ICT-Based Information Utilization for Production and Logistics Systems of Convenience Stores

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Innovations in ICT over the last two decades have moved business intelligence toward more large-scale business data utilization to efficiently and effectively improve business performance. This paper presents several typical information utilization examples, identifies appropriate business data utilization methods, and demonstrates how ICT techniques such as data mining and simulation technology are technically used as analytical implementation tools for production and logistics systems in convenience store supply chains. One example of data mining techniques is an application using demand order data of new products proposed to forecast demand trends of new short life-cycle products in this study. The other example of simulation technology is an application using the delivery data of convenience stores proposed to understand and validate the operations of a retail cross-docking center which is an actual supplier between multiple product enterprises and convenience stores.

Keywords: Demand Forecasting, Data Mining, Simulation, Convenience store.

Ⅰ. Introduction

The methods of production and the logistics management of supply chains have changed with advancements in ICT over the last two decades in terms of hardware, software, and network technologies. These profound changes have enabled high-speed transfers of large amounts of business data, thus enabling supply managers to accurately and effectively perform more informed decision-making for their business operations. This paper presents several actual examples, illustrates appropriate business data utilization methods, and demonstrates how ICT techniques such as data mining and simulation technology are technically used as an analytical implementation tool for the production and logistics systems in convenience store supply chains.

The first example is an information utilization using data mining techniques that is proposed to forecast the demand trends of new short life-cycle products. The demand order data are supplied from an actual food processing enterprise in the Tokai area of Japan. Based on the actual demand order data of the first selling week, the sales amounts and the demand trends for the second and third selling weeks can be precisely forecasted. Otherwise, sales association rules are extracted to forecast the demand trends of whether a new product would be favorable or not in the second and the third selling weeks through the sales data of the first selling week. The second example is an information utilization using simulation technology to understand and validate the operation of a retail logistics system. The simulation is developed as a discrete-event simulation model to test and confirm its effectiveness at an actual retail cross-docking center. Furthermore, the model is found to be both practical and powerful in providing critical support for logistics managers in management decision making at the cross-docking center in this study. All of the examples were developed based on the research results of a collaboration project between industry and academia.

Ⅱ. Information utilization using data mining techniques in a production system

1. Characterization of new products in supply chains of convenience stores

The demand forecasting approach is key to accelerating marketing activities in order to achieve a sustainable competitive advantage for manufacturing enterprises whose new product life cycle is relatively short when their products are put on the market. Because of this, data mining techniques are proposed to forecast new commodity market demand based on an actual sales database that describes customer purchasing behavior at the early stages in order to promote more efficient production activities and minimize raw material waste (Gaku, 2014).

The subject of this study is a food manufacturing enterprise which is a box lunch plant located in central Japan. The enterprise annually produces 100~150 new items with short life-cycles between one week and three months for 260 regional convenience stores. The life-cycle of these new items is so short that 70 percent of the new box lunch products are newly developed and produced each year; the selling cycle is no more than 3 months (Liu, 2008).

The demand amount variation from the first selling day is shown in Figure 1. Once new products were launched on the market, the competitive relation structure between products became increasingly complicated. Sales topped on the first selling day, plummeted in the following week, and then slowly decreased until the end of the sales period.

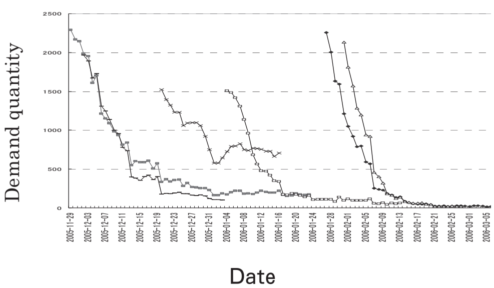

Figure 1. Demand amount variation from sales release.

2. Data mining techniques

Data mining is a business intelligence methodology concerned with customer-oriented marketing. Table 1 shows pioneering studies concerned with applying data mining techniques to various case studies related to marketing analysis.

Data mining is a process for finding useful business associations or marketing sales rules from a large amount of data collected and stored to facilitate the decision-making process. This study adopts two methods to forecast the demand trends of new short life-cycle products: a Neural Network and a Decision Tree.

A neural network is a computer-simulated mathematical model that resembles the visible functional portion of the cerebral cortex. In this study, a hierarchical neural network model receives as input the actual sales data of the new short life-cycle products during the first selling week to forecast the sales amounts for the second and the third selling weeks.

