Application of Machine Learning and RFID in the Stability Optimization of Perishable Foods

Ehsan Mohebi*a and Leorey Marquezb

*aFaculty of Science, Federation University Australia, Mt Helen, Ballarat, Australia 3353.
bCSIRO DPAS, Gate 5, Normanby Road, Clayton, Australia 3168.
*Corresponding author: e.mohebi@federation.edu.au

Abstract
Radio frequency identification (RFID) technology has been applied for automation processes in the supply chain for more than a decade. RFID technology can be employed in the supply chain for real time food tracing and quality control to reduce food wastage and food-borne illnesses. In this paper, an approach to the integration of RFID technology with the perishable food supply chain for further decision making is proposed to optimize the quality of the perishable products with minimum cost. A simulation model based on the available transportation systems and stochastic environmental factors in the supply chain is presented to illustrate this approach. Moreover, a kernel logistic regression as a nonlinear decision support system at each node of the supply chain is adopted to the system for real time decision making. The numerical results from two simulation experiments demonstrate the efficiency of the proposed integrated model in the sense of cost minimization and product quality maximization in the supply chain.

Keywords: Supply chain management, real time decision support system, RFID, food quality control, kernel logistic regression, food stability optimization

Introduction
Perishable foods such as dairy and meat are susceptible to spoilage in the supply chain. In North America alone, over $33 billion in food losses is incurred annually in the food supply chain (Wang et al., 2010). On the other hand, customers are asking for high product quality and retailers are demanding longer shelf life products. RFID (radio frequency identification) embedded in real time monitoring and online decision systems has significant potential in improving the delivery systems of perishable products.

RFID technology have been developed for several decades, with successful applications for access control systems, airport baggage handling, livestock management systems, and automated toll collection systems, especially in logistics and retail businesses (Kelly and Erickson, 2005; Hou and Huang, 2006; Ergen et al., 2007). An RFID system consists of tags, readers, and middleware. A tag is usually a microchip with an antenna. The tag keeps and transmits data to a reader, which is an electronic device used to wirelessly communicate information from the tag to a back-end database (Tajima, 2007). An RFID-based system can provide real time information to operators, managers, and supervisors in order to control actual situation in the supply chain. Therefore, they can manage customer’s demands and timely adjust the production plan to improve the whole supply chain efficiency and effectiveness (Ko et al., 2011; Poon et al., 2011; Cheung et al., 2012).

The real potential of RFID lies in the possibility to capture new types of information in real time and support decisions rather than simply replace barcodes with RFID tags for automation processes (Chatziantoniou et al., 2011). Many decision support systems have been proposed to facilitate the supply chain management such as demand forecasting, shelf availability and inventory replenishment, supplier selection and product planning (Banks, 2007; Chuang and Shaw, 2007; Kim et al., 2008). However, the application of RFID in food supply chain and supporting decisions to decrease the quality loss and increase the shelf life of the products can be demanding in a technical and logistical sense.

The quality control of perishable products plays a vital role in food wastage and food borne illnesses. This paper aims to discuss issues in the employment of machine learning and RFID technology in the perishable food supply chain for real time decision making to optimize the quality of the products with minimum cost. A simulation model based on the available transportation systems and stochastic environmental factors in the supply chain is proposed. Moreover, kernel logistic regression as a nonlinear decision support system is adopted to the system for decision making. The numerical results on
two simulation models demonstrate the effectiveness of the proposed model in cost minimization and product quality maximization in the perishable food supply chain.

The rest of the paper is organized as follow. Related work in the application of RFID technology in the food supply chain, and its integration with decision support systems are discussed in Section 2. The simulation model and the methodology are presented in Section 3. Section 4 presents the proposed integration of RFID and decision support system (kernel logistic regression) with the supply chain for food product quality control and cost minimization. The numerical results are presented in Section 5 and Section 6 concludes the paper.

Related Work

Excellent literature reviews on the impact of RFID technologies on the supply chain have recently been provided by Sarac et al. (2010) and Ngai et al. (2014). In this study, we focus on the advantages RFID and supply chain integration in general, and on food traceability in particular. Moreover, the efficiency and effectiveness of existing decision support systems in the supply chain are discussed.

RFID in supply chain management system

Radio frequency identification has been shown as a promising technology for the optimization of supply chain processes since it improves manufacturing and retail operations from forecasting demand to planning, managing inventory, and distribution of products by providing container, pallet, or item level tracking and leading to advanced inventory flows and more accurate real time information (Ustundag and Tanyas, 2009; Chow et al., 2006; Sarac et al., 2010; Tajima, 2007). RFID integration with the supply chain has been credited with reducing the discrepancies between physical and system inventory on the whole supply chain occurring due to misplacement, damage, shipping, and theft errors (Patterson et al., 2003).

The impacts of radio frequency identification technology on supply chain costs are investigated by Ustundag and Tanyas (2009) using a simulation model. The expected benefits obtained from an RFID integrated supply chain are calculated considering the factors of lost sales, theft, inventory, order, and labor costs. It is shown that the factors of product value and demand uncertainty have a considerable influence on the expected benefits of RFID integrated systems. The results also indicated that each member of the supply chain does not benefit equally from RFID integration. The retailer has the highest cost savings, and the lost sales cost factor has a high impact on the integrated RFID supply chain.

