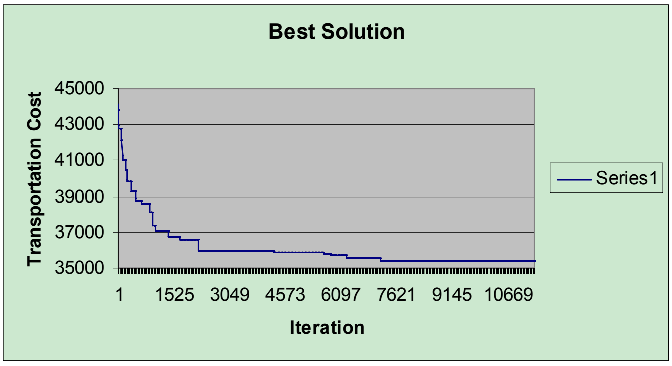


Figure 6.11 Best Solution

As the figures show, the computational results are good. Figure 6.11 shows the best solution changes in a tendency to be less. It proves that the proposed algorithm can be used to optimise a problem. Figure 6.10 shows how the proposed algorithm works. At the start of the sub-iteration the algorithm searches a wide area. The solution may be not very good, but there is a chance for it to jump out of the local optimal solution. In the later period, the algorithm just searches the area near the best solution that is recorded. It tries to find the most optimal solution in that area. Figure 6.12 is a part of Figure 6.10. A clearer tendency of search can be seen there.

Compared with GA, the population of the proposed algorithm can be much smaller than GA. In fact the population of the present IQEA only has one individual. The good characteristic of population diversity is the main advantage of quantum encoding. There are still many limitations of IQEA. Though IQEA can achieve an optimal solution very fast and uses a smaller population it is also easily trapped in the local optimisation. In this case, the final result is not the best result. With the same iterations, the result achieved by GA is slightly better. But the change in tendency is not as good as IQEA and GA takes a longer time. A better result can be achieved if the IQEA program continues running. But it takes a very long time to arrive at the global optimisation, because IQEA needs a very long time to jump out of the local optimisation. This is also the biggest obstacle for applying IQEA to large-scale combinational problems. We ascribed the problem to the number of quantum. In the next phase of our research, more than one quantum will be applied in the IQEA.

Table 6.9 Final Schedule

Vehicle	Consignments				
A	41	43	45	47	
B	49	51	53	55	
C	33	35	***37***	***39***	
…	…	…	…	…	…
S	121	125			
T	105	107	109		

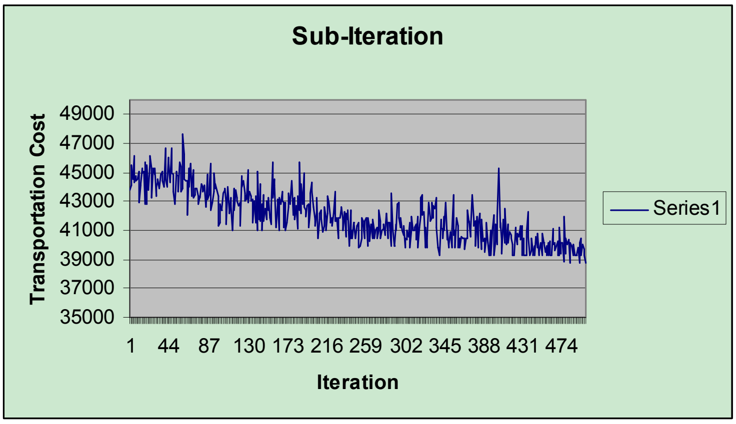


Figure 6.12 Partial Experimental Results

After generating the optimal schedule, the vehicles begin work in accordance with the schedules in Table 6.9. And RMM begins to monitor the situations of transportation and containers. Along the way the monitoring system finds that Vehicle C was involved in a traffic accident on its way to get Consignment 35, and the warning module determines the present time is later than the latest starting time of both consignment 37 and consignment 39. As shown in Table 6.9, consignments 37 and 39 are in bold and italics. After dynamic adjustment, consignment 37 could be inserted between consignment 121 and consignment 125 which are transported by vehicle S. Consignment 39 can now be transported by vehicle C, as vehicle C does not need to transport consignment 37. Then, the schedule is changed as shown in Table 6.10.

Though the new schedule costs 793 more in transportation fees than the original schedule, without this system consignment 37 and consignment 39 could not be transported, thus not fulfilling the customers' requirements, and then the losses would be much greater.

Table 6.10 New Schedule

Vehicle	Consignments				
A	41	43	45	47	
B	49	51	53	55	
C	33	35	***39***		
…	…	…	…	…	…
S	121	***37***	125		
T	105	107	109		

6.5 Summary

In this chapter the approaches to vehicle management and dynamic adjustment for coping with emergencies are discussed. A new algorithm, IQEA, has been proposed. The structure of IQEA consists of two parts. The upper level is a standard QEA. It generates Q-bit values according the state probabilities of all quanta for cutting the sequence of all the consignments that need to be delivered to consignment subsequences. Furthermore it rotates the quantum gate to update the state probabilities of all quanta. The lower level is the well-designed greed heuristic. It recombines consignment subsequences to minimise the transportation costs. However, it is hard to use the current IQEA to find the global optimal solution in a relatively reasonable time for solving large scale problems. So a modified GA algorithm is used for problems at large scale. If WFM finds that something abnormal has happened, dynamic adjustment applies HCES to cope with the emergency. Finally, a simulation is used to test the performance of this module.

CHAPTER 7 CASE STUDY

7.1 Case Study Background

ZM Logistics (alias) is a 3PL company in mainland China. Its headquarters is in Shanghai. The main business of the company is cold chain transportation. A cold chain is a temperature-controlled supply chain. It requires that the distribution maintains a given temperature range, and is common in the food and pharmaceutical industries. They all belong to perishable products. The clients of the company include Pizza Hut, KFC, McDonalds, Ajisen Ramen, Mengniu Milk, Yili Milk and so on. The company has more than 600 hundred refrigerated vehicles working over 50 cities for cold chain transportation. Moreover, the company also has some warehouses in several cities for the storage of products. There was a visit to this company in February 2012. From the numerous cases we chose the transportation of ice-cream as the case study. That was because the delivery requirements of ice cream are very stringent. The products require transportation under a constant temperature condition. They are best stored with a stable temperature between -23 ℃ and -18 ℃. Accidental time out of the limited temperature range is not allowed for more than 10 minutes, because product thawing and refreezing can create large ice crystals which result in undesirable grainy texture and diminished quality. Moreover, the products have their respective best storage temperatures, but it is difficult to distinguish them since the packages look similar. If the clients finds that the products are not transported under the required temperature, the logistics company may face claims for compensation. This is another challenge to ZM Logistics.

In the selected case, the client of ZM Logistics is an international ice cream company. It produces "super-premium" quality ice cream by using the world's finest and purest ingredients which is sold at a high price. To guarantee product quality, the company produces ice cream in overseas factories. All products imported to China first arrive at Shanghai and are then distributed by trucks to other cities. Consequently, the business of the logistics company includes long-distance transportation and product distribution in the same city. Besides long-distance transportation, the ice cream company also has many retail outlets, supermarkets, hotels and restaurants that need to be delivered to. The ice cream company only supplies ZM Logistics with an operation manual for the distribution of their products. When the retailers receive the product they check the product quality. If the quality is substandard they will reject the products, and ZM logistics has to compensate the client for the losses. Sometimes it is not their responsibility, but it is hard to prove. In summary, the long-distance transportation, the multi-delivery destinations and the strict delivery requirements bring great challenges to ZM Logistics.

Additionally, as for most food and dairy suppliers, the ice cream company also suffers from food safety, food contamination and counterfeiting problems. If there is a real-time monitoring and management system for the logistics company it not only can help the logistics company decrease the transportation losses and save transportation costs, but also help suppliers avoid the issues stated at the beginning of this paragraph that can occur during transportation.

In this chapter, data was collected from ZM Logistics for a simulation, including applying the proposed approach introduced in previous chapters, prototyping the MDSS and providing solutions to ZM Logistics to improve the current situation.

7.2 Problem Description

In the visit to ZM Logistics, interviews and questionnaires were conducted to determine the weak points in current transportation system the company used, and what their expected system should be like. The company also supplied their previous orders for us to build a database for simulation.

The interviews were conducted among three representative staff, including managers, operators and drivers of the company. They were randomly chosen from people who have worked in cold-chain distribution and long-distance transportation.

According to the interviews with the staff at ZM Logistics, it can be found that though the economic losses during transportation only forms a small part of the benefits, the reputation losses seriously affect the company. Usually they will lose the client if the distribution has only once not satisfied their requirements. The interviewed manager thought the current system was good enough, but when he heard that the transportation system can monitor delivered items during transportation in real-time he showed great interest in it. Compensation for the losses that were not their responsibility has occurred, so the company improved their system and the current system can monitor the environmental conditions in the vehicle. However people only see the results when the vehicle has arrived at the destination. The current vehicle schedule is arranged based on the experiences of operators. They have never thought to optimise the vehicle schedule to save on transportation costs. For urgent consignments the common action is to arrange an available vehicle to deliver it. If there are not enough vehicles they will rent vehicles from other companies, and drivers may also need to do some extra work. Meanwhile, both the operator and the driver did not have effective ways to cope with accidents; it was usually too late to take any action when the problem was encountered.

Based on the interviews, a questionnaire was also formulated. One manager, seven operators and two drivers helped complete it. The results are presented in Table 7.1.

As shown in Table 7.1, though most users were satisfied with the current system they did not think its management was good enough, especially its crisis management. Obviously they were not clear as to what the problem was and how to improve the system. The additional functions added to the system were all welcomed. This encouraged us to apply MDSS in this company, and the case of ice cream distribution was chosen as the study.

We collected a set of data for a quarter on the orders and operations, since ZM Logistics only saved data for three months. The frequency of accidents was low; the amount of data collected is relatively limited when compared with the data size required to train MDSS. Therefore, we built a database for simulation based on the real data collected from ZM Logistics, and also extra data that was created based on the real data. The real data forms 25 percent of the database.

