Available online at www.sciencedirect.com
ScienceDirect
Applied Soft Computing 7 (2007) 136–144
Applied Soft Computing
www.elsevier.com/locate/asoc

Improved supply chain management based on hybrid demand forecasts ☆

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Received 11 May 2004; received in revised form 27 May 2005; accepted 12 June 2005

Abstract

Demand forecasts play a crucial role for supply chain management. The future demand for a certain product is the basis for the respective replenishment systems. Several forecasting techniques have been developed, each one with its particular advantages and disadvantages compared to other approaches. This motivates the development of hybrid systems combining different techniques and their respective strengths. In this paper, we present a hybrid intelligent system combining Autoregressive Integrated Moving Average (ARIMA) models and neural networks for demand forecasting. We show improvements in forecasting accuracy and propose a replenishment system for a Chilean supermarket, which leads simultaneously to fewer sales failures and lower inventory levels than the previous solution.

Keywords: Supply chain management; Neural networks; Hybrid intelligent systems; Demand forecasting

1. Supply chain management in the retail industry

The retail industry has undergone major changes during the past two decades. One of the main developments has been the introduction of supply chain management systems, which affects all agents of such a chain. Especially for supermarkets it has become necessary to apply advanced technologies in order to stay competitive in a highly dynamic environment [21].

In this paper, we describe the development of a hybrid intelligent system for demand forecast, which helped to improve supply chain management in the Chilean supermarket Economax.

This supermarket, as well as any retail company, offers a broad range of products (about 5000 different stock keeping units, SKUs) purchased from a large number of manufacturers and distributors. In order to successfully provide such a variety of items to its customers at competitive prices, the supermarket and its providers have to manage efficiently the respective

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doi:10.1016/j.asoc.2005.06.001

supply chain. Based on the data flow generated by the consumers the supermarket has to decide what, how much, and when to buy.

Solving this problem satisfactorily requires a reliable prediction of future demand. This task, however, presents difficulties, since sales depend on many factors, such as: past sales, prices, advertising campaigns, seasonality, holidays, weather, sales of similar products, competitors' promotions, among others.

Section 2 describes briefly the current state-of-the-art of supply chain management and hybrid intelligent systems for demand forecasting. Section 3 provides a comparison of two techniques for time series prediction (Autoregressive Integrated Moving Average (ARIMA) and neural networks) and analyzes their respective advantages and weaknesses. Based on this analysis, we present a hybrid forecasting model in Section 4 and compare its results to those of different alternative forecasting models for a certain product. The impact of sophisticated demand forecasts for an improved supply chain management is presented in Section 5. Section 6 concludes this work and points at future developments.

2. Related works

Supply chain management systems on one side and hybrid intelligent systems on the other have emerged significantly but mainly independently during the last decade. Next, we present a brief state-of-the-art of both systems as it is relevant in the context of this paper. In subsequent sections, we present approaches combining them.

2.1. Supply chain management

"Supply chain management (SCM) is the practice of coordinating the flow of goods, services, information and finances as they move from raw materials to parts supplier to manufacturer to wholesaler to retailer to consumer. This process includes order generation, order taking, information feedback and the efficient and timely delivery of goods and services" (http://www.computerworld.com/softwaretopics/erp).

While the entire area of SCM has many different aspects (see, e.g. [13]) we want to focus in this paper on topics related to demand forecasts in supermarkets. Each agent of the respective chain has to take decisions regarding products to be purchased, purchase time, and quantities to be purchased using demand information from its respective customers. Fig. 1 shows the flow of products and flow of information between supplier, manufacturer, distribution center, supermarket, and consumer.

Demand forecast is already a difficult task for a supermarket, but it gets much more complex for