Sari (2010) investigates the benefits of using RFID technology within a four-stage supply chain under different environmental and operational conditions via a simulation study. Through comprehensive simulation experiments and subsequent statistical analysis of the simulation outputs, the results demonstrate that the development and implementation of RFID technology provides substantially greater benefits to a supply chain under some certain conditions. An example of operational process improvements is the complete elimination of shelf inspection at Wal-Mart stores (Seideman, 2003). The efficiency of RFID practices on supply chain performance is evaluated by Vlachos (2014). Results show that the implementation of RFID practices significantly affect the supply chain performance in the following areas: supplier, inventory, distribution, plan, sales, and forecasting. RFID can improve the performance of distribution systems, including products dispatched and inventory in transit by 33.8% and stock availability by 45.6%.

Bottani and Rizzi (2008) described a research whose aim is to quantitatively assess the impact of radio frequency identification technology and electronic product code (EPC) system on the main processes of the fast moving consumer goods supply chain. The results indicate that reengineering models increased possible benefits gained through RFID for all processes of distribution centers and retailers. Ferrer et al. (2010) studied 21 RFID applications across a wide variety of industries. Their conclusion was that there were four common benefits: replacement of labor through automation, cycle time reduction, enabling self-service, and loss of prevention. Through these numerous benefits, RFID technologies can provide cost reduction, increased revenue, process improvement, service quality (Whitaker et al., 2007; Saygin et al., 2007).

A three-tier spare parts supply chain with inefficient transportation, storage and retrieval operations is investigated by Chen et al. (2013). Preliminary experiments show that the total operation time can be saved by 81% from current stage to future stage with the integration of RFID and lean manufacturing techniques. Moreover, the savings in total operation time can be enhanced to 89%. In addition, utilizing RFID technology, the cost of labors can be significantly reduced while maintaining current service capacity at the members in the studied supply chain.
RFID in food traceability

Food hazards can appear at any stage of global food supply chains. It is essential to define critical control points to collect the data about the supply chain environment and provide suitable information for manufacture, supply chain participants and consumers. McMeekin et al. (2006) state that the use of RFID technology enables the food industry to increase the accuracy and speed of gathering source information about foods in traditional retail environments.

The importance of a traceability system and an analysis of its potential costs and benefits by applying RFID technology to the British livestock industry is presented by Meuwissen et al. (2003). Li et al. (2006) proposed an innovative planning model which utilizes RFID technology to identify the product quality status for a perishable food supply chain based on the real time information received from RFID enabled control systems. Moreover, the objective is to minimize lost value of products and maximize profits for supply chain partners. A financially viable business model for a radio frequency identification application to a food traceability system is discussed by Hong et al. (2011). In this research a case study of RFID implementation in the chain of convenience stores in Taiwan is conducted. The results show that the proposed model is beneficial for promoting a food traceability system to estimate costs and develop an appropriate price strategy.

Kelepouris et al. (2007) suggest an information infrastructure for enabling traceability which supports efficient information management across the food supply chain utilizing RFID technology. A data reference model is used for modeling traceability information throughout the chain. A model like this will provide an effective way to map a company’s internal operations in our information model, with no need for complicated and time consuming operations analysis. Zhang and Li (2012) studied a management method in food supply chain to optimize internal costs and productivities based on benefit and safety degree using the application strategies of RFID. The authors introduced agri-food supply chain management system, which typically starts on farms and involves many different types of facilities, including processors, packers, distributors, transporters, and retail stores, before finally reaching the consumer.

A replenishment policy for perishable products, that considers the age of inventories based on RFID technology is proposed by Broekmeulen and van Donselaar (2009). The results show that in an environment, which contains important features of a real-life retail environment, this policy leads to substantial cost reductions compared with a base policy that does not concern about the age of inventories.

Decision support systems in supply chain using RFID

Recently, research attention has shifted to the structural effects of RFID technology, where real time RFID tags information are exploited to support decisions and create new experiences for manufacturers and customers. Real time information capturing and decision support is a challenging problem, related to managing huge streams of data coming from multiple data sources and converting them into meaningful information in a way to support decisions. Various approaches for real time supply chain control (Lau et al., 2008), configuration (Piramuthu, 2005), demand forecasting (Carbonneau et al., 2008; Reiner and Fichtinger, 2009; Ferbar et al., 2009; Guanghui, 2012) based on multi-agent systems, machine learning and heuristics have been proposed. A systematic review of literature on application of decision making techniques in supply chain is presented by Chai et al. (2013).

An RFID-based resource management system (RFID-RMS) is presented by Chow et al. (2006). The authors investigated a case-based system incorporating the RFID technology to explore important customer attributes for case retrieval and matching process. In addition, a new customized route optimizing programming model, using real time data of an RFID tag to solve the order picking problems of material handling equipment is developed and installed at the route allocation optimizer, a sub module of resource management engine in the proposed system. The results show that the utilization of warehouse resources is maximized while work efficiency is greatly enhanced. Recent studies have found that RFID and artificial intelligence techniques drive the development of total solution in logistics industry. For instance, automatically classifying the distribution patterns within the complex demand and supply chain to determine the correct replenishment strategy (Lee et al., 2011).

