Dynamic supply chain decisions based on networked sensor data: an application in the chilled food retail chain

Dong Li[1], Xiaojun Wang[2*]

[1]*Liverpool Management School, University of Liverpool, Liverpool L69 7ZH, UK*
[2]*Department of Management, University of Bristol, Bristol, BS8 1TN, UK*

*Corresponding author: Department of Management, University of Bristol, 8 Woodland Road, Bristol, BS8 1TN, UK. Email: xiaojun.wang@bristol.ac.uk

Abstract: With large volume of product flows and complex supply chain processes, more data than ever before is being generated and collected in supply chains through various tracking and sensory technologies. The purpose of this study is to show a potential scenario of using a prototype tracking tool that facilitate the utilization of sensor data, which is often unstructured and enormous in nature, to support supply chain decisions. The research investigates the potential benefits of the chilled food chain management innovation through sensor data driven pricing decisions. Data generated and recorded through the sensor network are used to predict the remaining shelf-life of perishable foods. Numerical analysis is conducted to examine the benefit of proposed approach under various operational situations and product features. The research findings demonstrate a way of modelling pricing and potential of performance improvement in chilled food chains to provide a vision of smooth transfer and implementation of the sensor data driven supply chain management. The research finding would encourage firms in the food industry to explore innovation opportunities from big data and develop proper data driven strategies to improve their competitiveness.

Keywords: Sensor data, food supply chain, tracking and monitoring, shelf-life prediction

1. Introduction

The food supply chain is made up of organisations that are involved in the production and distribution of food products. There is a growing concern about the sustainability of the food supply chain (Smith 2008, van der Vorst et al. 2009, Leat and Revoredo-Giha 2013, Li et al. 2014). For instance, millions of tonnes of food produced worldwide is lost or wasted before it reaches consumers (Parfitt et al. 2010, Hodges et al. 2011) while more people are facing food poverty in the current economic environment. Unlike most other commodity flows, food is biological material subject to degradation and its quality can be affected by varied conditions when going through various supply chain processes over time. Therefore, to preserve the food quality and extend their shelf life, food products are often stored in either frozen or chilled condition in the grocery retail industry. The filled food chain, on which this study focuses, is more widely adopted since it usually leads to better quality as compared to the frozen condition.

Despite the wide adoption of temperature controlled supply chain in the food retail sector, one limitation of current practice in the chilled food chain management is that the printed ‘‘sell-by-date’’ does not reflect the real temperature variations when going through different stages of the food supply chain (Blackburn and Scudder 2009; Rong et al. 2011; Wang and Li 2012). In fact, food quality can be compromised if actual conditions deviate from pre-specified conditions. The emergence and extensive implementation of advanced product identification and sensory technologies such as ratio frequency identification technology (RFID) and time-temperature integrator (TTI) provide great opportunities for effective management of chilled food supply chains (Li *et al.* 2006; Kelepouris *et al.* 2007, Sahin et al. 2007, Zhou et al. 2009). For instance, Ruiz-Garcia *et al.* (2008) investigated the potential use of wireless sensor technology for monitoring fruit storage and transport conditions. Their findings show that such devices can be placed in transport vehicles enabling environment sensing together with data processing.

With large volume of product flows and complex supply chain processes, more data than ever before is being generated and collected in the food supply chain through tracking and sensory technologies. There are frequent updates for new locations and movements in distribution centres, transportation units, and retail stores, and not only where it is, but what is close to it, its path to get there, its storage conditions (e.g. temperatures), and location positions that are time sampled from tracking and sensor devices (Ruiz-Garcia et al. 2008; Wang and Li 2012; Waller and Fawcett 2013). The vast amount of data generated enables food companies to make decisions in a timely manner where operations can be more optimized and performance can be improved. However, sensor data is also characterised by volume, variety, and velocity of change in the content, three key differences of so called "big data" (McAfee and Brynjolfsson 2012). Similar to the challenges of big data revolution in other management domains, it is important for supply chain researchers to develop new ways of obtaining value from the sensor data and understand its implications for supply chain decisions. In fact, it will only create value if the 'terabyte' of data continuously generated by sensor devices can be collected, analysed and interpreted. Nevertheless, it is also the difficulty that most food organisations have in contemplating the advantages of big data. According to LaValle et al. (2011) most organizations have more data than they know how to use them effectively. Therefore, several questions are addressed in this article:

(1) How sensor data generated by tracking systems can be used to support supply chain decisions?

(2) What effect does the data-driven business decision have on supply chain performance?

(3) What are the challenges for organisations to implement data-driven decision support systems?

To answer these questions, this research investigates the potential benefits of the chilled food chain management innovation through sensor data driven supply chain decisions. Sensor data generated and recorded through the tracking and sensory technologies are used to predict the remaining product shelf-life. We quantitatively analyses a dynamic pricing strategy for chilled food retailing based on the sensor data driven pricing decision. Such a strategy might transform pricing into a more active manner to dynamically manage demands and reduce the food waste. Such a transformation would not only improve food quality and consumer safety, but also provide a strategic innovation method for marketing, quality management and supply chain optimisation.

The rest of the paper is organised as follows. After a brief review of related literature in Section 2, the sensor data driven dynamic pricing model is presented in Section 3. After that, a chilled food retail chain case is provided to simulate the performance of the proposed model. Numerical analysis is also included in section 4. Finally, concluding marks are presented in section 5.

2. Literature Review

Dynamic pricing, planning and inventory control models for the perishable food have been reported extensively in the literature. To highlight our contributions, we only review the literature that is representative and particularly relevant to our study.

Among the relevant work, one type of the research focuses on maximising business profits through pricing or allocating perishable products in an operational process according to their fixed shelf-life (Bhattacharjee and Ramesh, 2000; Zhao and Zheng, 2000; Lin and Chen, 2003, Van Donselaar et al. 2006). In such research, the product shelf-life is a constraint to a pricing or delivery planning decision. Another type of research focuses on optimisation of inventory control through dynamic pricing or planning (Fujiwara and Perera, 1993, Chakrabarty, *et al.*, 1998, Chatwin 2000). In the research, the stock level depletes over time due to the product deterioration and demands. The product deterioration in the optimal inventory control models implies full disposal of the unusable products, i.e. the loss in quantity of available products instead of their shelf lives. More relevant research can be found in a review of literature carried out by Elmaghraby and Keskinocak (2003) that examined the current practices in dynamic pricing in inventory. Moreover, some research employs a concept, product value, to represent product quality and utility attributes based on which a decision on pricing or operational planning can be made (Kopalle *et al*. 1996, Blackburn and Scudder 2009). Kopalle *et al*. (1996) presented a dynamic pricing model incorporating the relationship between reference price and expected quality. Blackburn and Scudder (2009) developed an optimal ordering model that minimises the lost value of the perishable food during the delivery process. In the above research, questions still remain about how to assess the impact of product quality deterioration on the business revenue in a situation that the products are still acceptable or usable. In our case of perishable food management, the question would be how to assess the food shelf-life and its impact on the retailers' revenue. With such a challenge, the sensor data through the tracking and sensory technologies would be a key enabler.