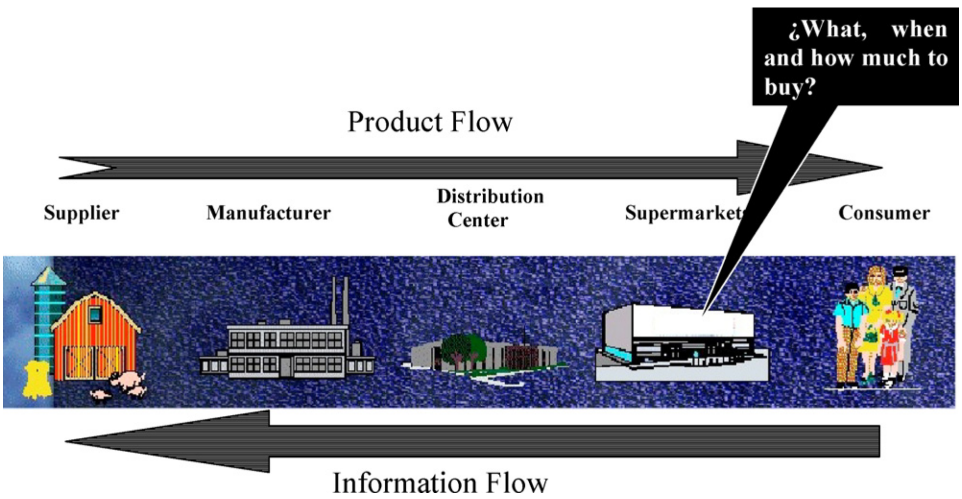

Fig. 1. Supply chain for a supermarket.

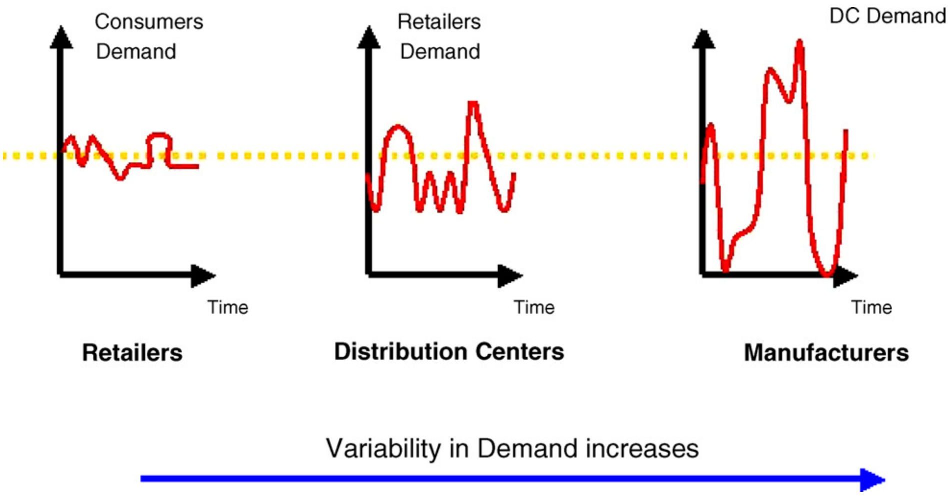

Fig. 2. Bullwhip effect in a supply chain.

the other agents since variability of demand increases backward the supply chain. This effect is known as ''bullwhip effect'' [13,8], which is the distortion of true end-customer demand that comes from lack of coordinated and shared information in the supply chain. In general, a demand forecast performed by a supermarket will not be 100% correct, so that any prediction based on it will increase variability and further distort the demand anticipated by each agent of the chain. Fig. 2 shows this effect graphically.

There are several ways to ''solve'' this problem of high demand variability:

- Each agent of the supply chain can increase its inventory levels.
- A better coordination between all agents of the chain and/or a better flow of information helps to improve the respective management decisions [18]. A related initiative is known as ''Collaborative Planning, Forecasting, and Replenishment'' (see: http://www.cpfr.org).
- Better demand forecasts allow reliable operations at low inventory costs throughout the entire supply chain.

The latter point is exactly where the present work comes in: Improved supply chain management based on advanced demand forecasts using hybrid intelligent systems.

2.2. Neural networks and hybrid intelligent systems for time series prediction

Neural networks are mathematical models that ''learn'' pattern from data. They have proved to be very effective in order to solve classification and regression problems by handling non-linearity between input and output variables, being able to approximate any function under certain conditions [11].

Based on these capacities, neural networks have been used to solve problems in different areas, e.g. time series prediction. It has been shown that such networks provide competitive results in forecasting stock exchange indexes [15], corporative bonds [16], and sales [19]. A combination of neural networks with fuzzy logic has been proposed for modeling electricity demand [1]. This hybrid intelligent system outperformed pure neural networks and also ARIMA models. Other successful applications of neural networks have been developed in relation to operations management and have led to huge inventory cost savings [3,17].