Lao et al. (2012) illustrated RFOF-FOAS, a system for safety plan development in a food distribution center receiving operation with the support of RFID technology and case-based reasoning technique. A real-time food management system was developed that integrated RFID technology and case-based reasoning technique for the distribution center operators in launching a food safety plan. The study concluded that the real time data capturing nature of RFID technology further improved the efficiency and timeframe requested for the actions.
Problem Formulation

In this section the problem of quality control of perishable foods based on real time information captured by RFID technology in supply chain is formulated. The supply chain consists of multiple processing centers at different levels of the product manufacturing procedure. These processing centers are connected using different transportation systems. The structure of these transportation systems can be distinct in general or can be different in particular.

Generally, companies receive demands of products from retailers. The demands are dispatched to be processed in the next level of the supply chain and move forward until deliver to the destination using a particular transportation system at each level. The transportation systems follow different cost, travel time, warning and forecasting models. These models are formulated in such a way that those systems with high cost have less travel time and low impact warning modules. The warning modules are delay and temperature fluctuations throughout delivery, which deteriorate the quality of perishable products in the supply chain.

The perishable products have an expiration time and the quality of products in each demand is modeled based on the elapsed time after manufacturing procedure in the company. The attached RFID tags to the products collect information, such as vehicle type, time of the day, delay and temperature fluctuations from the environments to be used in calculation of the real time product quality and the handling cost from one processing center to the next processing center. At each level of the supply chain, based on the current product quality and real time information, the optimal transportation system is suggested to maximize the quality and minimize the cost at the next level. The cost function of total demands in the supply chain is formulated as,

$$F(S_1, \ldots, S_n) = \frac{1}{n} \sum_{i=1}^{n} \sum_{z_i \in S_i} z_i^j$$  \hspace{1cm} (1)$$

where \(|.|\) is the cardinality of a set, \(n\) is total number of demands and \(S_i\) is the set of costs \(z_i^1, z_i^2, \ldots, z_i^{|S_i|}\) for transportation of demand \(i\) in the supply chain. One can notice that \(|S_i|\) is the number of processing levels in the supply chain, where \(z_i^j\) is the cost of handling demand \(i\) from processing center at level \(j-1\) to \(j\). The quality function of total demands in the supply chain at the delivery point is formulated as,

$$f(Q_1, \ldots, Q_n) = \frac{1}{n} \sum_{i=1}^{n} \sum_{\chi_i^j \in \Omega_j} \chi_i^j$$  \hspace{1cm} (2)$$

where \(\chi_i^j\) is the quality of demand after using a particular transportation system from level \(j-1\) to \(j\).

There is a trade off between cost minimization and quality maximization, therefore the demands which have been delayed and their quality is close to the best usage time are forwarded using the efficient transport systems (which has less travel and delay time) although this might increases the transportation costs. If the quality of the product is higher than a threshold then the transportation system with less cost (high travel time) is selected. Otherwise the one with less travel time is selected. This criterion is modeled in transportation cost systems as a logistic function of time with respect to the quality control model (see Figure 1).
Figure 1. The product quality (left) and transportation cost models (right).

Assume that we have a product with its quality modeled as in Figure 1. Moreover, there are three transportation systems, $r_1$, $r_2$, and $r_3$ subject to $t_{r_1} < t_{r_2} < t_{r_3}$ and $c_{r_1} > c_{r_2} > c_{r_3}$. Therefore, $r_1$ and $r_2$ have less travel time and are more costly than $r_3$. One can see that the quality of the product is high at early stages of the supply chain, thus the $r_3$ is selected due to its minimum cost. In the $T_1$ and $T_2$ intervals, $r_1$ and $r_2$, which are the most efficient ones, are selected to prevent significant product quality loss. The structure of the transportation system is illustrated in Figure 2.

Figure 2. Structure of the transportation system

In Figure 2, the nodes in level 1 and level $n$ represent companies and retailers in the system, respectively. A particular transportation system may not be available to be used from one node at level $i$ to the node at level $i+1$, moreover the RFID real time information are visible to all nodes in the supply chain system.

Simulation model

In this section we develop a simulation model that will have the capability to represent several scenarios in the supply chain. In the simulation model, the routes between two nodes refer to different transportation systems. The proposed simulation model includes the following parameters:
The simulation model consists of a set of nodes, \( N_l \), and a set of corresponding connection matrices, \( S_l \) at each level \( l \) of the supply chain. The set of connection matrices, \( S_l \), is defined as,

\[
S_l = \{ M^l_i | 1 \leq i \leq \left| N_l \right| \}
\]

where \( M^l_i \) is a \( 1 \times \left| N_{l+1} \right| \) matrix. For \( a^l_{ij} \in M^l_i \), \( j = 1, \ldots, \left| N_{l+1} \right| \),

\[
a^l_{ij} = \begin{cases} \omega & \text{if node } i \text{ connected to } j, \\ 0 & \text{o.w.} \end{cases}
\]

where \( \omega > 0 \) is the number of different connections between node \( i \) and \( j \).