Another stream of relevant research centres on inventory and pricing decisions on perishable food product based on auto identification and sensory technologies. Li et al. (2006) developed an automatic tracking enabled business model that employs a dynamic pricing approach to optimise retail chain profits. RFID technology was discussed and tracking information from the technology is used to optimise the retail price. The research showed that the real-time product tracking information would improve the business performance. The research did not discuss details about what form of the tracking information is used in the model, and how the tracking information is quantitatively related to the model parameters. Rong et al. (2011) developed a methodology to model food quality degradation which is integrated in a mixed-integer linear programming model used for production and distribution planning. In their study, food quality changes are traced through the entire supply chain network under the temperature-controlled logistics environment for planning logistics distribution operations. Wang and Li (2012) proposed a pricing approach based on dynamically identified food shelf-life information captured through innovated tracking and monitoring technologies. Different to this paper, their research focuses on discrete discount pricing strategy instead of dynamic pricing strategies. Complementary to above studies, Herbon et al. (2014) analysed customers' utility, cost of the technology, penalty cost, and other parameters in the perishable inventory management using time-temperature indicators linked to automatic detecting devices.

In our research, the proposed pricing strategy will focus on utilising the sensor data predicted food shelf-life information. In depth analysis of the relationship between the perceived deterioration information and retail operations performance is conducted. We adopt the collaborative planning strategy, and investigate the ways in which the sensor data adds values to the innovation of the chilled food retail chain management.

3. Sensor data driven dynamic pricing model

To highlight the investigation on the sensor data based dynamic pricing model and describe the potential benefits of the proposed strategy, two scenarios are considered: the present 'conventional scenario' S_1 and the proposed 'sensor data driven scenario' S_2. With scenario S_1, before a selling period the planned demand is estimated based on the pre-specified food shelf-life and the agreed price. During a selling period, the retail price remains unchanged, and the remaining product shelf-life decreases over time as perceived by consumers against a given expiration date. As the demand is assumed determinative and the expiration date (or deterioration rate) is known, exceptional promotions for nearly perished food is not considered in this scenario. With scenario S_2, at the distribution centres, the orders and sales price agreed before the beginning of the selling period may be collaboratively adjusted according to dynamically identified product time-temperature profile (TTP) through the sensor data that tracks the supply chain operation conditions. During the selling period, both of the food deterioration rate and the sales price are uncertain due to the uncertain product quality control and weather conditions. The price is dynamically set through a marking down rate based on the identified deterioration rate in real-time by the sensor data. The parameters and variables for model development are shown as the following notations in Table 1.

Table 1 Parameters and variables

Notation	Descriptions
ED_c ,ED_s	The expected demand for a selling period (0, T) in scenarios S_1 and S_2 respectively;
P_c, P_s	The unit prices set at the beginning of a selling period (0, T) in scenarios S_1 and S_2 respectively, $P_c > 0$;
P_l	The maximum price at which consumer would stop buying, $0<P_s<P_l$;
V_c	The product value agreed in a contract in scenarios S_1, $0 < V_c < 100$ %. The value of V_c is dependent on the product shelf-life features and is proportional to remaining product shelf-life derived from a given expiration date;
V_s	The identified food value in scenarios S_2. It is proportional to the dynamically identified remaining product shelf-life;
V_e	The minimum value with which consumers would stop purchasing the product;
V_t	The present product value at time t.
V_0	The original product value when t = 0.
V_r	The product value at the beginning of a retail selling process;

V_f	The product value at the beginning of the supply chain;
λ_c	The nonnegative deterioration rate of product value based on a given expiration date scenarios S_1;
λ_s	The nonnegative average deterioration rate of product value in a selling period in scenarios S_2. It can be determined by the food kinetic modelling approach;
θ	The nonnegative average marking-down rate of a price in a selling period. It is a decision variable that will be determined through the optimised pricing decision;
$f(D_t)$	Demand function or unit demand at a time e.g. an hour or a day the food kinetic modelling approach;
α and β	The nonnegative coefficients representing the demand sensitivity to a product price, and the demand sensitivity to the identified shelf-life (or value) respectively, $\alpha, \beta > 0$;
K	The demand parameter (dependent on product utility features) (Lau and Lau, 2002), $K > 0$;
T_c	The length of a selling period. The selling period T_c is estimated based on the agreed product value V_c. After T_c, the product quality is assumed unacceptable to consumers, $T_c = (1 - \frac{V_e}{V_c}) \cdot \frac{1}{\lambda_c}$;
T_e	The time at which the perceived product value reaches V_e from the given initial product value V_s, $V_s\, e^{-\lambda_s t} \geq V_e$; $T_e = \{t \mid e^{-\lambda_s t} = \frac{V_e}{V_s}\}$; $t \sim [0, T_e]$;
k_A	The rate constant in the food kinetic modelling approach;
E_A	The energy of activation for the reaction that controls quality loss;
R_{gas}	The ideal gas constant in the food kinetic modelling approach;
$T\,(t)$	An inverse absolute temperature at some reference temperature $T_{ref.}$;
C_p	The re-planning penalty cost for an unplanned replenishment from a distributor to avoid loss of sales when the actual demand is greater than the planned demand.
C_d	The penalty cost for disposal when the actual demand is less than the planned demand.
C_o	The unit operations cost.

3.1 A sensor network enabling application of big data approach to supply chain management

Short shelf-life food products are stored and delivered in chilled supply chains, temperature is therefore a main environment parameter for chilled food quality control. In the chilled chains, sensors at different business partners generate massive data recording time and temperature with which food products are stored and delivered. While the sensors are connected across supply chains as sensor networks, the massive data about time and temperature can be shared by different partners to dynamically manage storage, packaging, delivery and selling according to the data collected from the sensor networks. A sensor network infrastructure of a chilled chain can be illustrated as in figure 1. To support the research reported on dynamic food retail pricing in this paper, a prototype for imitating the sensor networking scenario and food quality monitoring as Big Data application has been developed (Tao et al., 2012) as seen in figure 2. The sensor data are collected and analysed in the system which employing RFID and temperature sensors. The system keeps tracking food products' time-temperature profile and abstracting key data in product identity, product batch/package identity, location, period of time at each location, temperature to be transferred into a database. The web based interface not only presents product tracking information, but also statistical results to demonstrating impacts of the chilled chain environment on product quality deterioration with decision support function. The system demonstrates aggregate time when the temperature is beyond required range at each stage of a supply chain, estimated impact of this improper quality control on the foods' shelf-life, e.g. percentage of shelf-life has been reduced, risk of spoilage before the foods are sold. The information forms the basis of dynamically managing the chilled food chain. The dynamic pricing modelling proposed in this research is one of the potential innovation opportunities facilitated by the data analytics approach.