The decision tree technique is one of the most intuitive and divisive hierarchical methods for providing explicit rules for classification. It is also used to investigate the relationships between an objective variable and multiple input variables from a large volume of marking database. In this study, the relationship between the sales data during the first selling week and the sales amounts for the second and third selling weeks could be obtained with CART techniques.

3. Data utilization in production system

The data related to the 228 short life-cycle products are provided by an actual food processing manufacturer in Japan. The data used in this study include the following:

(i) Product types: Box lunches-new products sold during the period below for 228 types.

(ii) Production period: Approximately 2 years and 3 months.

(iii) Data items: Date of order, delivery date, product ID, product name, total quantity, and category.

A random sample of 46 products was extracted from the total of 228 for the verification dataset, and the remaining 182 products were used as the learning dataset. The two datasets were kept in respective files. The learning dataset was used to generate a forecasting model called a "learning process" and the verification dataset was used to evaluate the generated model and was called a "verifying process." The details of the learning process are shown in Figure 2.

Figure 3 shows a representative portion of the results obtained from the verification process. For example, taking "sweet and sour pork" shown as item No. 62, the sales amount forecasted in the second selling week was 4323, while the actual value was 4381. The value forecasted in third selling week was 3291, while the actual value was 3187.

A CART (Classification and Regression Tree) was used to extract the sales association rules. The construction of this tree consisted of the input nodes and terminal nodes shown in Figure 4. The set of rules for all terminal nodes forms the classification model as shown in Figure 5. With these rules, we can forecast the demand trends of new products for the second selling week to determine whether the items would be favorable or unfavorable.

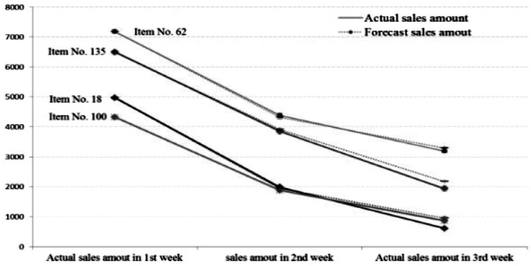

Figure. 3. Forecasting results using verification data.

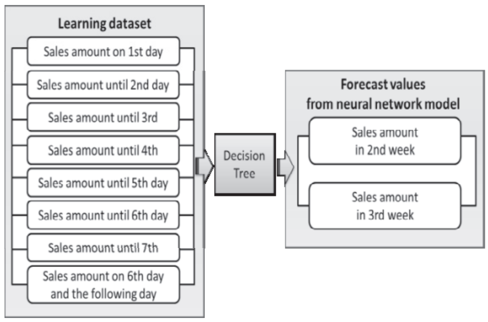

Figure 4. Construction of the decision tree.

For example, in the second selling week, the total number (n) of items to be provided was 182, which accounts for one hundred percent of the total items, and the average forecasted

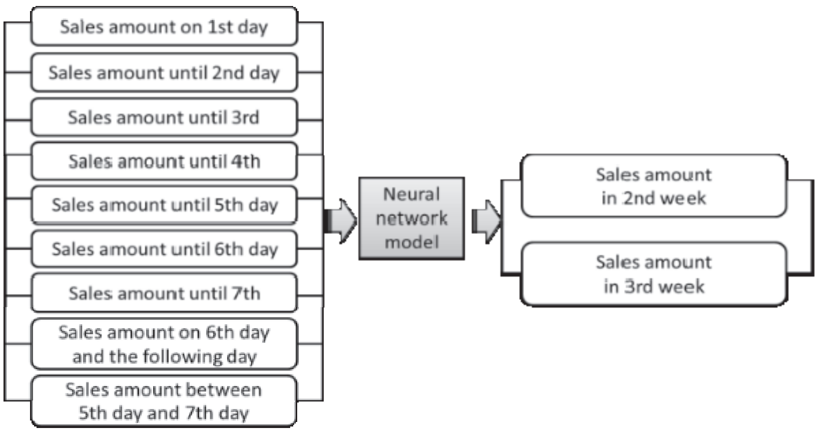

Figure 2. Detail of the learning process.