Assume that we have a set of demands, \( D = \{ \Upsilon p_1, \ldots, \Upsilon p_n \} \) of product, \( p \), which is generated based on an exponential distribution,

\[
\Upsilon_p^p (\varepsilon; \lambda) = (d^p_{\text{max}} - d^p_{\text{min}}) e^{-\lambda \varepsilon} + d^p_{\text{min}},
\]

where \( \varepsilon \in [0, 1] \) and \( \lambda \in \mathbb{R}^+ \). Note that \( d^p_{\text{max}} \) and \( d^p_{\text{min}} \) are the maximum and minimum amount of product \( p \), respectively.

The quality of product \( p \) in demand \( d \), \( q^p_d(t) \), at time \( t \) is formulated as,

\[
q^p_d(t) = (d^p_{\text{max}} - d^p_{\text{min}}) \left( 1 + e^{-1(t-t^p_{\text{best}})} \right)^{-1} + d^p_{\text{min}},
\]

where \( t^p_{\text{best}} \) is the time of best quality of the product \( p \) after manufacturing procedure.

Assume that the demand \( d \) with current online information \( x_{ld}, x_{ld} \in \mathbb{R}^n \) is being processed at node \( i \) of level \( l \), which has a route to demand destination by passing node \( j \) at level \( l + 1 \). That is \( a^l_{ij} = 1 \), then there is a set of routes,
connecting node $i$ to node $j$ (see Figure 2). Note that to pass the routes $r_k$ ; $k = 1,..,h_{ij}$, a random vehicle $e$; $e = 1,..,q$ with the probability of $v_e$ is selected. The $v_e$ is the probability of using vehicle $e$ for product transportation. Let the different time frames in a day be the set $Q = \{T_1,..,T_{\mu}\}$ then the travel time through the routes $r_k$ ; $k = 1,..,h_{ij}$ depends on the selected time frame in the day, let say $T_y$ and the delivery time, $\Psi(e)$, using vehicle $e$ , $e = 1,..,q$. The travel time of the time frame $T_y$ $\Phi(T_y)$; $y = 1,..,\mu$, is calculated as:

$$
\Phi(T_y) = \frac{\tau_y^p e^{\tau_y}}{\mu!} - t_{\text{const}},
$$

$$
t_{\text{const}} = \frac{t_{\text{max}}}{2l},
$$

where $T_y \in \mathbb{N}$, $\mu \in Q$ and $l$ is the number of levels in the simulation model. The delivery time of vehicle $v_e$ is given by,

$$
\Psi(e) = v_e \times t_{\text{const}}.
$$

The route travel time $t_k(T_y, e)$ is formulated as,

$$
t_k^l(T_y, e) = \Phi(T_y) + \alpha_k^l t_{\text{const}} + \Psi(e),
$$

where $\alpha_k^l \in (0, 0.5)$, $k = 1,..,h_{ij}$ subject to

$$
\alpha_1^l < \alpha_2^l < \ldots < \alpha_{h_{ij}}^l.
$$

One can see that the condition (11) guarantees that the routes travel time do not follow same patterns and in similar situations the travel time of routes from $1$ to $h_{ij}$ are sequentially increasing. Thus, the first route in each node is the one with less travel time, making it the most efficient one.

**Warning modules**

The warning modules are naturally included in the real time monitoring of perishable products in the supply chain. In this section, we introduce unexpected delays in routes and temperature fluctuations as warning modules. The unexpected delay is related to the routes and the temperature fluctuations is due to vehicle storage system malfunctions. The probability of unexpected delay of routes $r_k$ are $\beta_k$; $k = 1,..,h_{ij}$. The unexpected delay time $\theta_k$ is defined as follows:

$$
\theta_k^l = \beta_k^l t_{\text{const}},
$$

where $\beta_k \in (0, 0.2)$ subject to

$$
\beta_1^l < \beta_2^l < \ldots < \beta_{h_{ij}}^l.
$$

Therefore, the total elapsed time for demand $d$ at level $l+1$ after passing route $k$ is,

$$
t_{d+1}^k = \Delta_d^l + t_k^l(T_y, e) + \theta_k^l,
$$

Where $\Delta_d^l$ is the elapsed time of handling demand $d$ until the processing center at level $l$ and the product quality at level $l+1$ is calculated based on the time $t_{d+1}^k$. 