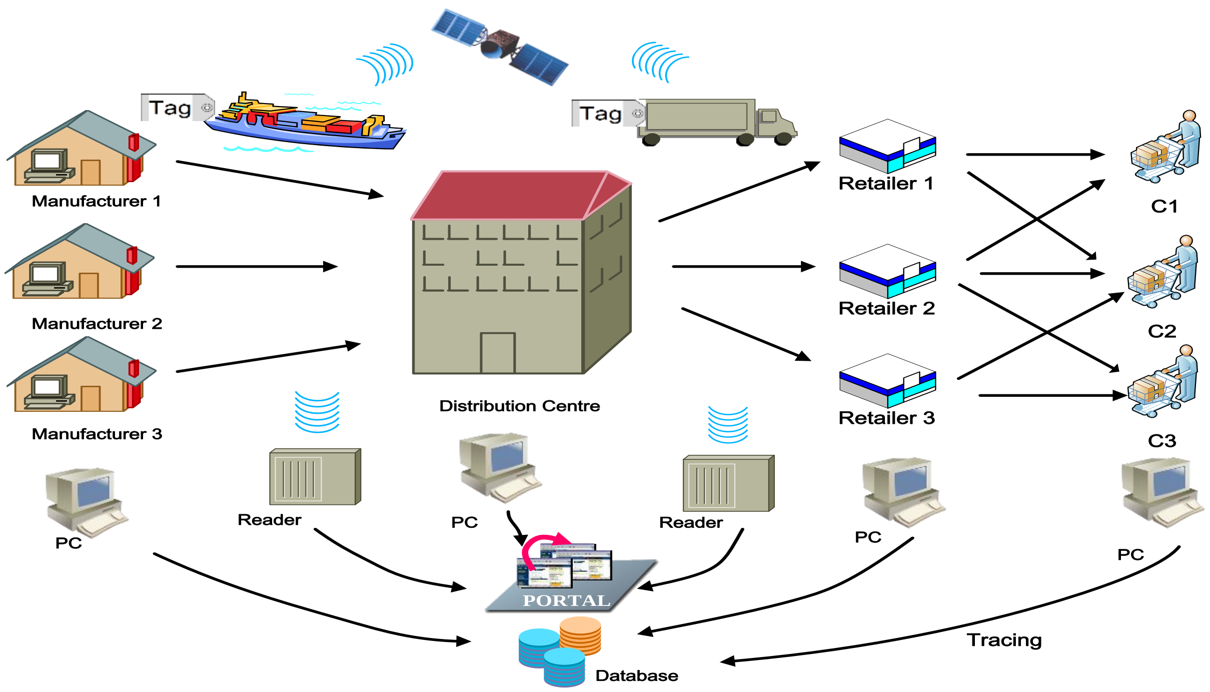

Figure 1. Sensor network in chilled food supply chains (Source: Tao, et al. 2012)

Figure 2. Senor network enabled food quality monitoring in supply chains. (Source: Tao, et al. 2012)

3.2 A sensor data enabled product value tracing model

The data generated through sensor network is mainly for the tracking and quality control purpose. However, it provides a potential solution to detect "actual" product quality deterioration in real time for large volume product flows and complex supply chain processes. As food products go through different supply chain stages, extracting the relevant time and temperature information from the dataset where the sensor data is recorded allows the evaluation of quality in discrete or continuous time as a result of the temperature history experienced by the product. It means that the quality change in food products can be estimated through the extracted time temperature data. In order to reduce the complexity of the model we are proposing, a temperature dependent quality deterioration rate (λ) is introduced, where:

$$\lambda = k_A \cdot e^{-\lfloor E_A / R_{gas} T(t) \rfloor} \tag{1}$$

Here, as defined in Table 1, k_A is the rate constant; E_A is the energy of activation for the reaction that controls quality loss; R_{gas} is the ideal gas constant; $T(t)$ is an inverse absolute temperature at some reference temperature $T_{ref.}$, is defined as:

$$T(t) = \left| 1/T_{ref} - 1/T \right| . \tag{2}$$

According to Taoukis and Labuza (1989) and Fu and Labuza (1993), the change of the quality during a known variable temperature exposure $T(t)$ can be calculated following a linear to exponential function. Through the sensor network, the continuous information of time and temperature to which food products are exposed can be provided for modelling food quality degradation. With the available discrete values of temperature with respect to time, the quality deterioration rate λ can be calculated by analytically solving the integral for the simple $T(t)$ functions giving the known kinetic parameters k_A and E_A. Furthermore, we adopt a form of the exponential functions (see Equ.2) and use the term “product value” to represent the remaining product shelf-life (Blackburn and Scudder, 2009). The function consists of a time variable and a value deterioration parameter λ that is a constant in the time period $T \sim [0, t]$. The value of V is positively related to the remaining product shelf-life.

$$V_t = V_0 \cdot e^{-\lambda \cdot T} \tag{3}$$

When products enter a succeeding supply chain process (e.g. unloaded at a warehouse or placed in a queue of a packaging line), a new time period will start, and then the deterioration parameter may change if the temperature has a considerable deviation. This tracing process can be quantitatively modelled through aggregating the food deterioration processes in each time period. It can be therefore described as a chain of individual deterioration processes of the chilled food as:

$$V_L = V_{L-1} \cdot e^{-\sum_{i=1}^{M} \lambda_i \cdot T_i} \tag{4}$$

V_L is the food value identified at beginning of the supply chain process L (e.g. at a distribution centre), and V_{L-1} is the food value identified at beginning of the process L-1. Where the deterioration parameter λ remains unchanged throughout the process L-1, we have M = 1. For the purpose of collaborative decision making in our research case, we extend the tracing model to the whole chilled food chain process (before the food enters retail stores) through aggregating all preceding supply chain processes as:

$$V_r = V_f \cdot e^{-\sum_{i=1}^{N} \lambda_i \cdot T_i} \tag{5}$$

Here, V_r is the product value at the beginning of a retail selling process. V_f is the product value at the beginning of the supply chain. N is the overall number of tracing processes.