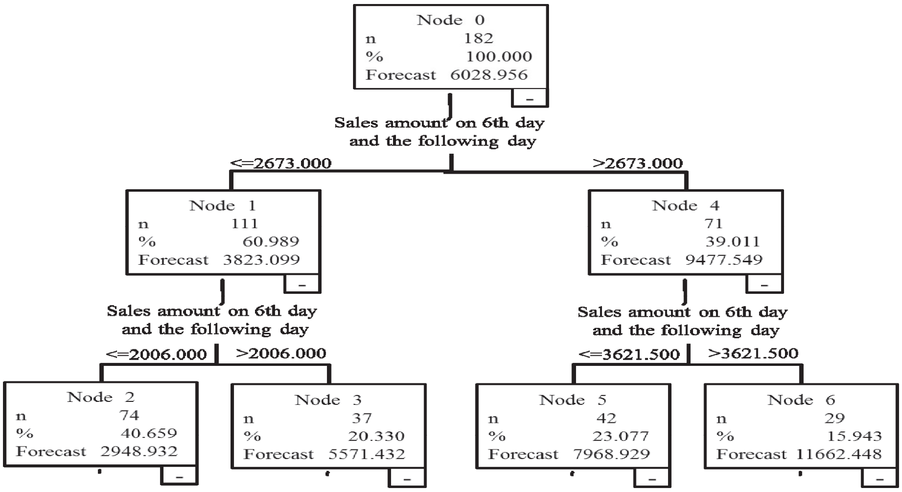

Figure. 5. Decision tree for the second week

sales amount in the second selling week was 6028.956. Furthermore, according to the rules, the sales amounts in the sixth and seventh days were the most import input variable for forecasting the demand trends in the second selling week or later. For example, if the total demand quantity in the sixth and seventh day is more than 2673, the sales amount forecasted in the second selling week should be 9477.549, which accounts for 39.011 percent of the total items. Otherwise, when the actual delivery data in the first selling week is used to forecast the demand trends in the second or the third selling week, the floor level of the hot items for the second selling week is similar to the third selling week, and the floor level of the favorable items in the second selling week is almost similar with that of the third selling week.

The major sales association rules extracted for the second selling week are as follows:

(i) New products whose sales amounts in the sixth and the seventh days totaled over 2673 should continually maintain their "favorable sales condition" in the second selling week.

(ii) New products whose sales amount in the sixth and the seventh days totaled over 3621 should continually maintain their "extremely hot sales condition" in the second selling week.

Ⅲ. Information utilization using simulation technology in a logistics system

In a retail distribution environment, the material handling of logistics systems is complicated and labor intensive. Managers are typically under enormous pressure to optimize staff shifts, inbound schedules, and operating rules to minimize handling costs while ensuring just-in-time shipments (Liu and Takakuwa, 2009). In this section, a discrete-event simulation model is illustrated to understand and validate the operation of a retail cross-docking center that is an actual supplier between multiple product enterprises and convenience stores in this study (Liu and Takakuwa, 2010).

1. Operations of a cross-docking center in the supply chain of convenience stores

The cross-docking center of the HAMAKYOREX Co. handles fresh and chilled foods, including beverages, soft drinks, and sweet desserts. The daily operations management is critical to this cross-docking center, where operations are ongoing 24 hours and 3 shipping services a day, 7 days a week, and where all items (approximately 300 items) must be received, sorted, and shipped to 236 stores across the Tokai region of Japan by a fixed time. According to the logistics manager at the company, an average of 110,000 vats (a vat is a standard container of items) of throughput were handled each day over the past two years. As the essential operations flow, items from multiple suppliers are received and then sorted in two steps called the prep. sorting process and the sorting process. Prep. sorting is a preliminary operation that sorts items by distribution zones. Following this, the sorting process sorts items by stores within a distribution zone.

2. Simulation technology

Computer simulation is a leading strategic technology in operations management. It is frequently used for predicting the effect of complicated systems with analytical methods such as queueing theory, probability, simple algebra, or calculus. In order to provide more flexible decision making as business intelligence, simulations can be used to mimic every complicated action taken in business linked with the data (Kelton, Smith and Sturrock, 2014).