Table 7.1 Questionnaire Analysis Results

<table>
<tr><td colspan="6">Part 1: What do you think about the current transportation system?</td></tr>
<tr><td></td><td>Very Dissatisfied</td><td>Dissatisfied</td><td>Neutral</td><td>Satisfied</td><td>Very Satisfied</td></tr>
<tr><td>Adequacy of current system</td><td>-</td><td>1 (10%)</td><td>5 (50%)</td><td>3 (30%)</td><td>1 (10%)</td></tr>
<tr><td>Current Crisis Management</td><td>2 (20%)</td><td>6 (60%)</td><td>1 (10%)</td><td>1 (10%)</td><td>-</td></tr>
<tr><td>Current Schedule Method</td><td>-</td><td>3 (30%)</td><td>4 (40%)</td><td>1 (10%)</td><td>2 (20%)</td></tr>
<tr><td colspan="6">Part 2: Improvements to the current system.</td></tr>
<tr><td rowspan="2">Which functions do you think necessary?</td><td>GPS</td><td>Real-time Monitoring</td><td>Schedule Optimisation</td><td>Time Forecasting</td><td>Timely Warning</td></tr>
<tr><td>10 (100%)</td><td>10 (100%)</td><td>6 (60%)</td><td>8 (80%)</td><td>9 (90%)</td></tr>
<tr><td colspan="6">Part 3: Future plans to increase profits</td></tr>
<tr><td colspan="2"></td><td>Unnecessary</td><td>Neutral</td><td colspan="2">Necessary</td></tr>
<tr><td colspan="2">Increase number of vehicles</td><td>8 (20%)</td><td>2 (20%)</td><td colspan="2">-</td></tr>
<tr><td colspan="2">Increase business scale</td><td>2 (20%)</td><td>5 (50%)</td><td colspan="2">2 (30%)</td></tr>
<tr><td colspan="2">Decrease costs</td><td>-</td><td>1 (10%)</td><td colspan="2">9 (90%)</td></tr>
</table>

For an effective demonstration of the system, we increased the probability of accidents and simulated the supply chain in extreme cases. If MDSS can solve the extreme cases very well, it will be also capable for handling normal cases. The probability of a vehicle being caught in a traffic jam, a container having problems and the sudden arrival of an urgent consignment are all set a few times higher than the usual conditions. The chosen case includes six events. They are:

Event 1: Arrival at Shanghai Port

Event 2: Transportation from Shanghai to Shenzhen

Event 3: Storage in the warehouse in Shanghai

Event 4: Vehicle schedule

Event 5: Delivery

Event 6: Product quality evaluation

From the database, the data needed is listed below. Some examples (see Table 7.2 to Table 7.6) are also given for better illustration.

The main function of DSM is optimisation. Some mathematical algorithms are applied in this module. So it needs to build a mathematical model for the distribution of products. This is introduced in this section.

Storage: Sensors and RFID monitor the environmental conditions in warehouses and record them.

Table 7.2 Example of Storage Information

Product ID	ePedigree	Product	Arrival Time	Warehouse ID	Temperature	Departure Time	Others
30373004-01290001	30373004-00000000	Ice Cream: Strawberry	16:50:13 17/02/2011	003012	-20.3℃	10:04:17 04/04/2011	N/A
30373004-01290002	30373004-00000000	Ice Cream: Strawberry				10:04:19 04/04/2011	N/A
30373004-01290003	30373004-00000000	Ice Cream: Strawberry				N/A	N/A
30373004-01290004	30373004-00000000	Ice Cream: Strawberry				N/A	N/A
30373004-01290005	30373004-00000000	Ice Cream: Strawberry				N/A	N/A

Delivery: Includes container information and consignment information.

Table 7.3 Example of Container Information

Container ID	Vehicle ID	Driver ID	Capacity (t / m^3)	Start Time	Running Time (h)	Remaining Time	Location	Destination	Tempera-ture	Others
CH002	N/A	N/A	8 / 24	N/A	N/A	N/A	30.3820° N 122.2490° E	N/A	-20.7 ℃	N/A
CH005	ST 9350	2414	8 / 24	15:00 27/04	3:47:08	15:38:52	29.3951° N 119.3331° E	22.3380° N 113.5835° E	-20.4 ℃	N/A
SH007	N/A	N/A	0.5 / 4.5	N/A	N/A	N/A	30.382° N 122.249° E	N/A	N/A	N/A
SH011	ZM 4256	3543	3 / 8	16:45 27/04	0:46:39	0:56:21	31.1380° N 121.2460° E	31.1136° N 121.2615° E	-21.4℃	N/A
SH016	ZM 4255	3507	0.5 / 4.5	16:25 27/04	0:15:27	0:34:33	31.1646° N 121.2727° E	31.1324° N 121.2826° E	-20.0 ℃	N/A

Table 7.4 Example of Consignment Information

Product ID	ePedigree	Product	Weight (g)	Container ID	Retailer ID	Required Time (Earliest/Latest)	Temperature	Others
30373004-01290001	30373004-74110000	Ice Cream: Strawberry	20	SH016	SH052	10:00 27/04 18:00 27/04	-21.4℃	N/A
30372804-01740019	30372804-94110000	Ice Cream: Strawberry	20	SH016	SH 039	16:00 27/04 18:00 27/04	-21.4℃	N/A
30392804-00370001	30392804-84110000	Ice Cream: Green Tea	20	SH016	SH 052	10:00 27/04 18:00 27/04	-21.4℃	N/A
30352804-02550016	30352804-84110000	Ice Cream: Chocolate	20	SH016	SH 052	10:00 27/04 18:00 27/04	-21.4℃	N/A

Retailer: Destination of the consignments

Table 7.5 Example of Retailer Information

Retailer ID	Name	Location	Contact
SH 039	SP	31.1136° N 121.2615° E	58427726
SH 047	HD	31.1339° N 121.2916° E	57473924
SH 052	HD	31.1324° N 121.2826° E	69774537
SH 177	JG	31.1325° N 121.2647° E	61532086

To simplify the problem it is assumed that the driver's abilities are identical, and there are enough drivers for the container trucks. For this distribution problem we assume that there are n containers which can be used for the transportation of perishable products. There are m containers on the way. l ($l \leq m$) containers are transporting products; m-l containers are empty containers on the way to distribution centres; and n-m empty containers remain at the distribution centres. There are k retailers to which ZM Logistics need to deliver products. The retailer is defined on a direct graph G = (K, A), where K={1,2,…,k} is the set of retailer locations, and A is the set of arcs.

Referring to Section 6.4, for any $i \to j \in A$, let t_{ij} denote the normal travel time from retailer i to retailer j. There are m vehicles available, where each of them has a capacity C. Set p_v as the price of vehicle v running 1 kilometre. All vehicles start from the same distribution centre called the depot. All consignments are also first stored in the depot. There are n consignments for ZM Logistics to deliver. In the problem a vehicle is only allowed to deliver consignment i within a given time window [a_i, b_i], which means that the retailer only deals with the consignment after a_i and before b_i. A vehicle is allowed to arrive at the distribution centre before a_i and has to wait until the consignment becomes available, but arrivals after b_i are forbidden. Let s_i denote the operation time of consignment *i*. Let w_i denote the weight of consignment *i*. Let u_i denote the volume of consignment *i.* The opening time of the distribution centre is defined as [*a*, *b*]. The lunchtime for driver is set as *l*. The problem can be stated as follows:

Minimise $\sum_{v \in M}(p_v \sum_{(i,j) \in A} d_{ij} + f_v)$ (7.1)

where f_v represents the fee for using vehicle *v*, such as the driver salary and depreciation cost of vehicles *v*.

The schedule of each vehicle is subject to:

$$t + t_{ij} <= b_m \tag{7.2}$$

where b_m denotes the latest time for the consignment *m*:

$$t = \max(t, a_m) + s_m \tag{7.3}$$

$$\sum W_n \leq C_v \cap \sum U_n \leq C'_v \tag{7.4}$$

where W_n denotes the total weight of *n* consignments in vehicle *v*, C_v denotes the weight capacity of vehicle *v*, U_n denotes the total volume of *n* consignments in vehicle *v*, and C'_v denotes the volume capacity of vehicle *v*.

Table 7.6 Example of Product Information in retails

Product ID	ePedigree	Product	Retailer ID	Arrival Time	Due Data	Temperature	Others
30373004-01290001	30373004-74110052	Ice Cream: Strawberry	SH 052	16:50 27/04/2011	17/02/2012	-19.8℃	N/A
30392804-00370001	30392804-84110052	Ice Cream: Green Tea		16:50 27/04/2011	28/02/2012		N/A
30391604-00240046	30391604-13560052	Ice Cream: Green Tea		14:27 10/04/2011	16/01/2012		N/A
30321203-00130083	30321203-53290052	Ice Cream: Cookies		17:15 01/04/2011	12/01/2012		N/A

Table 7.7 Example of an Order Form

Order Key	57937394647695		
Customer ID	C003		
Destination	SH 052		
Product	Quantity	Weight (kg)	Volume (L)
Ice Cream (Strawberry)	40	2	16
Ice Cream (Green tea)	20	1	8
Early Arrival Time		Late Arrival Time	
10:00		12:30	

Based on the problem model, the input includes four parts Vehicle Information (see Table 7.3), Consignment Information (see Table 7.4), Destination Information (see Table 7.5) and Order Information (see Table 7.7). The output will be an optimal schedule of vehicles.

In this simulated problem some probabilities are set for accidents. Based on the analysis of data obtained from ZM Logistics, we chose three most common situations as accidents in the simulation. We also increased their probabilities of occurrence by 5 times higher than the real data analysis, to make the problem an extreme case to solve. In the study, the probability of a vehicle being caught in a traffic jam is set as 0.1, a container having problems is set as 0.01, and the sudden arrival of an urgent consignment is set as 0.05.

7.3 Suggested Solutions based on MDSS

In this section we applied MDSS to help in the transportation of ice cream. The case includes 6 events. The system results in positive effects for each event.

Event 1: Arrival at Shanghai Port

If possible the supplier is asked to provide the relevant information about the products in the supply chain. For example, all material information including supplier, arrival time, quality and so on, needs to be recorded. The storage information of products after manufacture is also needed. Such records can help evaluate the quality of the final products in at the point of sale and they are also convenient for recall if some materials have problems. EPCglobal and ePedigree is recommended as the platform for different parties to share information. When the product is completed, a RFID tag can be attached on the package. The RFID tag records the unique ID of the product. It is not changed. The product also has an ePedigree ID, which will change following the experiences of the product. If two products are produced on the same day, stored in the same warehouse, delivered in the same way to the same retailer and so on, they will have the same ePedigree. The ePedigree is updated when the RFID reader reads the tag. In this way the entire supply chain can be monitored. This case study focused on the solutions for the delivery in the supply chain. It is discussed in the following parts.

Event 2: Transportation from Shanghai to Shenzhen (Long-distance Transportation)

When the products arrived at Shanghai Port, the supplier employed ZM Logistics for delivery. Some products needed to be delivered to Shenzhen. Others first needed to be stored in the warehouse. Then they would be delivered to supermarkets, retailer shops and so on when orders arrive. The ice cream for long-distance transportation was put in a refrigerated vehicle. The transportation usually takes 25 hours. In this period, the RFID and sensor networks also monitored the temperature in the container and transmitted the information to MDSS with a 5 minute frequency. In the simulation of this event, when the vehicle travelled 4h 35mins, MDSS found that the temperature was over the upper limit, and the cooling equipment in the container seemed not working. Figure 7.1 shows the temperature change. FWM cannot find an approach to deal with this accident. Consequently the best solution is to drop these products and deliver new products to Shenzhen. Though the product losses are not avoided, the transportation costs for the remaining trips are saved. Meanwhile, the company can deliver new products to Shenzhen immediately. The arrival time is about 5 hours later. If such a real-time monitoring system was not available the problem may be discovered when the vehicle arrived at Shenzhen. Suitable products would then arrive after another 25 hours, and a shortage of products may result at the Shenzhen market.