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Mohebi and Marquez, IWFSC 2014
Temperature fluctuations reduce the quality of perishable products in a transportation stage. The quality loss, $q_{\text{loss}}$, based on fluctuations are formulated as follows:

$$q_{\text{loss}}^p = (q_{\text{max}}^p - q_{\text{min}}^p) \Phi_{\text{temp}}^e,$$  \hspace{1cm} (15)

where, $\Phi_{\text{temp}}^e$ is the probability of failure in temperature while using vehicle $e$. Therefore, the quality of product $p$ at time $t_{l+1,k}$ using (6) and (14) is given by

$$q_{\text{loss}}^{l+1} = q_{d_k}^p(t_{l+1,k}) - q_{\text{loss}}^p.$$

\hspace{1cm} (16)

**Route cost formulation based on quality forecasting**

The cost of delivering products through the routes $r_k$, $k=1,..., h_{ij}$ follows an exponential pattern with respect to time $t$. Assume that there are $h_{ij}$ paths between node $i$ and $j$, therefore we have cost $c(t)$ for each path $r_k$,

$$c_{l_k}^j(t) = (c_{\text{max}}^j - c_{\text{min}}^j) \left(1 + e^{(t_{l+1} - t)}(e^{t_{l+1} - t})\right)^{-1} + c_{\text{min}}^j,$$

\hspace{1cm} (17)

Subject to

$$c_{\text{max}}^1 > c_{\text{max}}^2 > \ldots > c_{\text{max}}^{h_{ij}},$$

$$c_{\text{min}}^1 > c_{\text{min}}^2 > \ldots > c_{\text{min}}^{h_{ij}},$$

$$s_{l+1}^1 < s_{l+1}^2 < \ldots < s_{l+1}^{h_{ij}},$$

\hspace{1cm} (18a, 18b, 18c)

where $t = (t_{\text{max}} - t_{\text{best}})/k$.

In the simulation model, the quality of products at the next level is forecasted and then a penalty function is formulated to calculate the extra cost if the quality of the product at the next level is less than the forecasted quality. Thus, the cost penalty function at level $l+1$ by passing route $k$ is defined as

$$\chi_{l+1,k}^f = \max \left(0, \frac{\chi_{l+1,k}^{f+1} - \chi_{l+1,k}^{f+1} (c_{\text{max}}^j - c_{\text{min}}^j)}{q_{\text{loss}}^p - q_{\text{loss}}^p} \right),$$

\hspace{1cm} (19)

where $\chi_{l+1,k}^f$ is the forecasted quality by choosing route $k$, $k=1,...,h_{ij}$. The $\chi_{l+1,k}^f$ is calculated based on the real time information in the supply chain. Therefore, the cost of demand $d$ at level $l+1$ after passing route $k$ using Eq. (17) and Eq. (19) is given by

$$\chi_{l+1,k}^d = c_{l+1,k}^d(t_{l+1,k}) + \chi_{l+1,k}^f,$$

\hspace{1cm} (20)

The simulation structure is illustrated in Figure 3. Demands are processed based on online information such as time of the day, available vehicle or transportation system. In the simulation process the demands are delivered through all possible routes and transportation systems, the impact of warning and forecasting modules on each individual demand using Eq. (12) and Eq. (15) and the simulated results, quality and cost of each demand, are calculated using Eq. (16) and Eq. (22), respectively.

The simulation process from node $i$ at level $l$ to node $j$ at level $l + 1$ is summarized as Algorithm 1 (see Table 1). The output of Algorithm 1 are the set of product quality,
and the set of product costs,

$$\mathcal{N}_d^{l+1} = \{z_{d1}^{l+1}, \ldots, z_{dh_{ij}}^{l+1}\}$$

(24)

of the demand $d$ at level $l + 1$ by passing routes $k, k = 1, \ldots, h_{ij}$ from node $i$ to node $j$.

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**Algorithm 1** Simulation process of demand $d$ from level $l$ to $l + 1$.

**Input**: Demand $d$ of product $p$ with current online information $x_{ik} = (q_d^p(\Delta_{ik}), \tau_y, e)$ at node $i$ of level $l$.

**Output**: The simulation results, $\mathcal{M}_d^{l+1}$, quality and cost, $\mathcal{W}_d^{l+1}$ of the demand $d$ at level $l + 1$.

1. Select $r_{ij}^k \in R_{ij}^k$.
2. Calculate transportation time, $t_{ik}^k(\tau_y, e)$, using (8), (9) and (10).
3. (Warning module) Calculate delay time, $\theta_k$, and quality loss, $q_{\text{loss}}$, using (12) and (15).
4. (Forecasting) The forecasted quality, $\chi_{kij}^{l+1}$ is calculated based on online information.
5. The total elapsed time for demand $d$, $t_{ik}^{l+1}$, and the quality of product $p$, $\chi_{kij}^{l+1}$, using (14) and (16).
6. The cost penalty function at level $l + 1$, $c_{ik}^{l+1}$, and the cost, $z_{ik}^{l+1}$ is calculated using (21) and (22).
7. Set $\mathcal{M}_d^{l+1} = \mathcal{M}_d^{l+1} \cup \chi_{kij}^{l+1}$ and $\mathcal{W}_d^{l+1} = \mathcal{W}_d^{l+1} \cup z_{ik}^{l+1}$.
8. If all $r_{ij}^k \in R_{ij}^k$ are visited terminate, otherwise, go to Step 1.

**Table 1. Procedures in Algorithm 1**

Assume that the demand $d$ is at node $i$ of level $l$ with real time information $x_{ik}$. In Step 1, one of the routes between node $i$ at level $l$ and node $j$ at level $l + 1$ is selected. The warning module (delay time and the product quality loss) are calculated in the Step 3. In Step 5, the quality of the product at the next level is calculated with respect to the delay time in the warning module. The cost penalty function and the cost of handling product from level $l$ to level $l + 1$ through the selected route are calculated in Step 6. The quality at the next level and the cost are collected for each route in the model to train the decision support system.