3. Descriptions and comparison of forecasting techniques

We describe ARIMA models and neural networks for time series prediction and provide a comparative analysis of these two techniques.

3.1. ARIMA models

The problem to predict time series has been solved so far mainly by applying the ARIMA model family proposed by Box et al. [4,14]. It is based on the following terminology:

- X_t is the observation of a time series at time t and has a probability distribution $f(X_t)$.
- A is the time series of n white noise observations with average zero and variance σ_A^2.
- B is the delay operator, e.g. $BX_t = X_{t-1}$ and $BA_t = A_{t-1}$.
- $\nabla = 1 - B$ is the differentiating operator, e.g. $\nabla X_t = (1 - B)X_t = X_t - X_{t-1}$.

The autoregressive part AR(p) models a time series as a linear function of p previous observations in order to predict the current one [5]. The moving average part MA(q) determines the moving average of the series with a time window of size q.

Finally, the ARIMA process (p, d, q) is based on a series that has been differentiated d times, with p autoregressive terms and q moving average terms (for further details, see, e.g. www.forecastingprinciples.com). The respective equation is:

$$\phi_p(B)(\nabla^d X_t - \mu) = \theta_q(B)A_t \tag{1}$$

The result of these models is the continuous μ and the parameter vectors θ_q (moving average) and ϕ_p (autoregressive) that best fit the data.

The process can be generalized even more by incorporating seasonal elements. First, the seasonal differentiating operator is defined as: $\nabla_s = 1 - B^s$, where s is the seasonal factor. Besides, the time series X_t can be explained by external variables or predictors (also called regressors). The most general model is defined by SARIMAX(p, d, q)(sp, sd, sq)Y, where Y is the vector of r external variables of the process. The general equation of the model finally is:

$$\phi_p(B)\Phi_{sp}(B)\left[\nabla^d\nabla_s^{sd}\left(X_t - \sum_{i=1}^{r} c_i Y_i\right) - \mu\right] = \theta_q(B)\Theta_{sq}(B)A_t \tag{2}$$

where $\Phi_{sp}(B)$ is the sp seasonal autoregressive polynomial, $\Theta_{sq}(B)$ the sq seasonal moving average polynomial, and c_i are the regressors' coefficients.

3.2. Neural networks

A neural network is a net of units (neurons), linked by connections [10]. Such networks are trained by some kind of learning rule that adjusts the connections' weights according to available data trying to minimize an appropriate error function.

One of the most popular models among neural networks is the multi-layer perceptron (MLP), which can be trained using the back-propagation learning rule [10]. This rule tries to minimize the error between desired and calculated output by adjusting the network's weights.

A problem that can occur during training is that the learning process leads to an overfitted model; i.e. the model learns the received data by heart, losing its ability to generalize. The literature provides several ways to control this problem, such as, e.g. advanced stopping rules (see, e.g. [10]).

Neural networks have been used to solve different kinds of problems such as classification, regression, optimization, clustering, and forecasting. The present work will focus on the latter using a MLP-type neural network. Fig. 3 shows an architecture typically used in this context.

The respective model used for time series forecasting requires two specific parameters. The first one (k) indicates the size of the time window, which will be used as input to predict the time series. The second parameter (s) represents the number of future periods for which the network provides a forecast.

3.3. Comparing ARIMA and neural network models

There are many publications comparing ARIMA and neural networks, both theoretically [6,20] and empirically [7,12]. One main limitation of ARIMA models is the linear relation between independent and dependent variables they assume (see, e.g. [6]). Besides, as, e.g. Wan [20] states, MLP networks allow us to model NARX processes, i.e. they are able to model autoregressive non-linear processes with