3.3 Price-dependent demand modelling

In our research, to describe the response of consumer demands to price changes, we adopt a price-dependent linear demand description (see Equ.5) that has been widely used in the economic and operations research literature (Chakrabarty, *et al.*, 1998; Lau and Lau, 2002; Abad and Aggarwal, 2005; Chen and Wang 2015).

$$\mu = a - b \cdot P \tag{6}$$

a (scale parameter) and *b* (parameter of demand sensitivity to price) are nonnegative coefficients. μ and P are the mean of a demand and the price respectively (Abad and Aggarwal, 2005). Both of the price P and the perceived product value that represents the remaining food shelf-life are taken into account as influential factors – a price increase normally leads to a demand decrease, and the product shelf-life or value has a positive effect on demands. In this research, the product value or shelf-life is included in the determinate demand function as an important attribute of the chilled food and the retail operations. Therefore, the demand function in Equ.6 is extended to combine the effects from the two driving factors, product price and value, as described in Equ.7 and Equ.9.

Furthermore, the demand of food products is also influenced by other factors such as competitors' price and seasonal demand (Binkly and Connor 1988; MacDonald 2000). Since this research focuses on investigating on the impact of the massive dynamic tracking data driven pricing decisions on retailing performance, we assume that the business should have already considered the competitive environment when setting up the initial price with targeted/predicted demand. For the seasonal demand factor, the chilled food shelf-life is short and the modelling is applied to limited time horizon. The seasonal demand fluctuation would not be a significant factor to the demand fluctuation in the short time horizon as we define the demand as average demand in that season.

With scenario S_1, as the given expiration date is fixed in a selling period, the deterioration rate can be derived straightforward because the product shelf-life decreases linearly (see Equ.7). The fixed price and the remaining shelf-life against the expiration date (as the consumer perceived "product value") generate a combined impact on the demand. With scenario S_2, the changing price and accurately identified food shelf-life variations generate an aggregate impact on the demand. As the deterioration rate and the marking-down rate are unknown in a selling period (dependent on environment changes), we use *average deterioration rate* and *marking-down rate* to represent the dynamic values in the model of S_2. This would be acceptable as the analysis is focused on comparing the overall performance of the two scenarios, instead of calculating the profit from S_2.

3.3.1. Demand modelling with scenario S_1

As defined for scenario S_1, the product deteriorates linearly against a given expiration date. We therefore extend the model in Equ.5 into a determinate demand function in Equ.6.

$$f_c(D_t) = K - \alpha P_c + \beta V_c (1 - \lambda_c t) \geq 0. \qquad ED_c = \int_0^{T_C} f_c(D_t)\, dt \tag{7}$$

From Equ.5, we have: $$ED_c = \begin{cases} (K - \alpha P_c + \beta V_c) \cdot T_c - \dfrac{\beta V_c}{2} \cdot \lambda_c T_c^2 \geq 0 & 0 \leq T < T_c \\ 0 & T \geq T_c \end{cases} \tag{8}$$

3.3.2. Demand modelling with Scenario S_2

Due to the food deterioration and dynamic pricing, the demand is defined as a function of time as an extension from the traditional demand model in Equ.6. The demand function (see Equ.9) describes the unit demand at time t. The expected demand ED_s in Equ.10 is an integral of the unit demand function.

$$f_S(D_t) = K - \alpha P_S e^{-\theta t} + \beta V_S e^{-\lambda_S t} \geq 0. \tag{9}$$

$$ED_s = \int_0^{T_e} f_s(D_t)\, dt \tag{10}$$

Here, $P_s e^{-\theta t}$ is the dynamically set retail price at time t during the selling period according to the sensor data.

From Equ.8, we have: $$0 < P_s e^{-\theta t} \leq \frac{1}{\alpha}(K + \beta \cdot V_s \cdot e^{-\lambda_s \cdot t}) \tag{11}$$

With the constraint of the product value of V_s, the nonnegative demand function in Equ.7 can be further transformed into Equ.12.

$$f_s(D_t) = \begin{cases} K - \alpha P_s e^{-\theta t} + \beta V_s e^{-\lambda_s t} \geq 0, & when\ t \leq T_e\ ; \\ 0 & when\ t > T_e\ . \end{cases} \tag{12}$$

From Equ.7 and Equ.8, we have:

$$ED_s = K \cdot T_e - \frac{\alpha P_s}{\theta}(1 - e^{-\theta T_e}) + \frac{\beta V_s}{\lambda_s}(1 - e^{-\lambda_s T_e}), \tag{13}$$

Through Equ.13, an expected demand can be calculated based on the dynamically set price P_s and the marking-down rate θ of the pricing policy at the beginning of a selling period by accurate TTP.

3.4 Optimal pricing

The proposed pricing strategy aims to maximise the expected profit (*EP*) of the retailers based on given product shelf-life and demand features of the chilled food. The sales revenue and operational costs are taken into account in the optimisation. We focus on investigation of the benefit of the dynamic pricing strategy in scenario S_2 against scenario S_1that uses a fixed optimal price without using sensor data.

3.4.1 Optimal pricing with scenario S_1

The profit of a retailer can be derived by its sales revenue and the operational cost. From Equ.7, we have the expected profit (EP_c) in Equ.14.

$$EP_c = (P_c - C_o) \cdot ED_c = (P_c - C_0) \cdot [(K - \alpha P_c + \beta V_c) \cdot T_c - \frac{\beta V_c \lambda_c T_c^2}{2}], \tag{14}$$

To optimise the expected profit, we have:

$$\frac{\partial EP_c}{\partial P_c} = (K - 2\alpha P_c + \beta V_c + \alpha \cdot C_o) \cdot T_c - \frac{1}{2}\beta V_c \lambda_c T_c^2; \quad \frac{\partial^2 EP_c}{\partial^2 P_c} = -2\alpha T_c < 0$$

The derivative above confirms the convexity of the profit function and the optimal solution P_c^* is obtained as*:*

$$P_c^* = \frac{1}{2\alpha T_c}[(K + \beta V_c + \alpha \cdot C_o) \cdot T_c - \frac{1}{2}\beta V_c \lambda_c T_c^2] \tag{15}$$

Through Equ.15, the optimal price in the agreement can be determined based on the agreed product value V_c, the cost and the demand sensitivity features. Consequently, the demand based on the optimal price can be estimated through Equ.7. The estimated demand underlies the planned delivery or retail orders.