Event 3: Storage in the warehouse at Shanghai

The products for the Shanghai market were delivered to the distribution centre in Minhang, which is a suburban district of Shanghai. The products were stored in the warehouse in the distribution centre. There are RFID readers installed on the gate of the warehouse. When the products move though the gate the product information in the system will be automatically updated. There are also sensors installed in the warehouse, the temperature information is also transmitted to the RMM of the MDSS in real-time.

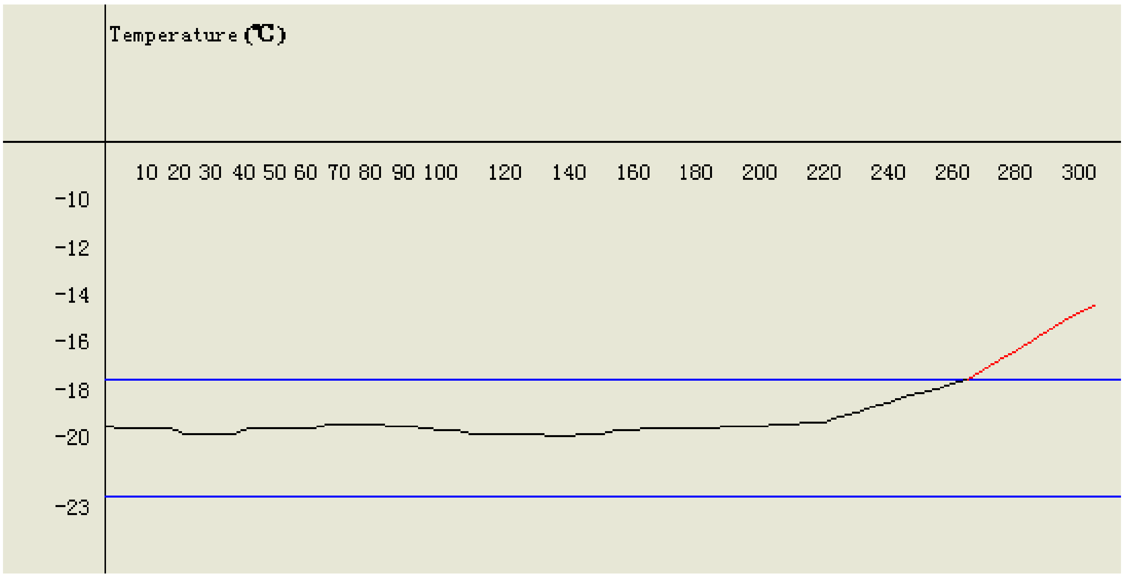


Figure 7.1 Screen Capture of Temperature Record in Simulation

Event 4: Vehicle Schedule

Every day the distribution centre receives orders from retailers. One example is given to illustrate the system.

DSM firstly computes the distance between each two destinations of the orders, and the distances between the depot and each destination (see Table 7.8). FWM estimates the travel time (see Table 7.9). Based on this information and vehicles available and satisfying the time requirements, DSM of MDSS generated an optimal vehicle schedule. In this study, there were 40 orders and 5 available vehicles owned by ZM Logistics. But the company can rent another 5 vehicles from a rental company if necessary. All the vehicles are identical. The allowed operation time is 15 minutes for each consignment. The drivers can have one hour rest for lunch between 12:00 and 14:00. This problem is judged a small scale problem. IQEA is applied to solve it. Table 7.10 presents part of the schedule.

Table 7.8 Sample of the Distances between Destinations (km)

	Depot	SH001	SH005	…	SH171
Depot	0	19.0	17.3		22.5
SH001	19.0	0	4.2		4.3
SH005	17.3	4.2	0		5.2
…					…
SH171	22.5	4.3	5.2	…	0

Table 7.9 Sample of the Distribution Centre Information (Time: Min.)

	Depot	SH001	SH005	…	SH171
Depot	0	45	32		34
SH001	45	0	11		6
SH005	32	11	0		7
…					…
SH171	34	6	7	…	0

Formula 7.1 is the fitness function used to compute transportation costs. In this case the distances and the vehicle quantities are optimised by the algorithm. The oil price is 2

CNY per kilometre. The driver cost is 100 CNY per day. And the vehicle depreciation is 150 CNY per day.

Table 7.10 Sample of the Vehicle Schedule

Vehicle	Consignments				
ZM 4255	1	6	17	36	…
ZM 4256	25	28	12	8	…
ZM 4257	16	24	22	31	…
ZM 4258	9	38	13	34	…

The initial value is generated by heuristics, which is the current approach of ZM Logistics for scheduling. The cost is 3527.27 CNY, which includes oil costs, driver daily salary, and vehicle depreciation costs. The final optimal schedule cost was 2887.30 CNY, so 639.97 CNY was saved.

Event 5: Delivery: Traffic Jam

During transportation the sensors in the containers are set to monitor the temperature. In the simulation, MDSS found that vehicle ZM 4255 was stopped at location 31.1646° N 121.2727° E for more than 10 minutes via GPS. MDSS judged that the vehicle was trapped in a traffic jam or was involved in an accident. Firstly 30 minutes were added on all predicted arrival times, meaning four consignments could not arrive in within their respective time windows. Then the schedule was modified by dynamic adjustment. Part of the new schedule is shown in Table 7.11. The number in Bold is the new added consignment. The transportation costs were 179.52 CNY more than the original plan. In the end the vehicle was 22 minutes late to its next destination. Without the adjustment the affected products may not have been received by the retailer. The reputation loss, however, cannot be measured.

Table 7.11 Part of the Schedule after Adjustment

Vehicle	Consignments				
ZM 4255	1	…	5	**27**	…
ZM 4256	25	28	12	8	…
ZM 4257	16	…	40	**13**	…
ZM 4258	9	…	**19**	…	**33**

Event 6: Evaluate Product Quality

When the products arrive at the destination the retailer should check the quality. Since there is not enough information about other links in the supply chain, we only compute the evaluation result with respect to distribution. The computation approach is discussed in Section 4.4. We use the data from one product (Product ID: 30373004-01290001) as an example to illustrate the result (See Table 7.12).

7.4 Simulation Results and Discussion

This case shows how the system works, and the results show that the system can optimise the vehicle schedule and effectively cope with accidents.

Table 7.12 Quality Evaluation Results

	Factors		Results
Storage1	Temperature	Storage Time	100
	100	100	
Delivery1	Temperature	Transportation Time	99
	99	100	
Storage2	Temperature	Storage Time	100
	100	100	
Delivery2	Temperature	Transportation Time	95
	89	100	
Final Results			93

MDSS mainly plays a role in the distribution. It monitors the product conditions in real-time. Accordingly any problems can be determined in time. Even though the system cannot deal with some accidents judged by FWM, such as the container problem on route, there is enough time for remedial measures and so on; it can also notify the company to take some remedial actions, such as in the case of transportation from Shanghai to Shenzhen. Meanwhile, the system helps optimise the vehicle schedule. In this case it can be determined that the final schedule saved 639.97 CNY compared to the initial one is generated by other rules, such as the harvest or the biggest consignment being arranged in priority, the consignment with the smallest time window being arranged in priority and so on. Furthermore, during transportation MDSS shows its effective performance in coping with an emergency. DSM adjusts the original schedule and the losses are reduced to

179.52 CNY. The waste transportation costs will reach to 315.5 CNY besides the reputation loss.

With regard to the simulation results, if there is no such system the accidents in the simulation cannot be discovered in time and the loss will be bigger than the current results. The company may find that the delivered products go bad when they finally arrive at Shenzhen, and when they finally transport new products to Shenzhen it may 25 hours late. The lead time of the inventory may be not so long. There may also be a shortage of the products in Shenzhen market. Furthermore, for the logistics company the unnecessary transportation was avoided. In the case of delivery in the same city, the traffic jam was found in time, and DSM performed a dynamic adjustment to the original schedule. Otherwise, some consignments would be out of the time windows, and when they finally arrived at the destinations they might be rejected and the costs for delivery would be wasted. Additionally, with such a system the transparency of the delivery increases. The environment in the containers was monitored in real-time, which guarantees the product quality to some degree. Ice cream is a temperature-sensitive product, its quality is affected by the environment. Meanwhile, the logistics companies can provide evidence about the transportation conditions to prove it is not their responsibility for any unreasonable rejection of the products.

In summary, the case study, including the problem study, data collection and simulation, proves that the system can increase the transparency of the supply chain. Accordingly it is helpful for the management of product safety issues. It also helps 3PL cope with accidents and to optimise vehicle schedules, plus the costs and losses are also reduced. The case study proves the good performance of the system. Furthermore, the effectiveness of the proposed approach is also demonstrated.

CHAPTER 8 DISCUSSION

8.1 General Discussion of MDSS

An approach has been proposed for the better management of perishable products. The approach aims to increase the transparency of the supply chain and to decrease the costs and losses of logistics companies through real-time monitoring, optimisation, positioning, warning and forecasting. Based on the approach, a system called MDSS has been proposed. The system has three modules: Real-time Monitoring Module, Forecasting and Warning Module, and Decision Support Module. These modules work together to manage the perishable product supply chains. RMM monitors products in each link of the supply chain and evaluates the product quality using a hybrid algorithm. The monitoring information and the evaluation results are transmitted to a web platform. Different parties included in perishable supply chain can access relevant information. The information builds the ePedigree of the products. Customers can better understand the goods and manufacturing companies can control product quality. It is also easy for officials to inspect the products. Moreover if any part of the supply chain has problems it is easy to recall all the corresponding products. More details about the application of the real-time monitoring module are discussed in Section 8.1.1. The FWM and DSM also access data about the products from the platform. Based on the road information monitored by RMM, FWM applies a hybrid approach to predict the travel time of vehicles. The warning function uses RBR due to its quick response and good explanations. It helps people judge whether there were anything abnormal or urgent occurred. With the help of RMM, if accidents occur the module can discover them in time and judge whether it is necessary to issue a warning. When the system receives warnings it will give the information to the DSM. The DSM applies HCES to rearrange the vehicle schedule to efficiently reduce the losses. But the main function of DSM is static optimisation. It optimises the vehicle schedule before the transportation. Two optimisation algorithms, GA and IQEA, are developed in this part, they both have advantages and disadvantages. The algorithm is chosen by considering the scale of the unsolved problem; GA is for problems in large-scale and IQEA is for problems in small-scale. We suggest that users in a company should have a pre-test of the proposed two algorithms using one or two existing problems. Then, the optimum one, which has a better performance, should be chosen for solving future problems. Since the scale of the vehicle management problem in a company is almost similar, the algorithm selected after the pre-test will be a suitable one for the future. With the three modules the system can increase the transparency of the perishable product supply chains, decrease the value of losses of perishable products in logistics, help companies control the products quality effectively, and optimise vehicle schedules to minimise the transportation costs for logistics companies.