Table 1: Product Attributes

Product code	Arrival time	Supplier code	Small quantity orders=1; General Product=0	Beverage Products=1; Athers=0	Returnable Packing =1; Cardboard Packing=O	Returnable Container Type	Maximum Case quantity on one four-wheeler	PCS in box
1720044	1330	14	0	0	0	–	16	24
1720051	1330	14	0	0	0	–	16	30
1721317	1330	14	0	0	0	–	9	12
1721324	1330	14	0	0	0	–	9	12
1721331	1330	14	0	0	0	–	9	12
1721348	1330	14	0	0	0	–	9	12
1721409	1330	14	0	1	1	4	10	12
1722215	1330	14	0	0	0	–	80	12
1723045	1330	14	0	0	0	–	15	12
1724257	1330	14	0	0	0	–	80	12
:	:	:	:	:	:	:	:	:

Table 2: Demand Data of Stores

Product code	Store 1	Store 2	Store 3	Store 4	Store 5	Store 6	Store 7	Store 8	Store 9	Store 10	…	Store 236
1720044		4									…	
1720051				3		4	4		5		…	
1721317	10	8	20	15	10	5		6	6	10	…	10
1721324		6		4	6	6					…	3
1721331			3			3	4		3		…	3
1721348	3		3						3	3	…	3
1721409							3		3		…	
1722215	6	6	5	40	12	5	12	6		10	…	6
1723045			3								…	
1724257	3		3			4					…	3
:	:	:	:	:	:	:	:	:	:	:	:	:

Table 3: Declared Time Interval Number

Time	12:45	13:00	13:15	13:30	...	19:45
Declared Number	0	1	2	3	...	28

Table 4: Demand Data of Stores

Product code	Store 1	Store 2	Store 3	Store 4	Store 5	Store 6	Store 7	Store 8	Store 9	Store 10	…	Store 236
1720044		4									…	
1720051				3		4	4		5		…	
1721317	10	8	20	15	10	5		6	6	10	…	10
1721324		6		4	6	6					…	3
1721331			3			3	4		3		…	3
1721348	3		3						3	3	…	3
1721409							3		3		…	
1722215	6	6	5	40	12	5	12	6		10	…	6
1723045			3								…	
1724257	3		3			4					…	3
:	:	:	:	:	:	:	:	:	:	:	:	:

Table 5: Operator Schedules

Operator No.	Operator Name	Skill-type	Beginning Time	Finishing Time	Working Quarterhours	Working Hours
1	Operator_1	3	0	26	26	6.50
2	Operator_2	2	1	27	26	6.50
3	Operator_3	3	2	12	10	2.50
4	Operator_4	1	2	19	17	4.25
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12	Operator_12	2	2	19	17	4.25