3.4.2 Optimal pricing with scenario S_2

With dynamically identified product value, the expected profit (EP_s) can be generated through the time-dependent demand function (refer to Equ.12), the operational cost and the dynamic price.

$$EP_s = \int_0^{T_e} f(D_t)\ (P_s e^{-\theta t} - C_o)\, dt\, ; \tag{16}$$

From Equ.13, we have the expected profit EP_s in Equ.17.

$$EP_s = \frac{\alpha}{2\theta} P_s^2 (e^{-2\theta T_e} - 1) + [\frac{K}{\theta}(1 - e^{-\theta T_e}) + \frac{\alpha \cdot C_o}{\theta}(1 - e^{-\theta T_e}) + \frac{\beta V_s}{\lambda_s + \theta}(1 - e^{-(\lambda_s + \theta) T_e})] \cdot P_s + \frac{C_o}{\lambda_s} \beta V_s (e^{-\lambda_s T_e} - 1) - C_o \cdot K \cdot T_e \quad (17)$$

To optimise the price P_s, the first and second order derivatives with respect to price is calculated:

$$\frac{\partial EP_s}{\partial P_s} = \frac{\alpha}{\theta} (e^{-2\theta T_e} - 1) P_s + \frac{1}{\theta} (1 - e^{-\theta T_e})(K + \alpha \cdot C_o) + \frac{\beta V_s}{\lambda_s + \theta} (1 - e^{-(\lambda_s + \theta) T_e})$$

$$\frac{\partial^2 EP}{\partial^2 P_s} = \frac{\alpha}{\theta}(e^{-2\theta T_e} - 1) < 0 \quad (18)$$

From Equ.18, the convexity of the profit function is proved. Then, we have the optimal price:

$$P_s^* = [\frac{1}{\theta}(1 - e^{-\theta T_e})(K + \alpha \cdot C_o) + \frac{\beta V_s}{(\lambda_s + \theta)} (1 - e^{-(\lambda_s + \theta) T_e})] \frac{\theta}{\alpha} (1 - e^{-2\theta T_e})^{-1} \quad (19)$$

Through Equ.19, the optimal price P_s^* can be calculated based on given operational cost, demand features, the price 'marking-down rate' θ, and the dynamically captured product value V_s through the accurate food TTPs and the length of time T_e. The estimated demand can then be dynamically adjusted.

3.5 Maximising retail chain profits

To maximise the retailer's profit, an aggregated profit function is built to assess the overall performance of the retail network. Based on Equ.14, with a given optimal price P_c^* and accordingly the expected demand ED_c^*, the planned overall profit P_{S1}^* of the retail stores with the S_1 can be described in Equ.20.

$$EP_{c,i}^* = (P_{c,i}^* - C_{o,i}) \cdot ED_{c,i}^*; \quad ED_{c,i}^* = (P_{c,i}^* - C_{0,i}) \cdot [(K - \alpha P_c + \beta V_c) \cdot T_c - \frac{\beta V_c}{2} \cdot \lambda_c T_c^2]; \quad P_{S1}^* = \sum_i EP_{c,i}^* \quad (20)$$

In a selling period, the actual demand in scenario one is probably different from the planned value ED_c as the real product value is V_s instead of V_c. The difference in product values represents different product shelf-life. This implies that the products will be sold against T_e instead of T_c. T_e may be either longer or shorter than T_c. The actual expected demand in the selling period can be therefore described in Equ.21 (T_c is replaced with T_e).

$$ED_{c,i}^{'} = (P_{c,i}^* - C_{0,i}) \cdot [(K - \alpha P_c + \beta V_c) \cdot T_e - \frac{\beta V_c}{2} \cdot \lambda_c T_e^2] \quad (21)$$

The difference between the planned demand ED_c^* and the actual demand $ED_c^{'}$ will lead to extra cost to the retailers, i.e. the disposal cost due to perished food or cost of unplanned replenishment. We use $ED_c^{'}$ to estimate the actual profit $EP_c^{'}$ as described in Equ.22.

$$EP_{c,i}^{'} = (P_{c,i}^* - C_{o,i}) \cdot ED_{c,i}^{'} - (ED_{c,i}^{'} - ED_{c,i}^*)^+ \cdot C_{p,i} - (ED_{c,i}^{'} - ED_{c,i}^*)^- \cdot C_{d,i}; \qquad P_{S1}^{'} = \sum_i EP_{c,i}^{'} \quad (22)$$

$C_{d,i}$ is the penalty cost for disposal when the actual demand is less than the planned demand. $C_{p,i}$ is the re-planning penalty cost for an unplanned replenishment from a distributor to avoid loss of sales when the actual demand is greater than the planned demand. An actual aggregated profit $P_{S1}^{'}$ for the retail stores can be calculated through Equ.22 and will be used for the comparative analysis of the actual benefits from the dynamic pricing strategy.

With scenario S_2, products are dynamically allocated to the retailers according to the identified product shelf-life and the estimated demand. This dynamic re-arrangement leads to variations against the planned deliveries in the agreement. An extra cost C_{pi} would be incurred in warehousing, delivery and stock control, etc. Therefore, we propose a single product model (see Equ.23) that optimise the overall profit P_{S2} of the retail network, and deduct the penalty cost from the revenue at each retail store. The constraints of the optimisation problem are described in Equ.26. For optimal price, P_s^* and P_c^*, refer to Equ.15 and Equ.19.

Objective: Max $$P_{S2} = \sum_i [EP_{s,i} - (ED_{s,i} - ED_{c,i}) C_{pi}] \quad (23)$$

Subject to:

$$EP_{s,i} = \int_0^{T_e} f_i(D_t)\,(P^*_{s,i}\, e^{-\theta_i t_i} - C_{o,i})\,dt \; ; \quad ED_{s,i} = \int_0^{T_e} f_i(D_t)\,dt \quad \text{(Refer to Equ.12 and Equ.16)}$$

$$f_i(D_t) = \begin{cases} K_i - \alpha P^*_{s,i}\, e^{-\theta_i t_i} + \beta V_s\, e^{-\lambda_{si} t_i} \ge 0, & when\ t_i \le T_{e,i}\ ; \\ 0 & when\ t_i > T_{e,i}\ . \end{cases} \quad V_s = V_r = V_f \cdot e^{-\sum_{j=1}^{N} \lambda_{sj} \cdot T_j} \quad (24)$$

$$ED_{c,i} = (P^*_{c,i} - C_{0,i}) \cdot [(K - \alpha P_c + \beta V_c) \cdot T_c - \frac{\beta V_c}{2} \cdot \lambda_c T_c^2] \quad ; \quad 0 < P_s\, e^{-\theta t} \le \frac{1}{\alpha}(K + \beta \cdot V_s \cdot e^{-\lambda_s \cdot t})\,;$$

$$T_{e,i} = \frac{1}{\lambda_{si}} \ln \frac{V_s}{V_e}; \quad 0 \le P_{s,i} = P^*_{s,i} \le P_{l,i}\ ; \ 0 \le P_{c,i} = P^*_{c,i} \le P_{l,i}\,;$$

As described in Equ.23, to determine the optimal price, the parameter θ needs to be specified. The decision variable decides how the price is reduced over time in a selling period. Due to the difficulty of analytically describing the optimum value of θ, the marking down rate θ is only numerically simulated in this research.