The respective discussions on the three modules can be found in the following sections.

8.1.1 Discussion on the Real-time Monitoring Module

RMM has two functions. One is real-time monitoring, which is the foundation and core of this system. RFID is used for the better and quicker identification of products and sensors. Combined with sensor networks, the module can monitor any factor that the sensors can detect and transmit it in real-time via mobile communication techniques, such as GPRS, CDMA and TDLTE. GPS is also added to this module for vehicle location identification. It can also be used to detect whether the vehicles are following the correct path and whether they are caught in a traffic jam. The transparency of the supply chain is increased due to real-time monitoring. It is important with perishable products. Food safety problem is a serious issue these years, especially in China. Building a real-time monitoring system for customers to better understand their products can also help them recover confidence in the products. Meanwhile, the combination of RFID and sensors also has infinite potential for be development. For example, the monitoring of vehicles can help customs guarantee that the transit products have not been opened and brings convenience to customs officials; the RFID tags attached on the products can help users find the correct products from lots of similar packages, and so on.

Based on the real-time monitoring, a hybrid approach is proposed to evaluate the product quality. The approach uses a *k*-NN and ANN hybrid algorithm to evaluate the product quality in each link of the supply chain with the information got by the sensor and RFID techniques. The results are used to build the product ePedigree on a web platform. The original value for the quality loss model applied in FWM can also be obtained by the evaluation method. Then the algorithm calculates the final product quality based on the product quality at each stage. The information can help retailers decide on the product prices and help customers better understand their products. In order to verify the operation of the module, a simulated case about the wine industry is studied in Chapter 4.

To improve the quality of the wine industry, a quality evaluation system with the application of RFID is developed based on the principle of the module. The system has two functions: quality tracking and quality evaluation. The quality tracking function is developed based on the real-time monitoring principle. It is used to monitor and manage the entire supply chain of wine products. The quality evaluation function is developed based on the quality evaluation approach. It is used to estimate the wine quality at each stage and also to give a final product quality result. Also as the architecture of the module, the quality evaluation process uses the data from the quality tracking part.

The system begins to work when grapes are delivered to the winery. During brewing, the quality tracking system can manage the barrels to avoid human errors. The environmental factors in the cellars are also monitored. After brewing, the quality of the distillate will be estimated by the evaluation system. If the mark of the distillate is high, the producer should pay more attention to aging and distribution. The marks of the RFID tags will be attached to the wine when they are marketed. Consumers can select the wine with consideration of the marks from the system. Additionally, the RFID tag on the wine bottle provides an effective tool for counterfeit identification.

The case shows that the quality evaluation system can improve the manufacturing process of wine. Moreover it can replace the present subjective and ineffective wine evaluation method. It helps consumers know more about their wine before they take the cork out of the bottles. Moreover, presently different regions have different evaluation rules and this module can combine hundreds of rules into one for all the wine around the world. The module can also help more people with little knowledge of wine better understand the quality of the products they have purchased.

From the case study it can be determined that the module can effectively monitor products in real- time to increase the transparency of the supply chain, build the product ePedigree and evaluate the product quality for reference.

8.1.2 Discussion on the Forecasting and Warning Module

The FWM has two functions as suggested by its name: forecasting and warning. In the design of the forecasting function the main contribution is to propose a soft case-based reasoning approach to estimate the travel time of vehicles. The approach is developed based on the traditional CBR system. It integrates fuzzy logic and ANN techniques. Consequently the approach means the module has a machine learning function, and it can update itself automatically. The brief procedures of the approach are described below. It firstly divides the planned route into several segments. Then it helps users search for the most similar case within each segment. If the deviation of the estimated time and real travel time is large the weightings will be trained using the neural network and the old case will also be replaced. The approach combines soft computing and CBR techniques to estimate travel time. With the application of the proposed approach, the arrival time can be predicted more accurately.

The warning function of this module mainly deals with urgent abnormal situations. The response speed is the main consideration. Additionally, the abnormal conditions are usually complex. RBR offers good explanation facilities, it gives the reasons for the warning and provides suggestions which users can judge whether they are suitable. Consequently, RBR is applied for the function development. Some simple suggestions are also given by the module. The suggestions aim to avoid accidents, which if they are not effective, another module, DSM, will try to deal with.

A simulated case is also used to test this module. In this case the module helps predict the arrival time and deals with accidents. The experiment proves that the module offers good performance in coping with accidents. In the test case, the system uses the rules set for that case to reschedule the vehicles and the containers. The new plan successfully reduced the loss by 50% in a particular accident. Meanwhile, the module also estimates the travel time. The accuracy increased with the help of the neural network and fuzzy logic after some training. However, the module cannot cope with all the warnings. Any difficult problems will be transmitted to the DSM to cope with.

8.1.3 Discussion on the Decision Support Module

Based on the data collected from RMM and with the assistance of FWM, DSM is developed. The main objective of the module is to generate a schedule for minimising the transportation costs of the company. It has two functions, one is static optimisation and the other is dynamic adjustment. Static optimisation aims to make an optimal vehicle schedule to minimise transportation costs, and dynamic adjustment aims to re-schedule the vehicle in a short time to minimise the losses once an accident or emergency occurs. For the static optimisation, consignment information comes from RMM and travel time between the destinations is estimated by FWM. Due to the good performance of QEA, a modified QEA, IQEA, is proposed for static optimisation. Some benchmark problems from the TSP library are used to show the effectiveness of the new proposed algorithm. But the results show that IQEA can get the solution in solving problems in small scale. For the problems in a large scale it is easy to become trapped in the local optimisation. Due to this limitation, a hybrid algorithm combing GA and heuristics is applied to the problems in large scale. When the schedule generated by the static optimisation module is in operation and the module receives a warning from FWM, the dynamic adjustment will start up to adjust the original plan. A proposed heuristic method, HCES, is applied in this part. Because dynamic adjustment aims to deal with urgent problems, the speed for getting the solution is the first consideration. Though the result may not be the best solution, a relatively optimal schedule will be generated to minimise most of the losses.

Finally, a practical problem is studied to investigate the performance of the module. The problem simulates the situations that may happen in the real world. IQEA is applied to solve the problem. The result shows that the module can optimise the schedule and effectively help companies avoid losses caused by accidents.

8.2 Discussion of MDSS in the Case Study

ZM Logistics faces challenges in the transportation of perishable products. A case study about the distribution of ice cream is carried out. In this case study we firstly had an interview with some of the staff of the company to discover the disadvantages of the current transportation management system. Based on the interviews, we designed a questionnaire to investigate their expected system, and determine whether the proposed

MDSS could improve the current system and whether people would accept it. We also collected data from them for simulation.

Then MDSS is applied to help in the transportation of ice cream. ZM Logistics has two businesses in ice cream delivery. They need to conduct long-distance transportation and also deliver products in the same city. During the long-distance transportation from Shanghai to Shenzhen, MDSS found that the container had a problem. Though MDSS could not cope with this accident, it could inform the ice cream company about the accident in time. And the company could decide whether transport new products to Shenzhen in time for remediation. If there is no such system the problem may only be discovered when the truck arrives at its destination, and a shortage would result at Shenzhen market. For product distribution in the same city, MDSS first optimised the vehicle schedule. The predicted transportations costs were 2887.30 CNY. Without the system the costs would reach 3527.27 CNY, thus 639.97 CNY was saved. During transportation, one of the vehicles was trapped in a traffic jam and there was not enough time for the vehicle to complete all its consignments within their required time windows. MDSS helped adjust the vehicle schedule and decrease the losses. Through using MDSS in this case it can be found that the proposed approach could effectively determine accidents, manage vehicles, decrease losses and save costs. It can also increase the transparency of the perishable product supply chain with an extension of the system applying the ePedigree. If each party involved in the supply chain provides information on a public web platform, a table like Table 8.1 can be obtained. The products can thus be better understood. It can also provide enough data to evaluate the product quality for the ePedigree

Table 8.1 ePedigree of the Product

<table>
<tr><td></td><td>Product ID</td><td>ePedigree</td><td>Product</td><td>Start Time</td><td>Material</td><td>Material Quality</td><td>Completed Time</td><td colspan="2">Others</td></tr>
<tr><td rowspan="5">Production</td><td rowspan="5">30373004-01290001</td><td rowspan="5">30373004-00000000</td><td rowspan="5">Ice Cream: Strawberry</td><td rowspan="5">10:52:07 17/02/2011</td><td>Strawberry</td><td>Good</td><td rowspan="5">16:45:32 17/02/2011</td><td colspan="2">N/A</td></tr>
<tr><td>Sugar</td><td>Perfect</td><td colspan="2">N/A</td></tr>
<tr><td>Egg york</td><td>Perfect</td><td colspan="2">N/A</td></tr>
<tr><td>cream</td><td>Perfect</td><td colspan="2">N/A</td></tr>
<tr><td>milk</td><td>Perfect</td><td colspan="2">N/A</td></tr>
<tr><td rowspan="2">Storage1</td><td>Product ID</td><td>ePedigree</td><td>Product</td><td>Arrival Time</td><td>Warehouse ID</td><td>Average Temperature</td><td>Departure Time</td><td colspan="2">Others</td></tr>
<tr><td>30373004-01290001</td><td>30373004-00000000</td><td>Ice Cream: Strawberry</td><td>16:50:13 17/02/2011</td><td>003012</td><td>-20.3 ℃</td><td>10:04:17 01/03/2011</td><td colspan="2">N/A</td></tr>
<tr><td rowspan="2">Delivery1</td><td>Product ID</td><td>ePedigree</td><td>Product</td><td>Weight (g)</td><td>Container ID</td><td>Destination</td><td>Required Time (Earliest/Latest)</td><td>Average Temperature</td><td>Others</td></tr>
<tr><td>30373004-01290001</td><td>30373004-74000000</td><td>Ice Cream: Strawberry</td><td>20</td><td>FR004</td><td>Shanghai</td><td>10:00 01/04
18:00 05/04</td><td>-19.4℃</td><td>N/A</td></tr>
</table>

<table>
<tr><td rowspan="2">Storage2</td><td>Product ID</td><td>ePedigree</td><td>Product</td><td>Arrival Time</td><td>Warehouse ID</td><td>Average Temperature</td><td>Departure Time</td><td colspan="2">Others</td></tr>
<tr><td>30373004-01290001</td><td>30373004-74000000</td><td>Ice Cream: Strawberry</td><td>16:50:13 04/04/2011</td><td>003012</td><td>-20.1 ℃</td><td>10:04:17 27/04/2011</td><td colspan="2">N/A</td></tr>
<tr><td rowspan="2">Delivery2</td><td>Product ID</td><td>ePedigree</td><td>Product</td><td>Weight (g)</td><td>Container ID</td><td>Retailer ID</td><td>Required Time (Earliest/Latest)</td><td>Average Temperature</td><td>Others</td></tr>
<tr><td>30373004-01290001</td><td>30373004-74110000</td><td>Ice Cream: Strawberry</td><td>20</td><td>SH016</td><td>SH052</td><td>10:00 27/04
18:00 27/04</td><td>-21.4℃</td><td>N/A</td></tr>
<tr><td rowspan="2">Retailer</td><td>Product ID</td><td>ePedigree</td><td>Product</td><td>Retailer ID</td><td>Arrival Time</td><td>Due Data</td><td>Temperature</td><td colspan="2">Others</td></tr>
<tr><td>30373004-01290001</td><td>30373004-74110052</td><td>Ice Cream: Strawberry</td><td>SH052</td><td>16:50 27/04/2011</td><td>17/02/2012</td><td>-19.8℃</td><td colspan="2">N/A</td></tr>
</table>

retailer to decide on a reasonable price. The successful application of MDSS proves that the proposed approach is an effective tool to improve perishable product management, especially in logistics.