**Real Time Decision Support System**

In this section a real time decision support system based on kernel logistic regression is proposed to optimize the quality of perishable products in the RFID integrated supply chain. The idea is to use the simulation model which is presented in
subsection 3 for training and testing the machine learning model. Therefore, the simulation procedure is set up to train the machine learning model on different scenarios and the result is a trained model minimizes Eq. (1) with maximum product quality.

Assume that we have a set of demand $D = \{\text{Y}_p, \ldots, \text{Y}_n\}$ of product $p$. The simulation model consists of $L$ processing levels and the demand $d$ is at node $i$ of level $l$, where the current online information is $x_d$. In the training phase, by applying Algorithm 1 on demands $d = 1, \ldots, n$, the feasible data tuples, $X_d = (x_d, o)$ are collected, where $o$ is the solution to the following problem:

$$
\sigma = \min_{k=1, \ldots, n} \left\{ x_{d+1}^{l-1} - \max_x \left\{ M_{d+1}^l(x) \right\} + x_{d+1}^l - \min_x \left\{ K_{d+1}^l(x) \right\} \right\},
$$

and $|.|$ is the absolute value of a number. The $o$ is the best decision for demand $d$ at node $i$ of level $l$ if the real time information is $x_d$. These data are collected in the set $\Xi_d$ to be used for training the machine learning model. Thus,

$$
\Xi_d = \left\{ \bigcup_{d=1}^{\tilde{n}} X_d^l \right\},
$$

subject to $\tilde{n}$ number of demands are passing the node $i$ at level $l$, where $\tilde{n} < n$.

### 4.1. Kernel logistic regression formulation

Kernel logistic regression (KLR) as a decision making approach is widely used in the fields of statistical and machine learning. Usually it is assumed that the training data of KLR are an independently and identically distributed sample from an unknown probability distribution. Moreover, KLR yields probabilistic outcomes based on a maximum likelihood argument. Assume that we are given a set of training data $(x_1, y_1), \ldots, (x_n, y_n)$, where $y_i$ is the best output with respect to input $x_i$. The feature mapping $\phi: x \rightarrow V$ in the KLR model is defined as,

$$
\phi(x) = (x_1, \ldots, x_n, x_1^2, x_1 x_2, x_2 x_3, \ldots, x_1^{n-1} x_2, \ldots, x_{n-1} x_n^{n-1}, x_n^n).
$$

The KLR is defined for binary outputs i.e $y \in \{0, 1\}$, which is not suitable to be used in many real-world applications. However, an extension to KLR for those systems with multiple outputs have been proposed by Karsmakers et al. (2007).

Assume that the set of training data $\Xi_d$ for demand $d$ at level $l$ is given. The aim is to find $\Theta_{dk}$ as a solution to the following least squares problem:

$$
\min J(\Theta_{dk}) = \frac{1}{2|\Xi_d|} \sum_{x_d^l \in \Xi_d} \left( H_{\phi_{dk}}(\hat{x}_d^l) - \hat{\sigma} \right)^2, \quad \hat{\sigma} \in \{0, 1\},
$$

where,

$$
\hat{x}_d^l = \phi(x_d^l),
$$

$$
H_{\phi_{dk}}(\hat{x}_d^l) = g\left( (\hat{x}_d^l, \Theta_{dk}^l) \right),
$$

$$
g(w) = (1 + e^{-w})^{-1},
$$

And

$$
\sigma = \begin{cases} 
0 & \sigma \neq k \\
1 & \sigma = k 
\end{cases}
$$

where $x_d, o \in X_d$. Note that problem (27) is nonconvex, therefore the interior point methods are not appropriate to solve such problems. Using (28) one can see that...
\[ P(\sigma = 1 | x^l, \Theta_{ld}) = H_{\Theta_{ld}}(x^l) \text{ and } P(\sigma = 0 | x^l, \Theta_{ld}) = 1 - H_{\Theta_{ld}}(x^l). \]

Thus, the log-likelihood formulation of the problem (27) is

\[
\min J(\Theta_{lk}^l) = -\frac{1}{|\Xi^l|} \sum_{x^l \in \Xi^l} \bar{\sigma} \log H_{\Theta_{lk}^l}(\bar{x}^l) + (1 - \bar{\sigma}) \log \left( 1 - H_{\Theta_{lk}^l}(\bar{x}^l) \right), \quad (31)
\]

where \( k \in \{1, 2, \ldots, h\} \) and \( \sigma \in \{0, 1\} \). Problem (31) is now convex, hence, the conjugate gradient algorithm is employed to solve this problem. The procedures for training the KLR model using the set of input data \( \Xi^l \) at level \( l \) is summarized as Algorithm 2 and presented in Table 2.