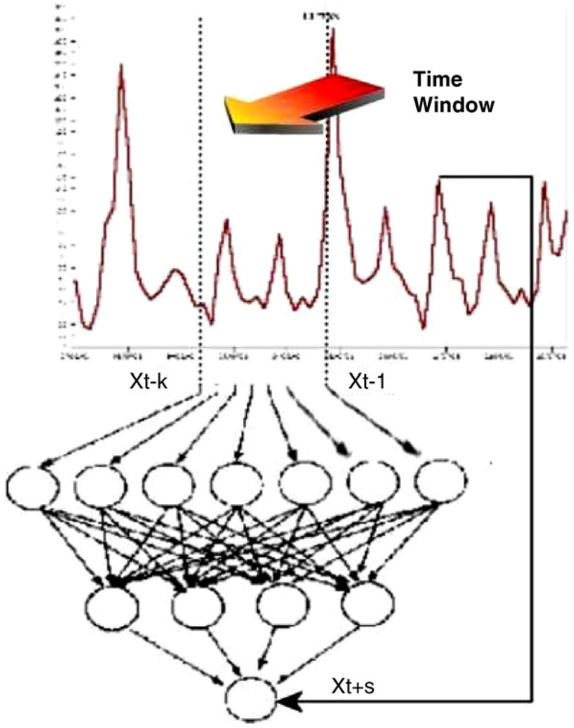

Fig. 3. MLP network for time series forecasting.

exogenous variables. According to Dorffner [6], MLP models provide the following advantages:

- By modeling non-linear processes, MLP can represent more complex time series.
- MLP models do not assume certain characteristics of the time series, such as, e.g. to be stationary.

However, ARIMA approaches present also advantages compared to neural networks, such as, e.g. a better understanding of the studied phenomenon. Analyzing the regressors' coefficients provides the importance each independent variable has in relation to the dependent variable. This way the model generates knowledge explaining the complex interdependencies regarding the considered time series.

Another disadvantage of neural network models is the high degree of freedom in their architecture. This implies several problems, such as:

- In order to obtain reliable results, a large number of training examples is necessary.
- Having many weights can easily lead to overfitting or to local minima of the respective error function.

As a conclusion, Table 1 summarizes the most important aspects comparing the two approaches.

4. Development of a hybrid forecasting model

Motivated by the comparison between the two forecasting approaches, it becomes interesting to combine their respective advantages. We developed a hybrid forecasting model using ARIMA-type approaches and MLP-type neural networks for demand forecast regarding several stock keeping units in the Chilean supermarket Economax.

4.1. The additive hybrid model

For our additive model, we consider the original time series as a composition of various series. The original one is modeled by an ARIMA process and the error associated to the respective forecast as another time series, which shall be modeled by a neural network. The hybrid forecast $\hat{X}(t)$ for the original series is expressed consequently as sum of an ARIMA-based forecast and a neural network model

Table 1
Comparison between ARIMA and MLP models

ARIMA	Neural networks (MLP)
Linear model: assumes a priori behavior of the time series	Non-linear model: more degrees of freedom for the model
Modeling requires the series to be stationary	Any time series can be analyzed
Requires interaction with the user	Requires fewer interactions with the user
The model provides insight and information through its parameters	Difficult to interpret the model (black box)
No overfitting	Overfitting is possible

as shown in the following equation:

$$\hat{X}(t) = \hat{Y}(t) + \hat{e}(t)$$

where $\hat{Y}(t)$ is the forecast for the original series using a SARIMAX(1, 0, 0)(2, 0, 0) process (see Section 3.1) that has shown to perform best among all considered models from the ARIMA family.

The error of this SARIMAX process has been analyzed as a separate time series and modeled by a neural network. The respective output $\hat{e}(t)$ is the MLP forecast for the errors of the SARIMAX process. The neural networks we used have the following architecture:

Input neurons ($12 + k$, where k depends on the time window used):

- Past sales with lag k, i.e. daily sales for the considered SKU from the last k days (tw$k$: time window of size k).
- Binary variables to characterize special days, such as:
  - *Payment*, characterizing the days at the end of each month when people receive monthly payment.
  - *Intermediate payment*, characterizing the days at the end of each fortnight when people receive two weekly payment.
  - *Before holiday*, characterizing days before a holiday.
  - *Holiday*, characterizing holidays.
  - *Independence*, characterizing Chilean independence days (18 and 19 September).
  - *Santa*, characterizing the days of the week before eastern.
  - *Vacation*, characterizing the days that belong to the period of summer vacation (January and February).
  - *Summer*, characterizing summer days (1 October–31 March).
  - *New year* (1 January), characterizing the only day when supermarkets are closed in Chile.
- Price variables:
  - *Price A* = original price of the considered SKU in Economax.
  - *Price B* = (Price A)/(Max price in micro-market).
  - *Price C* = (Price A)/(Min price in micro-market).

  Remark: The variables "Max price in micro-market" and "Min price in micro-market" are the maximal (minimal) price for a certain SKU in the relevant micro-market and are provided by a market research company.