8.3 Limitations of the Research

The approach proposed in this research can effectively improve the management of perishable products in distribution, and RMM can be extended to monitor the entire supply chain in real-time. The transparency of supply chain is increased in this way. Moreover, FWM and DSM can effectively help logistics companies cope with accidents for minimising the losses. And DSM also helps to optimise vehicle schedules to save costs for logistics companies. But there are still many limitations due to the limited time of my PhD degree study. In this section, the limitations of the research are discussed. And a future research plan is introduced in Section 9.3

The limitations of the research are as follows:

- The quality loss model used to calculate and forecast the value of perishable products can be further improved. In this research, the effects of environmental changes on perishable products are not considered.
- The RBR designed for warning forecasting still has some disadvantages. Its search engine is too simple and a hybrid system, combined with RBR and intelligent computation, will be developed in future work.
- The method for dynamic adjustment also needs to be studied further. Though the efficiency of dynamic adjustment in DSM is high, the final schedule it generates may

not be the best especially for complex problems, such as there being many warnings at the same time. If a logistics company has many identical vehicles, the order in which vehicles are mobilised will greatly affect the final result. Randomly selecting a vehicle for the consignment is not a scientific method. Earliest Query Answering (EQA) is proved to be a suitable algorithm by previous researchers. Some other dynamic optimisation algorithms are also considered for application in this part.

- The proposed IQEA is still not perfect. The tests show that it has great potential in combination optimisation problems. But the current design allows it to become easily trapped in local optimisation. We believe that some small changes can make the algorithm become more suitable for VRPTW.
- In static optimisation, the time uncertainty is not considered in the optimisation algorithm design. The travel time among different destinations of consignments is calculated by a hybrid CBR approach in FWM. The results have their respective certainty degree. Some travel time may be guaranteed to a high percent, but others may just be a rough estimation. Travel time is very important in VRPTW. The uncertainty also affects decisions. So it should be considered in the design of the algorithms.
- For the case studies, the data collections are not enough. Since the system needs a large amount of data to train, it is difficult to collect adequate data from companies in the real world. The proposed approach is only tested in the simulation. However, it is hoped that the system can be applied in real logistics companies and in industry in the future. The implementation of the system in multiple companies is also a challenge.

CHAPTER 9 CONCLUSIONS AND FUTURE WORK

9.1 Summary of the Research

The safety issues of perishable products are important to humans. For perishable product companies it is hard to control their product quality at each link of the entire supply chain, especially in logistics. That is because companies usually employ 3PL to undertake the delivery tasks; and it is hard for them to monitor the products. Moreover, losses incurred during the transportation of perishable products present a large logistical problem. Reducing the value loss of perishable products during transportation is a difficult problem because the value of the products is significantly affected by changes in environmental conditions. This research aims to find an approach to change the current serious value loss situation and to improve the quality control of perishable products. If the environmental factors in a container can be monitored, then people can adjust their decisions in time once they find their products are in danger. Thus, serious value losses can be avoided. The RFID technique developed can help people monitor, trace and track their products in real-time. With the application of RFID, sensor networks, GPS, machine learning and optimisation algorithms, an approach is proposed to increase the transparency of the supply chain and to save costs in transportation through real-time monitoring, optimisation, positioning, warning and forecasting. Based on the approach, MDSS is developed. It monitors perishable products, optimises vehicle schedules and gives suggestions to users on how to cope with accidents.

MDSS is composed of three modules; they are real-time monitoring module, forecasting and warning module and decision support module. The RMM combines the RFID technique, sensors, communication techniques and GPS to monitor the products' conditions during transportation, the location of vehicles and to transmit data to the online platform. It can also be extended for use in manufacturing, storage and once at the retailer. The module also includes a *k*-NN and ANN hybrid algorithm for product quality evaluation. The algorithm evaluates the product quality at each stage based on the monitoring results. When the products finally arrive at the retailer's stores, the algorithm will give a final quality value based on the evaluation results of all stages. The module provides a scientific way to calculate the product quality instead of subjective observation. The retailers can adjust the product prices by considering the evaluation results, and the customers can better understand their goods. All the information is shared on an online platform. The FWM accesses information from the platform. It detects whether the vehicle is in a traffic jam, whether there are abnormal conditions in the containers and forecasts the travel time of the vehicles and the value of the perishable products at the destinations. If something abnormal or urgent occurs, the module will give warnings to the DSM. The warning function of FWM is designed using RBR for its quick response. The forecasting function of FWM is designed with a hybrid approach of CBR, ANN and fuzzy logic. Fuzzy logic is used to classify the factors of the CBR. ANN uses the real travel time of the cases to train the weightings of CBR. CBR is the core, it selects the most similar case and calculates the travel time. DSM helps users deal with the warnings transmitted from FWM. The main function of this module is optimising the vehicle schedule to minimise the transportation costs; this function is called static optimisation. For problems at small scale a proposed optimisation algorithm IQEA is applied. This algorithm can quickly achieve optimal solution. However, it also easily becomes trapped in the local optimisation areas. So, if the problem scale is large it takes a long time for the algorithm to find the optimal result. Though the algorithm has a better performance than other optimisation algorithms, there is still some work to be done. Consequently, for problems of a larger scale, a hybrid algorithm combing GA and heuristics is applied to create the vehicle schedule. If DSM receives a warning from FWM and the schedule generated is in operation, dynamic adjustment will adjust the original plan. A heuristics method HCES is applied in this module. It can obtain a solution in a short time. A relatively optimal schedule can be generated to minimise the losses. The three modules work together to ensure the perishable product’s safety and decrease the value loss situations in logistics.

Finally, a case is studied to investigate the performance of the proposed approach. The case study considers the distribution of ice cream by ZM Logistics. We obtained some orders from ZM Logistics. A database is built for the simulation based on these orders. For more challenges, the frequencies of accidents are set at a higher rate. The results show that the transportation costs saved 639.97 CNY with the application of the developed system, and it also proves that the system can effectively deal with accidents and emergencies. Overall the losses can be reduced. In addition to these economic benefits, the system also increases the transparency of the supply chain. All the parties included in the supply chain can better understand their products through ePedigree and the quality evaluation algorithm. The good performance of the system proves the effectiveness of the proposed approach in perishable product management.

9.2 Contributions of the Research

The safety problems of perishable products have attracted attention in recent years. With more and more reports on the safety problems of products, customers lose confidence in the products they buy and suppliers also find it hard to control product quality, especially in distribution carried by 3PL. Moreover, the value loss of perishable products is also very serious during transportation. Logistics companies face losses for compensation. However, the increased use of RFID technology has a great impact on current systems. For example, real-time data can be obtained, effectiveness is improved, and transportation movements become more transparent and so on. Consequently, with the application of RFID, sensors, GPS, fuzzy logic, CBR, ANN and optimisation algorithms, an approach is proposed for real-time monitoring, positioning, optimisation, forecasting and timely warning. The most significant contribution of this research is the development of a system based on the proposed approach for the improvement of perishable products management, and utilizing the greatest advantages of RFID-based systems. The case study has proven that the MDSS can monitor products over the entire supply chain in real-time, discover potential damage in sufficient time for prevention, optimise the vehicle schedule and quickly adjust the original plan to avoid losses. It helps to increase the transparency of the whole supply chain, cope with accidents and to optimise vehicle schedules.

- Compared to the usual schedule generated by experience, a schedule after optimisation can save money.
- DSM adjusts the original schedule so that the losses can be reduced.
- The environment in the containers is monitored in real-time, which guarantees the product quality.
- Though the system cannot deal with certain accidents, such as a container problem on route, it can identify the problem in time, so that there is sufficient time for remedial measures.

In summary, the research proposes an approach for the improvement of perishable product management. Based on the approach, MDSS has been developed. The system can effectively improve the control of product quality and decrease the logistics value loss in the logistics. The system has three modules; in each module, there are some innovation points.

- In RMM, a hybrid algorithm with *k*-NN and ANN is proposed. The algorithm evaluates product quality at each stage and gives the evaluation result of the product based on its ePedigree. For products that have large price differences, the algorithm can help to distinguish the quality differences in a scientific way.

  RFID and sensors are applied for the real-time monitoring of perishable products during transportation. Thus transportation does not mean a black box to suppliers, and the real-time information on products means that avoiding accidents is possible.

Meanwhile, with the help of real-time monitoring, consumers can be informed on the source (e.g. where the product comes from) and the aspects of product transparency (e.g. where the product was inspected). As a result, users can be more confident regarding product safety.

- In FWM a new soft CBR method has been proposed. The new CBR method combines ANN, CBR and fuzzy logic to forecast the arrival time of vehicles. It can also train the weightings to make the computation results more accurate. The warning function helps to judge whether there is anything abnormal in applying RBR. Some simple decisions can also be given. The module plays an assisting role, and its main contribution is to calculate the travelling time between two locations. The DSM uses the time for optimisation. If the system receives a warning generated by the warning function, dynamic adjustment will alter the original schedule.
- In DSM, a new optimisation algorithm IQEA is proposed. The algorithm is designed using the principle of QEA. The improved algorithm can solve more complex combination optimisation problems, and the results show the performance in solving problems at small scale is good. Moreover, it shows the high potential of this algorithm. HCES is proposed for dynamic adjustment, and can quickly find a relative optimal solution, since accidents need to be coped with urgently. The main contribution of this module is to optimise vehicle scheduling and in coping with accidents.