4. Numerical Analysis

A case of UK supermarket chain has been investigated in the research. Two distribution centres supply products to twenty retail stores. Four local retail stores at a city are chosen for this case study, and a fresh vegetable product is used as an example. Most vegetable products are maintained in a temperature controlled supply chain using a temperature of around +2 ◦C to +5 ◦C. Temperature controlled vehicles are used to deliver products from producers to the distribution depot and from the depot to retail stores. In retail stores, most of vegetable products are placed in temperature controlled refrigerant shelves and the storage temperature is monitored by both sensor devices on product shelves and a central controlled senor network. Such a chilled food chain is increasingly used in the UK grocery retail industry. Based on our food supply chain case, numerical simulations are conducted with some sample data (see Table 2). Parameters in the model are simulated with various values in the analysis to investigate their impacts on the model performance. To verify and demonstrate expected benefits of the sensor data enabled dynamic pricing strategy, we compare profits generated by scenario S_1 and scenario S_2. $P_{S2\text{-}S1}$ is used as an indicator to describe the difference between the profits from S_1 and S_2.

Table 2. Sample data in the simulation

	C_p £/Box	C_d £/Box	C_o £/Box	K Box/Day
Retailer store1	0.1	0.6	0.05	70
Retailer store2				80
Retailer store3				75
Retailer stroe4				90

The numerical simulation is implemented by Microsoft Excel spreadsheet. We investigate the strategy performance through four indexes – "Product Value Difference" V_c-V_s, "Demand Sensitivity Ratio" β/α, "Pricing-Perishing Ratio" θ/λ_s and "Deterioration Difference" $(\lambda_c$-$\lambda_s)/\lambda_s$. The product value difference (*PVD*) indicates the difference between the dynamically identified product value and the planned value agreed in a contract. The Demand Sensitivity Ratio (*DSR*) shows the level of relative difference between consumer sensitivities towards price and product shelf-life. The Pricing-Perishing Ratio (*PPR*) (θ/λ_s) indicates the level of relative difference between a decision or a response of the price marking-down rate θ and a perceived product deterioration rate λ_s. Deterioration Difference Index (*DDI*) indicates the deviation of dynamically identified product deterioration rate (λ_s) from the expected deterioration rate (λ_c) according to the predefined product expiration date. During the analysis, all constrains given in the model are continuously satisfied when changing values of the four indexes. Through the investigation, we attempt to identify impacts of the key parameters on the model performance, and verify the benefits of the proposed sensor data driven pricing strategy under different situations.

4.1 Analysis with the Product Value Difference and the Demand Sensitivity Ratio

We expect that, with accurate product shelf-life features, sales can be promoted more properly to match the actual product quality through dynamic pricing. This consequently reduces costs of over stock, shortage or disposal. This implies that the difference in the observed product shelf between the two scenarios might be proportional to the benefit that can be attained through the proposed strategy. Figure 3 describes the simulation result. The following assumptions hold for this simulation:

- The deterioration rates of the chilled food λ_c, λ_s in the two scenarios are same.
- The price marking-down rate θ and the deterioration rate λ_s are fixed, and the ratio of the two parameters is 0.1 as described in Figure 3.

In figure 3, the benefit indicator $P_{S2\text{-}S1}$ is demonstrated against different *PVD*s with various demand sensitivity ratios (*DSR*). The simulation shows that, when the product value V_s is identified different from the planned value V_c, the proposed strategy performs better than S_1. Moreover, the benefit increases as the identified *PVD* increases. The simulation also interestingly demonstrates that the proposed strategy generates more benefits for more quality-sensitive products (with greater β/α) than more price-sensitive products, when V_c is over-estimated ($V_s<V_c$) in S_1. On the other hand, more price-sensitive products (with smaller β/α) gain more benefits from the proposed strategy, when V_c is under-estimated ($V_s>V_c$). Therefore, the strategy performance would not be significantly affected by the *DSR*. It can be seen that the curves tend to merge on the left hand side in figure 3.

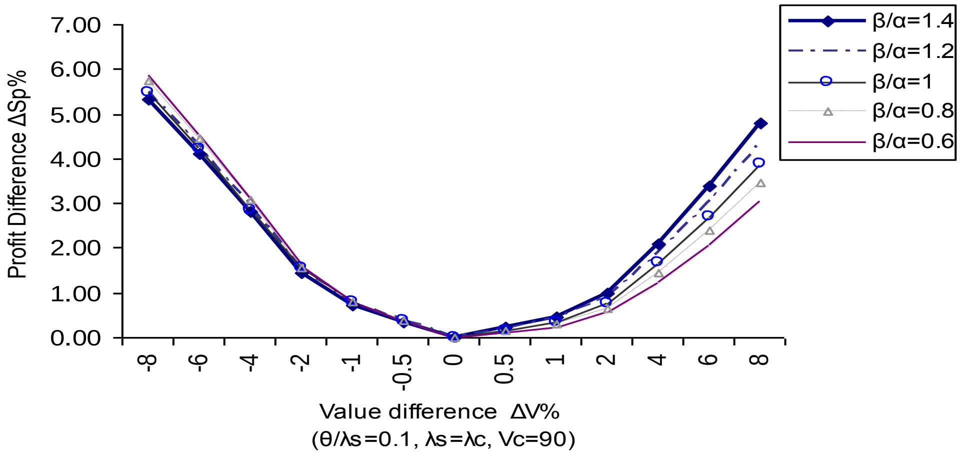

Figure 3. Performance with varying price-value sensitivity ratio (*β/α*).

4.2 Analysis of the Pricing-Perishing Ratio

The price marking down is to retain a satisfactory demand when the changing product shelf-life makes an impact on the chilled food demand. We therefore expect that, with a given deterioration rate λ_s, the marking-down rate would affect the price-dependent demand, and consequently the benefit from the strategy. Furthermore, we expect that certain price marking-down rates would exist to maximise or approximately maximise $P_{S2\text{-}S1}$. Through analysing the impact of *PPR*, we demonstrate the simulation result in figure 4. The following assumptions hold for this simulation:

- The same assumption for the deterioration rates λ_c, λ_s is held as described in section 4.1.
- The demand has equal sensitivities ($\alpha = \beta$) to variations of the product price and the shelf-life feature.