Hidden neurons: 15
Output neuron: present sale of the considered SKU
Parameters:

- Learning rate: 0.3.
- Momentum rate: 0.1.
- Stop conditions: Minimize the rms error in the test subset (rms: root mean square).

4.2. Application of the hybrid model

We applied traditional forecasting techniques (naïve, seasonal naïve, and unconditional average), a SARIMAX process, several neural networks and the proposed hybrid intelligent system in order to predict demand of 6 out of the 50 best-selling SKUs in our supermarket. The SARIMAX models were built using SPSS 8.0, whereas the MLP-type neural networks were developed with DataEngine 4.0.

Below, we analyze demand forecasts for SKU 100595 (vegetal oil, 1 l) in more detail. We determined the performance of each model using the following two error functions see, e.g. [14]:

Mean absolute percentage error, MAPE

$$= \frac{1}{n}\sum_{k=1}^{n}\left|\frac{X_k - \hat{X}_k}{X_k}\right|$$

Normalized mean square error, NMSE

$$= \frac{\sum_{k=1}^{n}(X_k - \hat{X}_k)^2}{\sum_{k=1}^{n}(X_k - \bar{X})^2} = \frac{1}{\sigma^2 n}\sum_{k=1}^{n}(X_k - \hat{X}_k)^2$$

All proposed models have been compared with the techniques the supermarket currently applies: naïve forecast (M1), seasonal naïve forecast (M2), and unconditional average (M3). Their performance is evaluated through MAPE and NMSE, over both training set and test set. Table 2 shows the results.

As can be seen SARIMAX (model M4) and neural networks (M5–M8) outperform traditional techniques (models M1–M3). The additive hybrid model (M9) gives best results among all approaches employed.

Table 2
Results from different forecasting approaches for SKU 100595

	100595	Training set		Test set	
		Percentage error (%)	Normalized error	Percentage error (%)	Normalized error
M1	Naïve	44.28	0.6972	56.83	1.2481
M2	Seasonal naïve	64.67	1.2212	45.75	1.9217
M3	Unconditional average	59.98	0.7759	48.54	0.9689
M4	SARIMAX(1, 0, 0)(2, 0, 0)	36.21	0.3301	40.49	0.6090
M5	MLP-tw21	32.93	0.4633	31.85	0.4973
M6	MLP-tw14	31.15	0.3115	34.64	0.5703
M7	MLP-tw3	29.61	0.3002	34.36	0.5281
M8	MLP-tw1	30.00	0.3405	35.31	0.5340
M9	MLP-tw21 with SARIMAX	26.12	0.2760	28.80	0.3544

5. An inventory control system based on demand forecasts

Based on the presented hybrid intelligent system for demand forecast we developed a system for inventory control in the supermarket Economax. Replenishment from the suppliers is done for most products every P days and the purchase order has to be sent at least L days before the delivery date.

The desired inventory level (T) has to be determined every period by the equation $T = m' + Z\sigma$, where m' is the average demand during $P + L$ days and $Z\sigma$ is the security stock, which depends on the desired service level (Z) and on σ, standard deviation of the demand during $P + L$