Finally, a case study is examined to prove that the system has a positive effect on perishable product management, especially in coping with accidents. In such a case, the system effectively saves transportation costs and reduces losses in distribution. It avoids unnecessary waste during transportation. The product conditions in the distribution system are monitored, thus the transparency of the product supply chain increases. The success of the system also proves the effectiveness of the approach in perishable product management.

9.3 Suggestions for Future Work

Aimed at solving the limitations described in Section 8.3, the following suggestions are suggested to improve the proposed system.

- Fuzzy neural networks will be used to improve the quality loss model, which will then have a better performance in forecasting the value of a perishable product. Since there are 4 curves to predict perishable product quality, fuzzy logic can help categorise the products.
- For the forecasting function, the forecasting of environment changes will be considered in the FWM. Multiple regression will be applied in this module. With the change in value of environmental factors, the tendency of change can be predicted. So, the future value of environmental factors can be predicted in this way.
- In DSM, the uncertainty of the travel time will be considered in static optimisation. An amplification coefficient set based on the similarity degree supplied by CBR in FWM will be applied to the problem model. The travel time between each set of points all need to multiply the coefficients as the data. Rush hour will also be considered during the model construction.
- IQEA will be studied further. The speed of the current algorithm in solving problems

in large scale is slow. The single quantum design needs to be changed to multi quantum. Optimal results hope to be obtained through this change.

- For dynamic adjustment, the present method can just obtain a relatively optimal solution. Some dynamic optimisation algorithms will be studied. Some warnings come regularly, and dynamic optimisation can solve this kind of problem better that the current heuristics method.
- The system is tested in emulation. In the future, it will be implemented in ZM Logistics and some real data can be collected for the further improvement of the system.
- Though RMM can be extended to monitor the entire supply chain. FWM and DSM are both limited in the management of distribution. In the SCM, inventory control is another challenge, especially for perishable products, because their shelf-life is short. If the warehouse stores different products, "first in first out" may not be suitable. Inventory management is complex and will be my research direction in the next stage.

APPENDICES

Appendix I - Interview Questions

Manager:
1. Does compensation affect the benefits of the company?
2. Are you satisfied with your current transportation management system? What functions should be added to the system?
3. Did you receive any complains about your service regarding the quality issues of the products, but which you do not think are your responsibility?
Operator:
1. How do you currently arrange the vehicle schedule?
2. How do you cope with an urgent consignment coming in suddenly?
3. If the vehicle or delivered items have problems during transportation, how do you cope with the situation?
Driver:
Have you experienced any abnormal conditions during transportation? How do you cope with such an emergency?

Appendix II - Questionnaire Used for System Design

For the purpose of a more suitable design of the transportation management system for ZM Logistics, we would be grateful if you could spend a few minutes to complete this questionnaire. The information you provide will only be used for the above purpose, so it is highly confidential.

Date: ______________

Part 1: What do you think about current transportation system?

Level of Satisfaction

	Very Dissatisfied	Dissatisfied	Neutral	Satisfied	Very Satisfied
The Entire System	☐	☐	☐	☐	☐
Crisis Management	☐	☐	☐	☐	☐
Vehicle Management	☐	☐	☐	☐	☐

Part 2: Which functions do you think are necessary in the new transportation system? (Multiple Choice)

☐ Schedule Optimisation ☐ Real-time Monitoring ☐ GPS

☐ Time Forecasting ☐ Timely Warning

Part 3: Do you think these actions are effective in increasing the profit of the company?

	Necessity Level		
	Unnecessary	Neutral	Necessary
Increase number of vehicles	☐	☐	☐
Increase business scale	☐	☐	☐
Decrease costs	☐	☐	☐

Thank you for your kind assistance!

REFERENCES

Aamodt, A. & Plaza, E. (1994). Case-based reasoning - foundational issues, methodological variations, and system approaches. *Ai Communications* 7(1): 39-59.

Abad, E., Palacio, F., Nuin, M., Zárate, A. G. d., Juarros, A., Gómez, J. M. & Marco, S. (2009). RFID smart tag for traceability and cold chain monitoring of foods: Demonstration in an intercontinental fresh fish logistic chain. *Journal of Food Engineering* 93(4): 394-399.

Abbass, H. A. (2002). An evolutionary artificial neural networks approach for breast cancer diagnosis. *Artificial Intelligence in Medicine* 25(3): 265-281.

Aha, D. W. (1998). The omnipresence of case-based reasoning in science and application. *Knowledge-Based Systems* 11(5-6): 261-273.

Ahumada, O. & Villalobos, J. R. (2011). Operational model for planning the harvest and distribution of perishable agricultural products. *International Journal of Production Economics* 133(2): 677-687.

Alba, E. & Dorronsoro, B. (2006). Computing nine new best-so-far solutions for capacitated VRP with a cellular genetic algorithm. *Information Processing Letters* 98(6): 225-230.

Amorim, P., Günther, H. O. & Almada-Lobo, B. (2012). Multi-objective integrated production and distribution planning of perishable products. *International Journal of Production Economics* 138(1): 89-101.

Arabacioglu, B. C. (2010). Using fuzzy inference system for architectural space analysis. *Applied Soft Computing* 10(3): 926-937.

Australian Academy of Science (1998). When bugs have you on the run. *Australian Academy of Science*. [online] Available at:< http://www.science.org.au/nova/030/030key.html> [Accessed 10 May 2009].

Bai, L., Ma, C. L., Gong, S. L. & Yang, Y. S. (2007). Food safety assurance systems in China. *Food Control* 18(5): 480-484.

Battarra, M., Monaci, M. & Vigo, D. (2009). An adaptive guidance approach for the heuristic solution of a minimum multiple trip vehicle routing problem. *Computers & Operations Research* 36(11): 3041-3050.

Bear Stearns (2003). Supply-chain technology: track(ing) to the future. [pdf] Available at: <www.bearstearns.com/bscportal/pdfs/research/supplychain/technology_rfid.pdf > [Accessed 3 September 2009].

Beliën, J. & Forcé, H. (2012). Supply chain management of blood products: A literature review. *European Journal of Operational Research* 217(1): 1-16.

Benioff, P. (1980). The Computer as a Physical System - a Microscopic Quantum-Mechanical Hamiltonian Model of Computers as Represented by Turing-Machines. *Journal of Statistical Physics* 22(5): 563-591.

Bergh, F. V. D. (2001). *An Analysis of Particle Swarm Optimizers.* Ph.D. Natural and Agricultural Science Department, University of Pretoria.

Bertolini, M., Rizzi, A. & Bevilacqua, M. (2007). An alternative approach to HACCP system implementation. *Journal of Food Engineering* 79(4): 1322-1328.

Biacino, L. & Gerla, G. (2002). Fuzzy logic, continuity and effectiveness. *Archive for Mathematical Logic* 41(7): 643-667.

Bogataj, M., Bogataj, L. & Vodopivec, R. (2005). Stability of perishable goods in cold logistic chains. *International Journal of Production Economics* 93–94(0): 345-356.

Borriello, G. (2005). RFID: Tagging the world. *Communications of the Acm* 48(9): 34-37.

Branigan, T. (2008). Chinese figures show fivefold rise in babies sick from contaminated milk. *The Guardian London,* Available at: < http://www.guardian.co.uk/world/2008/dec/02/china> [Accessed 7 June 2011].

Brock, D. L. (2001). The electronic product code (EPC): a naming scheme for physical objects.[pdf] Auto-ID Labs: Available at: < http://www.autoidlabs.org/uploads/media/MIT-AUTOID-WH-002.pdf>

Business Wire (2007). ThermaFreeze Products a Vital Link in Cold Chain Shipping. In *Business Wire*, [online] 18, June. Available at: <http://www.businesswire.com/news/home/20070618005430/en/ThermaFreeze-Products-Vital-Link-Cold-Chain-Shipping>.

CAC (2003). Hazard analysis and critical control point (HACCP) system and guidelines for its application – annex to CAC/RCP 1-1969 (REV. 4-2003) In *Codex Alimentarius Commission,* Rome (Italy).

Cai, X. Q., Chen, J., Xiao, Y. B. & Xu, X. L. (2010). Optimization and Coordination of Fresh Product Supply Chains with Freshness-Keeping Effort. *Production and Operations Management* 19(3): 261-278.

Castro, J. L., Navarro, M., Sanchez, J. M. & Zurita, J. M. (2011). Introducing attribute risk for retrieval in case-based reasoning. *Knowledge-Based Systems* 24(2): 257-268.

Caswell, J. A. &Hooker, N. H. (1996). HACCP as an international trade standard. *American Journal of Agricultural Economics* 78(3): 775-779.

Centre for Food Safety (2007). *Food Surveillance Programme*. Hong Kong: Centre for Food Safety. [online] Available at: <http://www.cfs.gov.hk/english/programme/programme_fs/programme_fs.html>.

Cerf, O., Donnat, E. &Grp, F. H. W. (2011). Application of hazard analysis - Critical control point (HACCP) principles to primary production: What is feasible and desirable? *Food Control* 22(12): 1839-1843.

Charters, S. & Pettigrew, S. (2007). The dimensions of wine quality. *Food Quality and Preference* 18(7): 997-1007.

Chen, F. L. & Ou, T. Y. (2009). Gray relation analysis and multilayer functional link network sales forecasting model for perishable food in convenience store. *Expert Systems with Applications* 36(3, Part 2): 7054-7063.

Cheung, B. K. S., Choy, K. L., Li, C. L., Shi, W. Z. & Tang, J. (2008). Dynamic routing model and solution methods for fleet management with mobile technologies. *International Journal of Production Economics* 113(2): 694-705.

China Daily (2007).WHO: Food safety 'a big problem' for all nations. *China Daily,* 19 July.

Coelho, L. D. (2008). A quantum particle swarm optimizer with chaotic mutation operator. *Chaos Solitons & Fractals* 37(5): 1409-1418.

Coley, D. A. (1999). *An introduction to genetic algorithms for scientists and engineers.* Singapore: World Scientific.

Croom, S., Romano, P. & Giannakis, M. (2000). Supply chain management: an analytical framework for critical literature review. *European Journal of Purchasing & Supply Management* 6(1): 67-83.

Delen, D., Sharda, R. & Hardgrave, B. C. (2011). The promise of RFID-based sensors in the perishables supply chain. *Wireless Communications, IEEE* 18(2): 82-88.

Dolgui, A. & Proth, J. M. (2008). RFID Technology in Supply Chain Management: State of the Art and Perspecti*ves. In: 17th IFAC World Congress*, 4464-4475. 6-11, July, Seoul, Korea.

Dupuit, E., Pouet, M. F., Thomas, O. & Bourgois, J. (2007). Decision support methodology using rule-based reasoning coupled to non-parametric measurement for industrial wastewater network management. *Environmental Modelling & Software* 22(8): 1153-1163.

Dutta, S. & Bonissone, P. P. (1993). Integrating case- and rule-based reasoning. *International Journal of Approximate Reasoning* 8(3): 163-203.