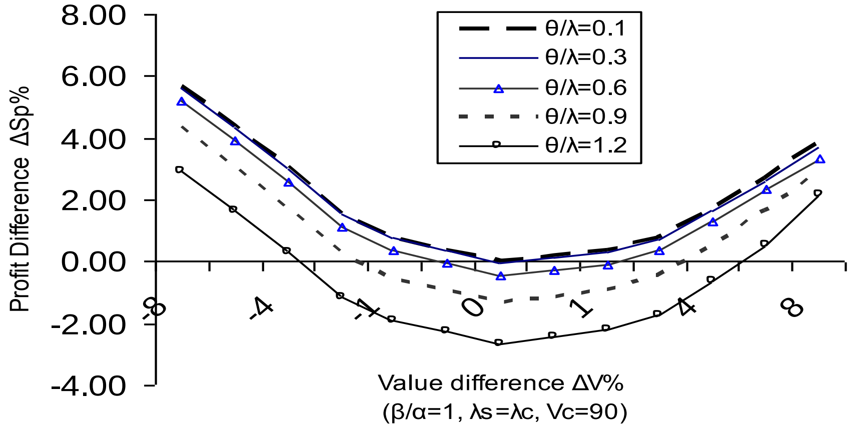

Figure 4. Performance with varying markdown-deterioration ratio (θ/λ_s).

In the numerical analysis, the deterioration rate λ_s is fixed at 0.05 to hold the first assumption above. With the cost structure and the given λ_s, an optimal value for the *PPR* index θ/λ_s is found around 0.1 (θ = 0.005) with the Newton Search method of nonlinear programming in Microsoft Excel Solver. Further simulation is performed with selected values of θ that changes the *PPR* from 0.1 to 1.2 discretely as described in figure 4. The simulation shows that, $P_{S2\text{-}S1}$ increases as the *PRR* index decreases (i.e. the price marking-down rate θ decreases). When *PPR* reaches the value 0.1, $P_{S2\text{-}S1}$ stops increasing. As described in figure 5 (with a given

PVD = 2%), the $P_{S2\text{-}S1}$ starts to decrease again after *PPR* is less than 0.1. The simulation also shows that the $P_{S1\text{-}S2}$ indicator keeps decreasing as the *PPR* index θ/λ_s increases above the value 1.2. The same conclusion holds when the deterioration rate λ_s varies in [0.001, 0.1]. This confirms the optimal point for the *PRR* index. The simulation stops when the dynamically set price reaches zero (when *PPR* is greater than 12), and the $P_{S2\text{-}S1}$ stops decreasing (when *PPR* is less than 0.002).

The impact of *PRR* on the strategy performance described in figure 4 implies that the proposed strategy would not perform better than S_1 with a large price marking-down rate when the actual product shelf-life feature is not significantly different from the planned value V_c. When the marking-down rate is too high (*PRR* is greater than 2 in this case), S_2 would not generate benefits against S_1 with any *PVD*s. The simulation result in figures 4 and 5 also shows that the pricing policy holds some flexibility in the marking-down rate around the optimal point. Slight changes in the *PRR* around the optimal point would not significantly affect the benefit generated by S_2. When the perceived actual product shelf-life feature is same as the per-specified value in contract, there would be no benefit generated from the proposed strategy.

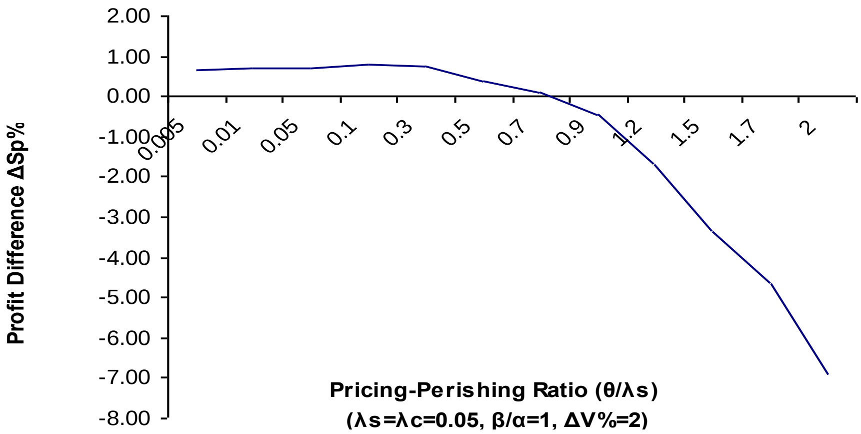

Figure 5. Performance against the markdown-deterioration ratio (θ/λ_s) with a given *PVD*.

4.3 Analysis of the Deterioration Difference

In previous numerical experiments, we have an assumption that the deterioration rates of the chilled food λ_c, λ_s in the two scenarios are same. Practically, it is likely that the product deterioration rate captured by the sensor data is different from what is perceived by consumers according to an expiration date. This discrepancy would affect the demand estimate and the length of the selling period during which the chilled food maintains acceptable quality to consumers. As discussed in section 3, both of the over-estimated and under-estimated demands will lead to costs to the business (disposal or shortage). We analyse the impact of this discrepancy through an index, Deterioration Difference Index (*DDI*), i.e. $(\lambda_c\text{-}\lambda_s)/\lambda_s$. The variations of the index and resultant changes in $P_{S2\text{-}S1}$ are simulated. Figure 6 describes the numerical analysis result. The following assumptions hold for this simulation:

- The same assumption for the demand sensitivities is held ($\alpha = \beta$) as in section 4.2.
- The marking-down rate θ and the deterioration rate λ_s are fixed, and the ratio of the two parameters is 0.1.

The simulation result shows that $P_{S2\text{-}S1}$ curves move downwards from left to right. $P_{S2\text{-}S1}$ is always positive when *DDI* is negative. This indicates that, when the actual deterioration rate identified by sensor data (λ_s) is greater than the rate λ_c derived from the expiration date, the proposed strategy always perform better. This result may be explained by the fact that the under-estimated deterioration rate in scenario one implies overestimated product shelf-life and demands. Consequently, it causes disposal cost. When the dynamically identified V_s is much greater than the estimated V_c, even more revenue can be generated by the proposed strategy as depicted on the most left hand part of figure 6. When the accurately identified rate λ_s is smaller than the pre-specified rate λ_c, the proposed strategy does not always perform better. From figure 6, some negative $P_{S2\text{-}S1}$ values appear alongside some large positive *PVD* values (smaller V_s). This may be explained by the fact that the comparatively smaller deterioration rate λ_s and shorter shelf-life V_s impose inverse impacts on the demand discrepancy between the two scenarios in a selling period. This consequently reduces the benefits generated by scenario two. With very large positive *PVD* values (V_s<<V_c), scenario two only generates rather small revenues (due to the small V_s). It therefore may not perform better than S_1.