**Algorithm 2** Training the KLR model at level \( l \).

**Input:** The set \( \Xi^l \).

**Output:** The set \( \{\Theta_{d1}^l, \Theta_{d2}^l, \ldots, \Theta_{dh}^l\} \).

1. Select, \( k, k \in \{1, \ldots, h\} \).
2. Calculate the set \( A \),
   \[ A = \{ x^l_k \in \Xi^l | \sigma = k, \sigma \in X^l \} \]
3. Using the set \( \Xi^l \), calculate the new set \( \hat{\Xi}^l = \bigcup_{d=1}^{D} X^l_d \) and \( X^l_d = (\hat{x}^l_d, \bar{\sigma}) \),
   \[ \bar{\sigma} = \begin{cases} 1 & X^l_d \in \{A \cap \Xi^l\} \\ 0 & \text{o.w.} \end{cases} \]
4. Find the solution, \( \Theta_{lk}^l \), to the problem (31) using the set \( \hat{\Xi}^l \).
5. If all \( k, k \in \{1, \ldots, h\} \) are visited terminate, otherwise, go to Step 1.

| Table 2. Procedures for Algorithm 2 |

In Step 2 of Algorithm 2, those data with best decision \( \sigma = k \) according to real time information \( x^l_d \) are collected in the set \( A \). In Step 3, the new set \( \hat{\Xi}^l \) with respect to the sets \( \Xi^l \) and \( A \) is calculated to be suitable for solving the problem (31).

**Integration of kernel logistic regression and the simulation model**

The online decision support system is constructed based on the integration of kernel logistic regression and the simulation model. Thus, for each node \( i \) at level \( l \) in the supply chain there is a \( \Theta_{ld} \) that is based on the real time information, \( x^l_d \), of demand \( d \), the best route \( k \) is selected as

\[
\max_{k=1,\ldots,h} P(\sigma = k | x^l_d, \Theta_{lk}^l) = H_{\Theta_{lk}^l}(x^l_d). \quad (32)
\]

The integration of decision support system and the simulation model is illustrated in Figure 4. One can see that the demand \( d \) at node \( i \) of level \( l \) is dispatched to the next level through the route \( k \) using Eq. (32) and the online information \( x^l_d \). Therefore the real time decision support system in the supply chain can be implemented using Algorithm 3 (see Table 3).

Note that before applying Algorithm 3, the procedures representing simulation (Algorithm 1) and training (Algorithm 2) are applied to the system. Assume that the output of Algorithm 1 are given. Then in Step 3 of Algorithm 3, based on the real time information, the next route is calculated using Eq. (32). In Step 4, the warning module and forecasted quality are calculated to estimate the delay time and quality loss. According to quality loss and cost penalty value, the cost of handling and the quality of the product at the next level are calculated in Step 5. These information are collected for all demands in Step 6.
Algorithm 3 The real time decision support system in the supply chain.
Input: The set of demands, \( D = \{Y_1, \ldots, Y_n\} \), of product \( p \).
Output: The set \( \{(S_1, Q_1), \ldots, (S_n, Q_n)\} \) to minimize Eq. (1) and maximize Eq. (2).
1: Select demand \( Y_j^p \in D \) and set \( l = 1 \).
2: Select node \( i \) at level \( l \) which has a route to \( Y_j^p \) destination.
3: Check the online information \( x^l_d \) find the best route \( k \) to the next level using Eq. (32).
4: Calculate the warning module and forecast the quality of demand using Eq. (8) - (15).
5: Calculate the cost and quality of product using Eq. (16) and Eq. (22).
6: Update the sets
   \[
   S_d = S_d \cup z^{l+1}_{dh}, \quad Q_d = Q_d \cup y^{l+1}_{dh}.
   \]
7: If \( l < L \) then \( l = l + 1 \), go to node \( j \) at level \( l \) and go to Step 3, otherwise go to Step 8.
8: If all demand \( Y_j^p \in D \) are visited terminate, otherwise, go to Step 1.

Table 3. Procedures for Algorithm 3

Numerical Results

To demonstrate the efficiency and effectiveness of the proposed model, Algorithms 1 - 3 have been coded under Java platform on a Mac OSX with 10 GB of RAM and 2.7 GHz Core i7 processor. These algorithms are tested on two supply chain simulation models and their comparative results with the same model, which does not employ machine learning techniques, are presented.

First model

The first model consists of three level of processing centers before the retailer's level. There are three companies in the first level, three and four processing centers at the second and third level and five retailers at the final level. The maximum and minimum quality of the product and the best usage time are set as \( q_{\text{max}} = 500, \quad q_{\text{min}} = 50 \) and \( t_{\text{best}} = 200 \), respectively. Five different vehicles are modeled in the system and each day is divided into four time frames. The connection matrix \( X \) of the simulation model using Eq. (3) is as follows,

\[
X = [S_1, S_2, S_3]^T
\]

where,

\[
S_1 = \begin{bmatrix}
2 & 0 & 0 \\
0 & 3 & 0 \\
0 & 0 & 2
\end{bmatrix}, \quad S_2 = \begin{bmatrix}
3 & 2 & 0 & 0 \\
0 & 2 & 2 & 0 \\
0 & 0 & 2 & 2
\end{bmatrix},
\]
The structure of the simulation model is illustrated in Figure 5. Different routes between two nodes in the model are presented as different dashed lines. The comparative results of the simulation model, which is integrated with real time decision support system, and the simulation model without real time decision support system for 500 to 10000 number of demands are presented in Table 4.