Eloranta, E., Hameri, A.-P. & Lähteenmäki, K. (1991). Experiences of different approaches in logistics. *Engineering Costs and Production Economics* 21(2): 155-169.

FALKEN Secure Networks, (2008). RFID for the wine Industry [pdf] Avaliable at < http://www.falkensecurenetworks.com/PDFs/0819_RFID_for_the_Wine_Industry.pdf >..

Fellows, R. & Liu, A. (2003). *Research methods for construction.* Malden: Blackwell Publishing.

Feng, L. (2009).Impact of RFID Technology on Supply Chain: A Simulation Approach. In: *International Conference on Management and Service Science,* 16-18, September, .Wuhan, China

Feng, X. Y., Wang, Y., Ge, H. W., Zhou, C. G. & Liang, Y. C. (2006). Quantum-inspired evolutionary algorithm for travelling salesman problem. In: Liu, G.R.; Tan, V.B.C.; Han, X. ed. 2006. *Computational Methods*: 1363-1367.

Ferrer, J. C., Mac Cawley, A., Maturana, S., Toloza, S. & Vera, J. (2008). An optimization approach for scheduling wine grape harvest operations. *International Journal of Production Economics* 112(2): 985-999.

Feynman, R. P. (1982). Simulating Physics with Computers. *International Journal of Theoretical Physics* 21(6-7): 467-488.

Fındık, O., Babaoğlu, İ. & Ülker, E. (2010). A color image watermarking scheme based on hybrid classification method: Particle swarm optimization and k-nearest neighbor algorithm. *Optics Communications* 283(24): 4916-4922.

Folinas, D., Manikas, I. & Manos, B. (2006). Traceability data management for food chains. *British Food Journal* 108(8): 622-633.

Fox News (2012). US Fungicide Detected in Brazilian Orange Juice. In *Fox News,* 12 January. Available at < http://latino.foxnews.com/latino/health/2012/01/12/us-fungicide-detected-in-brazilian-orange-juice/ >.

Freeman, V. T. & Cavinato, J. L. (1990). Fitting purchasing to the strategic firmframeworks, processes, and values. *Journal of Purchasing and Materials Management* 26(1): 1–12.

Ghandforoush, P. & Sen, T. K. (2010). A DSS to manage platelet production supply chain for regional blood centers. *Decision Support Systems* 50(1): 32-42.

Ghosh, A. K., Chaudhuri, P. & Murthy, C. A. (2005). On visualization and aggregation of nearest neighbor classifiers. *Ieee Transactions on Pattern Analysis and Machine Intelligence* 27(10): 1592-1602.

Goel, R. (2007). Managing RFID Consumer Privacy and Implementation Barriers. *Information Systems Security* 16(4): 217-223.

Goessl, L. (2011). Cancer causing toxin found in Chinese milk. *Digital Journal,* 26, December. Avalaibale at < http://digitaljournal.com/article/316730 >.

Gong, S. S. & Liang, H. L. (2006). On the logistics network modes of fresh food cold chain. *China Business and Market* 2: 7-9.

Grigorenko, I. & Garcia, M. E. (2001). Ground-state wave functions of two-particle systems determined using quantum genetic algorithms. *Physica A* 291(1-4): 439-448.

Han, K. H. & Kim, J. H. (2002). Quantum-inspired evolutionary algorithm for a class of combinatorial optimization. *Ieee Transactions on Evolutionary Computation* 6(6): 580-593.

Harland, C. M. (1996). *Supply Chain Management, Purchasing and Supply Management, Logistics, Vertical Integration, Materials Management and Supply Chain Dynamics.* UK: Blackwell.

Harper, P. R., de Senna, V., Vieira, I. T. & Shahani, A. K. (2005). A genetic algorithm for the project assignment problem. *Computers & Operations Research* 32(5): 1255-1265.

Hewett, E. W. (2003). Perceptions of supply chain management for perishable horticultural crops: An introduction. In: *Proceedings of the International Conference on Quality in Chains, Vols 1 and 2: An Integrated Viw on Fruit and Vegetable Quality*, 37-46, Wageningen, Netherlands.

Hey, T. (1999). Quantum computing: an introduction. *Computing & Control Engineering Journal* 10(3): 105-112.

Ho, S. C. & Haugland, D. (2004). A tabu search heuristic for the vehicle routing problem with time windows and split deliveries. *Computers & Operations Research* 31(12): 1947-1964.

Hong, I. H., Dang, J. F., Tsai, Y. H., Liu, C. S., Lee, W. T., Wang, M. L. & Chen, P. C. (2011). An RFID application in the food supply chain: A case study of convenience stores in Taiwan. *Journal of Food Engineering* 106(2): 119-126.

Horstkotte, E. (2000). Fuzzy Expert Systems. [online] Available at: <http://www.austinlinks.com/Fuzzy/expert-systems.html>

Hsu, C. I., Hung, S. F. & Li, H. C. (2007). Vehicle routing problem with time-windows for perishable food delivery. *Journal of Food Engineering* 80(2): 465-475.

Huang, Y. X., Wang, Y., Zhou, W. G., Yu, Z. Z. & Zhou, C. G. (2005). A fuzzy neural network system based on generalized class cover and particle swarm optimization. *Advances in Intelligent Computing,* 3645: 119-128.

Hunt, S. D. & Deller Jr, J. R. (1995). Selective training of feedforward artificial neural networks using matrix perturbation theory. *Neural Networks* 8(6): 931-944.

Hwang, H. S. (2002). An improved model for vehicle routing problem with time constraint based on genetic algorithm. *Computers & Industrial Engineering* 42(2-4): 361-369.

Jedermann, R., Behrens, C., Westphal, D. & Lang, W. (2006). Applying autonomous sensor systems in logistics - Combining sensor networks, RFIDs and software agents. *Sensors and Actuators a-Physical* 132(1): 370-375.

Jedermann, R., Ruiz-Garcia, L. & Lang, W. (2009). Spatial temperature profiling by semi-passive RFID loggers for perishable food transportation. *Computers and Electronics in Agriculture* 65(2): 145-154.

Jiang, J. Y., Tsai, S. C. & Lee, S. J. (2012). FSKNN: Multi-label text categorization based on fuzzy similarity and k nearest neighbors. *Expert Systems with Applications* 39(3): 2813-2821.

Kärkkäinen, M. (2002). Wireless product identification: enabler for handling efficiency, customisation and information sharing. *Supply Chain Management: An International Journal* 7(4): 242-252.

Katsaliaki, K. (2008). Cost-effective practices in the blood service sector. *Health Policy* 86(2-3): 276-287.

Keller, J. M., Gray, M. R. & Givens, J. A. (1985). A fuzzy k-nearest neigubour algorithm. *IEEE transactions on Systems, Man and Cybernetics* 15(4): 580-585.

Kuo, J. C. & Chen, M. C. (2010). Developing an advanced Multi-Temperature Joint Distribution System for the food cold chain. *Food Control* 21(4): 559-566.

Kvenberg, J., Stolfa, P., Stringfellow, D. & Garrett, E. S. (2000). HACCP development and regulatory assessment in the United States of America. *Food Control* 11(5): 387-401.

Kwok, S. K., Tsang, H. C., Cheung (2008a). *Realizing the potential of RFID in Counterfeit Prevention, Physical Asset Management, and Business Applications: Case Studies of Early Adopters.* Case Book, Hong Kong: The Hong Kong Polytechnic University *(Unpublished, the copy can be got from the website: http://www.rfid.ise.polyu.edu.hk/en/OurSolutions.html).*

Kwok, S. K., Albert, H. C.; Ting, S. L.; Lee, W. B.; Cheung, B. C. F. (2008b).An Intelligent RFID-Based Electronic Anti-Counterfeit System (InRECS) for the Manufacturing Industry. In: *17th IFAC World Congress*, 5482-5487, 6-11, July, Seoul, Korea.

Laturnas, J. (2008). *Monitoring, Verification and Validation.* Saskatchewan: Government of Saskatchewan. Available at: <http://www.agriculture.gov.sk.ca/Default.aspx?DN=3b6394ed-c078-42db-b1ab-879a52a93873>

Lee, H. (2011). Taiwan and China Recall Foods and Beverages Contaminated with DEHP and DINP. *Euromonitor International,* 17 June. [online] Available at <http://blog.euromonitor.com/2011/06/taiwan-and-china-recall-foods-and-beverages-contaminated-with-dehp-and-dinp.html>.

Lei, Y. & Zuo, M. J. (2009). Gear crack level identification based on weighted K nearest neighbor classification algorithm. *Mechanical Systems and Signal Processing* 23(5): 1535-1547.

Li, B. B. & Wang, L. (2007). A hybrid quantum-inspired genetic algorithm for multiobjective flow shop scheduling. *Ieee Transactions on Systems Man and Cybernetics Part B-Cybernetics* 37(3): 576-591.

Li, D., Kehoe, D. & Drake, P. (2006). Dynamic planning with a wireless product identification technology in food supply chains. *International Journal of Advanced Manufacturing Technology* 30(9-10): 938-944.

Li, P. & Li, S. (2008). Quantum-inspired evolutionary algorithm for continuous space optimization based on Bloch coordinates of qubits. *Neurocomputing* 72(1–3): 581-591.

Liu, B. L., L. & Ma, W. H., (2008). Application of quantity flexibility contract in perishable products supply chain coordination. In: *Control and Decision Conference,* 2-4 July, 2008, Yantai, Shandong, China , 2758-2761.

Liu, Y. & Sun, F. (2011). A fast differential evolution algorithm using k-Nearest Neighbour predictor. *Expert Systems with Applications* 38(4): 4254-4258.

Ma, J., Chen, S. & Xu, Y. (2006). Fuzzy logic from the viewpoint of machine intelligence. *Fuzzy sets and systems* 157: 628-634.

Mitchell, M. (1996). *An introduction to genetic algorithms.* Cambridge: MIT Press.

Mortimore, S. & Wallace, C. (1998). *Haccp: A Practical Approach.* Gaithersburg: Aspen Publishers.

Naoum, S. G. (1998). *Dissertation research and writing for construction students.* Burlington: Elsevier Butterworth-Heinemann.

Nasibov, E. N. & Peker, S. (2011). Time series labeling algorithms based on the K-nearest neighbors' frequencies. *Expert Systems with Applications* 38(5): 5028-5035.

Negnevitsky, M. (2005). *Artificial Intelligence: A Guide to intelligent systems*. Beijing: China Machine Press.

New York Times (2012).Food Safety in China. In *New York Times*. [Online] Avalaibale at:<http://topics.nytimes.com/topics/news/international/countriesandterritories/china/food-safety/index.html>.