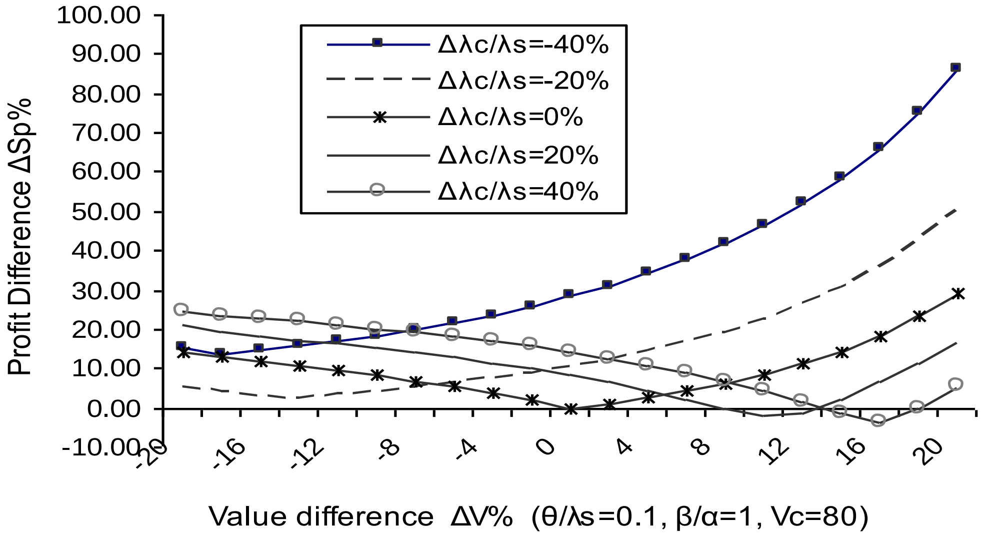

Figure 6. Performance with varying *PVD* and *DDI*.

In summary, the simulation provides following insights into the proposed strategy:

- More quality-sensitive chilled food gains more benefits from the strategy when the food shelf-life is over-estimated in current practice.
- The demand sensitivities of the chilled food do not significantly affect the strategy performance, when the food shelf-life is under-estimated in current practice.
- Optimal price marking-down rate exists in the proposed dynamic pricing policy. The pricing policy holds certain flexibility – slight changes in the marking-down rate around the optimal value would not significantly affect the strategy benefit.
- The strategy would not perform better than current practice if the price marking-down rate is far from the optimal solution and the actual product shelf-life feature is not significantly different from the pre-specified one.

- With the optimal pricing policy, the proposed strategy will always generate benefits where the chilled food shelf-life was better maintained than planned ($V_s>V_c$), or the control conditions (particularly the temperature to control the deterioration rate) of retailers were not maintained as well as planned ($\lambda_s>\lambda_c$).

4.4 Managerial implications

With the rapid development of advanced systems and innovative technologies, big data analytics platforms (e.g. SAP's Sybase IQ, HP's Vertica, and ParStream Analytics Platform) enable users to handle real time analytics on vast amounts of raw data and generate more accurate insights for decision-makers with the continuous import of historical as well as real-time data. Companies are able to efficiently process massive amounts of sensor data that is being generated throughout their supply chains. To extract the value of it, the modelling efforts presented in this paper are mainly focused on demonstrating the way of modelling chilled food pricing in retail supply chains and potential in performance improvement, and smoothly transfer from the vision of the implementation potential of the sensor data driven supply chain management. By comparison between the scenarios of conventional approach and sensor data driven dynamic pricing approach, the numerical results presented in this section illustrate that the proposed sensor data based dynamic pricing approach is feasible and capable of improving the chilled food supply chain management. As such, the sensor data driven supply chain decision model provides opportunities of technological development and strategic innovation in perishable food supply chain management. The analysis results in our paper will encourage firms in the food industry to explore more opportunities from big data and develop the proper strategies to improve their competitiveness.

5. Concluding remarks

With the wide adoption of tracking and sensory technologies, vast volume of structured, semi-structured and unstructured data is being generated in real time when products go through various supply chain stages before reaching end consumers. However, the recording and storage of these so called big data are useless unless they can be retrieved and analysed to generate the knowledge efficiently. This paper presents a sensor data driven dynamic pricing model and provides a novel application of big data approach to food supply chain management. The time and temperature information retrieved and extracted from the sensor network provides opportunities to predict more accurate product shelf-life information in real time. When consumers are able to perceive the product shelf-life variations over time, it is particularly crucial to dynamically price products based on the dynamically identified quality features. Numerical simulations have provided further insights into the performance and characteristics of the proposed strategy.

With the rapid technological advancements, there is no doubt that it will allow us to efficiently process big data and make impact on business decisions and performance. However, in order to convince firms to invest on the infrastructure and resources required for big data driven decision support systems, it is essential to provide firms more applications that can demonstrate the benefits and potential returns of such investments. It is also important to develop new ways of obtaining value from the big data and help business manager to deliver better fact-based decisions aimed at making impact or to generate knowledge. The purpose of this study was to examine new applications that facilitate the utilization of sensor data, which is often unstructured and enormous in nature, to support supply chain decisions.

By fulfilling this purpose, the study makes significant contributions to this important research field. First of all, our analytical and simulation results demonstrate that the proposed sensor data based dynamic pricing strategy would deliver benefits to food retailers. However, the magnitude of benefit also depends on the demand sensitivity nature of the food product, the pricing policy, and the actual product quality control conditions. This confirms the critical importance of data driven supply chain pricing decision for sustaining the business competitiveness. Secondly, although the application focuses on the sensor data driven pricing decision in the chilled food supply chain, there is similar demand in other management domains to bridge big data and effective management decisions. Our study explores the opportunities of big data driven decision support systems and demonstrates its potential of achieving a strategic supply chain innovation. As more data is being generated across different industry sectors, the sensor data driven decisions are expected to play more important roles in business innovations in the near future.

Despite the various contributions outlined in the paper, this study has some limitations which imply some fruitful directions for future research. For instance, a linear deterministic demand is assumed. One research direction would be given to the optimal pricing with stochastic demand functions reflecting seasonal demand patterns and with supply chain wide optimisation scenarios based on the sensor data. In addition, it is assumed that the competitive environment have been considered when the initial price is set up by the business. When competitors employ different pricing strategies, the influence would be complex depending on what are the differences between prices at a given time at different retailers. Although it is out of the scope of this research which focuses on timing and amount of price change during a limited time horizon, it will be an interesting extension to consider the competitors' price in the demand function. Furthermore, the implementation aspects of the proposed supply chain scenario would be another research initiative to gain interesting insights. This study can also be applied to explore other opportunities of using the available sensor data to support supply chain decisions.

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