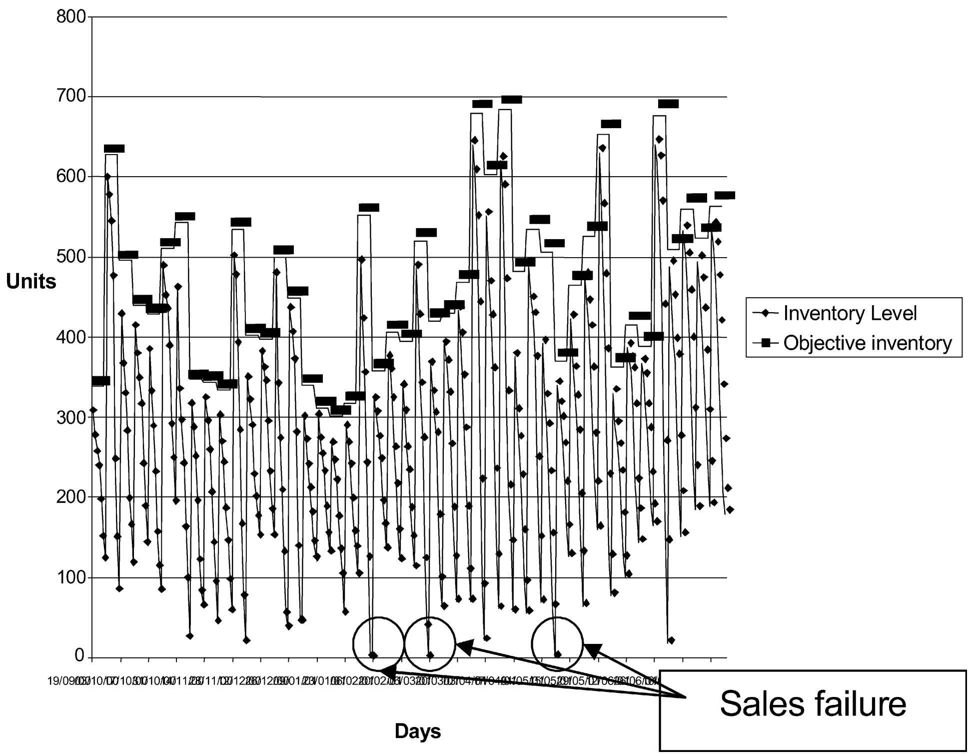

Fig. 4. Product 100595 daily inventory level.

Table 3
Performance between the current and the proposed replenishment system

Inventory control indicator	Current system	Proposed system
Reaching days (inventory/daily sales average)	30	5
Sales failures (% of days without products)	6	0.9

days. Both, the average demand (m') as well as the standard deviation (σ) are estimated based on the proposed model for demand forecast.

Using one year's sales data, we simulated the inventory level for product 100595 (vegetal oil, 1 l) applying the replenishment model mentioned before. Fig. 4 shows the real inventory level and the desired inventory level T (upper line).

Comparing the current situation to the results obtained by the proposed model exhibits improvements in customer service (measured as percentage of days with sales failure) and in inventory level (measured as inventory/daily sales average). Table 3 summarizes the results.

It should be mentioned that improving one of the two indicators shown in the above table is easy. A supermarket could, e.g. increase its inventory level reducing the number of sales failures. This will, however, lead to increased capital costs. On the other hand, reducing inventory level will result in more sales failures if we maintain the replenishment system. Based on the presented hybrid forecasting model, we could decrease both indicators *simultaneously*.

6. Conclusions and future work

We have presented a hybrid intelligent system for demand forecasting that helps to improve supply chain management in the retail industry. Providing advanced forecasts in a supermarket allows all agents of the respective chain to better manage their inventory decisions. The developed forecasting models leave valuable information for the respective business, e.g. they permit to quantify the effect special events (such as holidays, end of month, etc.) have for customers' behavior.

Regarding forecast accuracy, neural networks outperformed ARIMA models and the proposed additive hybrid approach gave best results. Better short-term forecasts allow the Economax supermarket to decrease inventory levels and to improve simultaneously service quality by reducing sales failures. This clearly results in a strategic advantage in the highly competitive supermarket industry.

We pretend to do future work in two directions: more advanced forecasting models will allow improving the results presented in this paper. First experiments with a Sequential Hybrid Forecasting Model (SHFM) developed by the authors gave very promising results (see [2]). New techniques, such as Support Vector Machines (SVM) have been used successfully to build competitive forecasting models [9] and are interesting candidates for multiple regression systems.

On the other hand, we will evaluate new technologies that promise high potentials for the supermarket business, such as, e.g. point-of-sales (POS) and electronic data interchange (EDI) (see also [21]). An interesting new technology with huge potentials in the retail industry is Radio Frequency Identification (RFID). RFID tags are small stickers containing a passive microchip and an antenna and carry basic information such as a product code and manufacture identification (see http://www.manufacturing.net/scm/article). This technology will generate an enormous amount of data related to the respective businesses providing a rich basis for future data mining applications.

Acknowledgments

The project described in this paper has been funded by the Millenium Nucleus on Complex Engineering Systems (www.sistemasdeingenieria.cl) and the Chilean Fondef project ‘‘Development of Management Tools for Improving Supply Chain Productivity in the Supermarket Industry’’, Project number D03I1057. Special thanks to Professor Hiroshi Yasuda, The Research Center for Advanced Science and Technology, RCAST, The University of Tokyo, Japan, who supported this research project.

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