![Figure 5. Structure of simulation model 1](image)

From the results, which are presented in the Table 4, one can see that the simulation model with KLR is more efficient and significantly minimizes the total cost of demands with maximum quality at the retailers stage. Note that the values of cost and quality in the Table 4 are calculated using Eq. (1) and Eq. (2) and the maximum quality is desirable. The $E_t$ represents the average of sum of handling time $t_i$ of each demand $i$ from companies to retailers. One can notice that the elapsed time reported by the KLR simulation model is less than $t_{p_{best}}$ in all cases with minimum cost. On the other hand, this value is always greater than $t_{p_{best}}$ and the system is costly, where the simulation model does not support decision making. In comparison with the model without KLR, the average of cost and product quality in all cases by employing the KLR machine learning technique are improved by 15% and 14%, respectively.

The efficiency of the machine learning integrated supply chain can be investigated by considering, for example, the routes, which are highlighted in red color in Figure 5. The results based on real time information $x$ of demands, which are directed to these routes in the KLR model and the model without KLR are presented in Figure 6. One can notice that the surface of the graphs (Figure 6b and Figure 6d) in the KLR model are significantly smoother than those by the model, which does not support decision making (Figure 6a and Figure 6c). This denotes that the demands in the KLR models with similar real time information in their RFID tag system are passed through the same routes.

![Figure 6. Comparative results of simulation models](image)
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Table 4. The simulation results of the model 1 with real time decision support system and the basic model.

Figure 6. The real time information, x, of demands (|D| = 10000) that have been passed through the highlighted routes in Figure 5.

**Second model**

The second simulation model is similar to the first one, but the number of nodes and routes are increased, which is more complex than the first model. In this model, the number of companies are five and the number of processing centers in the second and third level are six and seven. There are nine retailers in the last level. In this model the $q_{\text{max}} = 1500$, $q_{\text{min}} = 500$ and $p_{\text{best}} = 2700$. Five time frames in a day and six categories of vehicles are modeled. The structure of the second simulation model is illustrated in Figure 7. The connection matrix $X$ of the simulation model using Eq. (3) is as follows,
The comparative results of the second simulation model with and without real time decision support system for 1000 to 15000 number of demands are presented in Table 5. From the results, which are presented in the Table 5, one can see that the simulation model with KLR is more efficient in large and complex systems and significantly minimizes the total cost of demands with maximum product quality. The elapsed time obtained by the integration of simulation model and the KLR is less than \( t_{\text{best}} \) in all cases with minimum cost. On the other hand, this value is always greater than \( t_{\text{best}} \) and the system is significantly costly, where the simulation model is not integrated with KLR decision support system. In this model, the average of cost by KLR decision support system is improved by 21% and product quality by 5% compared to the model without KLR.

\[
X = [S_1 \ S_2 \ S_3]^T
\]

where,

\[
S_1 = \begin{bmatrix}
2 & 3 & 0 & 0 & 0 & 0 \\
0 & 2 & 3 & 0 & 0 & 0 \\
0 & 0 & 2 & 2 & 0 & 0 \\
0 & 0 & 0 & 3 & 2 & 0 \\
0 & 0 & 0 & 0 & 3 & 2 \\
\end{bmatrix}, \quad S_2 = \begin{bmatrix}
3 & 2 & 2 & 0 & 0 & 0 \\
0 & 2 & 3 & 2 & 0 & 0 \\
0 & 0 & 2 & 3 & 0 & 0 \\
0 & 0 & 0 & 2 & 2 & 0 \\
0 & 0 & 0 & 0 & 2 & 3 \\
0 & 0 & 0 & 0 & 0 & 2 \\
\end{bmatrix}
\]

and

\[
S_3 = \begin{bmatrix}
3 & 2 & 0 & 0 & 0 & 0 & 0 & 0 \\
2 & 3 & 3 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 3 & 2 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 2 & 2 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 2 & 2 & 3 & 0 \\
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\end{bmatrix}
\]
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Table 5. Simulation results from model 2 with real time decision support system and the basic model.

**Conclusion and Future Work**

Food wastage and health issues resulting from the spoilage of food products in the supply chain, are of great concern to both consumers and manufacturers. In this paper, we developed a real time decision support simulation algorithm based on RFID technology and the integration of machine learning in perishable foods supply chain to optimize the quality of the products at the delivery stage with minimum cost. A simulation algorithm has been formulated that integrates stochastic environmental factors in the food supply chain and RFID real time information. First, the simulation procedure provides the information about the best decision, which minimize the cost and maximize the quality with respect to real time situations. Then, based on these information, at each node of the model a kernel logistic regression (KLR) is adopted to optimize decision makings based on real time information of the further demands at that node. The numerical results on two simulation models demonstrate the efficiency and effectiveness of the proposed algorithm in comparison with the same algorithm, which does not support real time decision making. The results show that the integrated KLR supply chain model improves the cost of handling of demands by 15% in the first model and 21% in the second model. Furthermore, in the first and the second model, the proposed real time food quality control improves the quality of the products by 14% and 5%, respectively.

**References**