Nishimura, D., Matsuyama, R. (1989). *Maturation and maturation chemistry.* England: Longman

Ombuki, B., Ross, B. J. & Hanshar, F. (2006). Multi-objective genetic algorithms for vehicle routing problem with time windows. *Applied Intelligence* 24(1): 17-30.

Osvald, A. & Stirn, L. Z. (2008). A vehicle routing algorithm for the distribution of fresh vegetables and similar perishable food. *Journal of Food Engineering* 85(2): 285-295.

Park, J. S., Oh, S., Cheong, T. & Lee, Y. (2006).Freight Container Yard Management System with Electronic Seal Technology. In: *2006 IEEE International Conference on,Industrial Informatics:* 67-72. 16-18, August, Singapore.

Passone, S., Chung, P. W. H. & Nassehi, V. (2006). Incorporating domain-specific knowledge into a genetic algorithm to implement case-based reasoning adaptation. *Knowledge-Based Systems* 19(3): 192-201.

Pawsey, R. K. (1995). *Preventing losses and preserving quality in food cargoes.* Italy: Food and Agriculture Organization (FAO) of the United Nations.

Pierskalla, W. (2004). Supply chain management of blood banks. *Operations Research and Management Science* 70(2): 103-145.

Pisinger, D. & Ropke, S. (2007). A general heuristic for vehicle routing problems. *Computers & Operations Research* 34(8): 2403-2435.

Raptis, C. G., Siettos, C. I., Kiranoudis, C. T. & Bafas, G. V. (2000). Classification of aged wine distillates using fuzzy and neural network systems. *Journal of Food Engineering* 46(4): 267-275.

RFID, J. (2003). Wal-Mart draws line in the sand. *RFID Journal,* 11, June. [Online] Avalaibale at:< http://www.rfidjournal.com/article/view/462>.

Rong, A. Y., Akkerman, R. & Grunow, M. (2011). An optimization approach for managing fresh food quality throughout the supply chain. *International Journal of Production Economics* 131(1): 421-429.

Sadek, A. W., Smith, B. L. & Demetsky, M. J. (2001). A prototype case-based reasoning system for real-time freeway traffic routing. *Transportation Research Part C-Emerging Technologies* 9(5): 353-380.

Sahin, E., Babaï, M. Z., Dallery, Y. & Vaillant, R. (2007). Ensuring supply chain safety through time temperature integrators. *International Journal of Logistics Management* 18(1): 102 - 124.

Salamo, M. &Lopez-Sanchez, M. (2011). Adaptive case-based reasoning using retention and forgetting strategies. *Knowledge-Based Systems* 24(2): 230-247.

Santa, J., Zamora-Izquierdo, M. A., Jara, A. J. & Gomez-Skarmeta, A. F. (2012). Telematic platform for integral management of agricultural/perishable goods in terrestrial logistics. *Computers and Electronics in Agriculture* 80: 31-40.

Sarac, A., Absi, N., & Dauzère-Pérès S. (2010). A literature review on the impact of RFID technologies on supply chain management. *International Journal of Production Economics,* 128(1): 77 – 95.

Shen, Z. L., Lui, H. C. & Ding, L. Y. (1994). Approximate Case-Based Reasoning on Neural Networks. *International Journal of Approximate Reasoning* 10(1): 75-98.

Shih, K. M. & Wang, W. K. (2011). Factors influencing HACCP implementation in Taiwanese public hospital kitchens. *Food Control* 22(3-4): 496-500.

Shor, P. W. (1994).Algorithms for quantum computation: discrete logarithms and factoring. In: *Proceedings of 35th Annual Symposium on Foundations of Computer Science*, 124-134, 20-22, November, Santa Fe, United States.

Solomon, M. M. (1983).*Vehicle routing and scheduling with time windows constraints: models and algorithms*. Ph.D.: Department of Decision Science, University of Pennsylvania, USA.

Sorli, M. & Stokić, D. (2009). *Innovating in Product/Process Development: Gaining Pace in New Product Development.* London: Springer.

Talbi, H., Draa, A. & Batouche, M. (2004). A new quantum-inspired Genetic Algorithm for solving the travelling salesman problem. *2004 IEEE International Conference on Industrial Technology* 3: 1192-1197. 8-10, December, Hammamet, Tunisia.

Taormina, R., Chau, K. W. & Sethi, R. (2012). Artificial neural network simulation of hourly groundwater levels in a coastal aquifer system of the Venice lagoon. *Engineering Applications of Artificial Intelligence* DOI:http://dx.doi.org/10.1016/j.engappai.2012.02.009 .

Taoukis, P. S. & Labuza, T. P. (1989). Applicability of Time-Temperature Indicators as Shelf-Life Monitors of Food-Products. *Journal of Food Science* 54(4): 783-788.

Tarantilis, C. D. & Kiranoudis, C. T. (2007). A flexible adaptive memory-based algorithm for real-life transportation operations: Two case studies from dairy and construction sector. *European Journal of Operational Research* 179(3): 806-822.

Tavakkoli-Moghaddam, R., Safaei, N. & Gholipour, Y. (2006). A hybrid simulated annealing for capacitated vehicle routing problems with the independent route length. *Applied Mathematics and Computation* 176(2): 445-454.

Thonemann, U. W. (2002). Improving supply-chain performance by sharing advance demand information. *European Journal of Operational Research* 142(1): 81-107.

Thornley, J. & France, J. (1984). *Mathematical Models in Agriculture.* New York: Oxford University Press.

Thornley, J. H. M. (1976). *Mathematical Models in Plant Physiology.* London: Academic Press.

Thoukis, G. (1974). Chemistry of Wine Stabilization: A Review. In: A. D. Webb, ed. 1974. *Chemistry of Winemaking*, *Vol. 137*, USA: AMERICAN CHEMICAL SOCIETY. 116-133

Tijskens, L. M. M. & Evelo, R. G. (1993). Modeling color of tomatoes during postharvest storage. *Postharvest Biology and Technology* 4(1-2): 85-98.

Tijskens, L. M. M., Kooten, O. V. & Otma, E. C. (1994). Photosystem 2 quantum yield as a measure of radical scavengers in chilling injury in cucumber fruits and bell peppers. *Planta* 194(4): 478-486.

Tijskens, L. M. M. & Polderdijk, J. J. (1996). A generic model for keeping quality of vegetable produce during storage and distribution. *Agricultural Systems* 51(4): 431-452.

TSPLIB (1995). Standard TSPLIB. *MP-TESTDATA - The TSPLIB Symmetric Traveling Salesman Problem Instances*. [online] 1 June. Available at: <http://elib.zib.de/pub/mp-testdata/tsp/tsplib/tsp/>.

Vela, A. R. & Fernandez, J. M. (2003). Barriers for the developing and implementation of HACCP plans: results from a Spanish regional survey. *Food Control* 14(5): 333-337.

Vlachogiannis, J. G. & Østergaard, J. (2009). Reactive power and voltage control based on general quantum genetic algorithms. *Expert Systems with Applications* 36(3, Part 2): 6118-6126.

Véronneau, S. & Roy, J. (2009). RFID benefits, costs, and possibilities: The economical analysis of RFID deployment in a cruise corporation global service supply chain. *International Journal of Production Economics* 122(2): 692-702.

Wang, L., Kwok, S. K., Ip, W. H., (2010). An Radio Frequency Identification and Sensor-based System for the Transportation of Food, Journal of Food Engineering, 101: 120-129.

Wang, L., Kwok, S. K., Ip, W. H., (2011). A radio frequency identification-based quality evaluation system design for the wine industry. International Journal of Computer Integrated Manufacturing 25(1): 11-19.

Wang, L., Wu, H., Tang, F. & Zheng, D. Z. (2005). A hybrid quantum-inspired genetic algorithm for flow shop scheduling. *Computer Science* 3645: 636-644.

Wang, W. (2011).Analysis of Bullwhip Effects in Perishable Product Supply Chain Based on System Dynamics Model. In: *2011 International Conference on Intelligent Computation Technology and Automation (ICICTA),* Vol. 1, 1018-1021. 28-29, March, Shenzhen, China.

Wang, X. & Li, D. (2012). A dynamic product quality evaluation based pricing model for perishable food supply chains. *Omega* 40(6): 906-917.

Wang, X., Li, D. & O'Brien, C. (2009). Optimisation of traceability and operations planning: an integrated model for perishable food production. *International Journal of Production Research* 47(11): 2865-2886.

Wang, X., Li, D., O'Brien, C. & Li, Y. (2010). A production planning model to reduce risk and improve operations management. *International Journal of Production Economics* 124(2): 463-474.

Wang, Y., Feng, X. Y., Huang, Y. X., Pu, D. B., Zhou, W. G., Liang, Y. C. & Zhou, C. G. (2007). A novel quantum swarm evolutionary algorithm and its applications. *Neurocomputing* 70(4-6): 633-640.

Watson, I. & Marir, F. (1994). Case-based reasoning: A review. *The Knowledge Engineering Review* 9(4): 327-354.

Weigend, A. S., Rumelhart, D. E. & Huberman, B. A. (1991). Generalization by weight-elimination with application to forecasting. *Advances in Neural Information Processing Systems* 3: 875-882.

White, C. C. & Cheong, T. (2012). In-transit perishable product inspection. *Transportation Research Part E: Logistics and Transportation Review* 48(1): 310-330.

Wijtzes, T., van't Riet, K., Huis in't Veld, J. H. J. & Zwietering, M. H. (1998). A decision support system for the prediction of microbial food safety and food quality. *International Journal of Food Microbiology* 42(1-2): 79-90.

Woo, S. H., Choi, J. Y., Kwak, C. & Kim, C. O. (2009). An active product state tracking architecture in logistics sensor networks. *Computers in Industry* 60(3): 149-160.

Xiao, J., Xu, J., Chen, Z., Zhang, K. & Pan, L. (2009). A hybrid quantum chaotic swarm evolutionary algorithm for DNA encoding. *Computers & Mathematics with Applications* 57(11–12): 1949-1958.

Xiao, Y. B., Chen, J. & Xu, X. L. (2008). Fresh Product Supply Chain Coordination under CIF Business Model with Long Distance Transportation. *Systems Engineering - Theory & Practice* 28(2): 19-34.

Yeh, A. G. O. & Shi, X. (2001). Case-based reasoning (CBR) in development control. *International Journal of Applied Earth Observation and Geoinformation* 3(3): 238-251.

Yildiz, T., Yildirim, S. & Altilar, D. T. (2008). *Spam filtering with parallelized KNN algorithm.* Usak: Akademik Bilişim.

Zapfel, G. & Bogl, M. (2008). Multi-period vehicle routing and crew scheduling with outsourcing options. *International Journal of Production Economics* 113(2): 980-996.

Zhang, L. J. (2006). Analysis on the current situation and countermeasures of China food reefer logistics. *Logistic Technology* 1: 102-104.

Zhou, W. (2009). RFID and item-level information visibility. *European Journal of Operational Research* 198(1): 252-258.