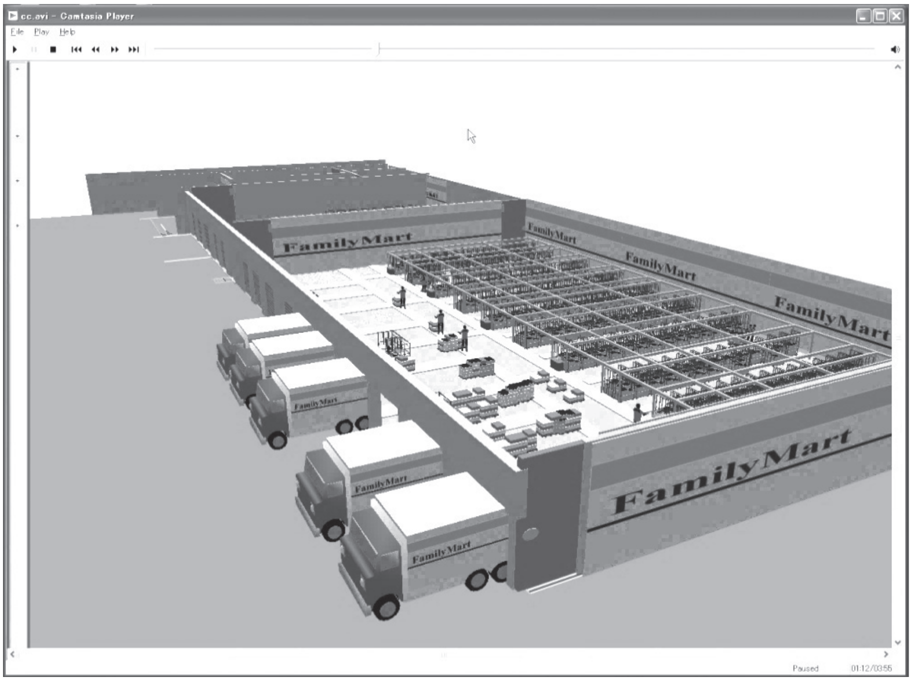

Figure 6. Part of the animation

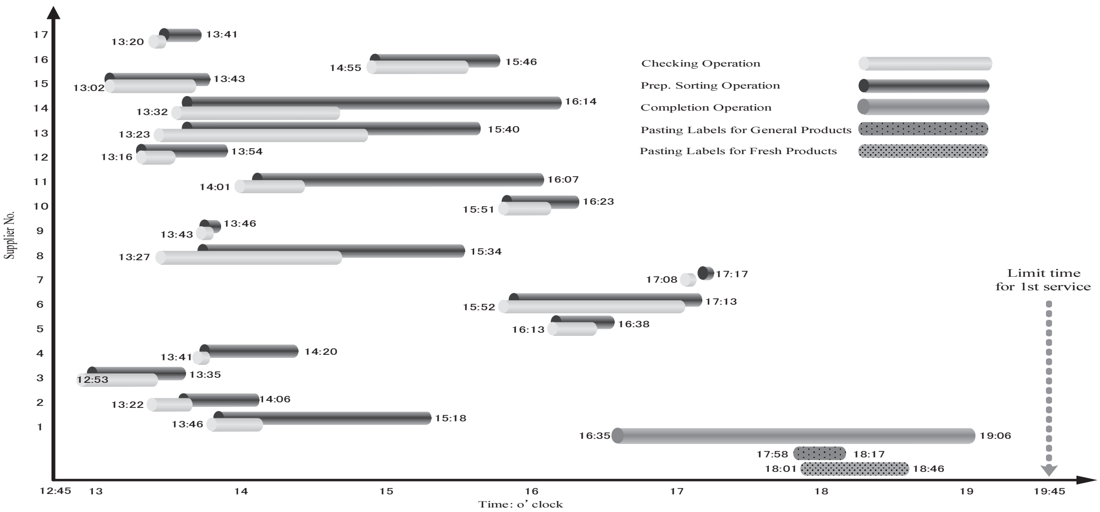

Figure 7. Operation Status (Gantt chart)

3. Data utilization in logistics system

A materials handling simulation model for the retail cross-docking center was created using the simulation package Arena (Kelton, Sadowski and Swets, 2010). The simulation was geared toward performance analysis, i.e., the utilization of resources (the inbound docks, the prep. sorting group) based on the inbound schedules and operator shifts that must be regularly decided by the logistics managers. The collected data from the cross-docking center are shown in Tables 1, 2, 3, and 4. The animation model was constructed with Arena 3D player, as shown in Figure 6. An animation screen, together with dynamic statistics and graphs, provides a general view of the system operation.

A Gantt chart result of the operation status by statistics in Arena is shown in Figure 7, indicating the beginning and ending times of each item from each supplier. The result can be compared with the actual status to verify the simulation model, which was called "AS-IS." Simulation results were obtained, such as the man-hours of each operating activity for each work-hour, as shown in Figure 8. This can be used to assist in assessing the operations balance of the cross-docking center.

The simulation outputted the utilization of the inbound docks and the scheduled utilization of the prep. sorting operators, as shown in Figures 9 and 10, respectively. These are used to provide critical decision-making support about inbound schedules and operator shifts for the logistics managers.

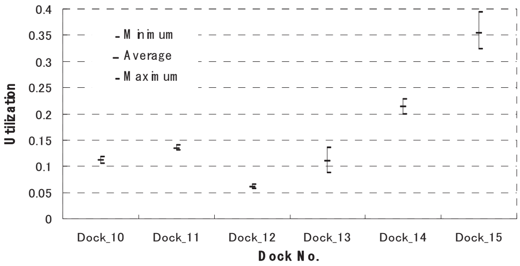

Figure 9. Utilization of inbound docks

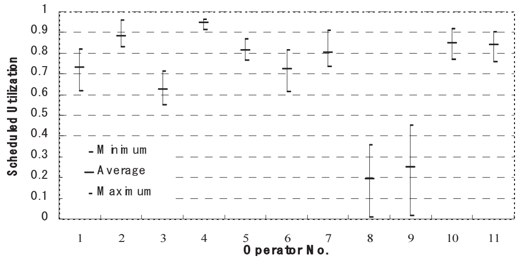

Figure 10. Scheduled utilization of operators

Ⅳ. Conclusion

(1) Applications of information utilization using ICT such as data mining and simulation technology were described, presenting two actual examples using the production and logistics systems of convenience stores.

(2) It must be stressed that actual business data such as demand order data and delivery data are important for analyzing and improving the complicated performance of

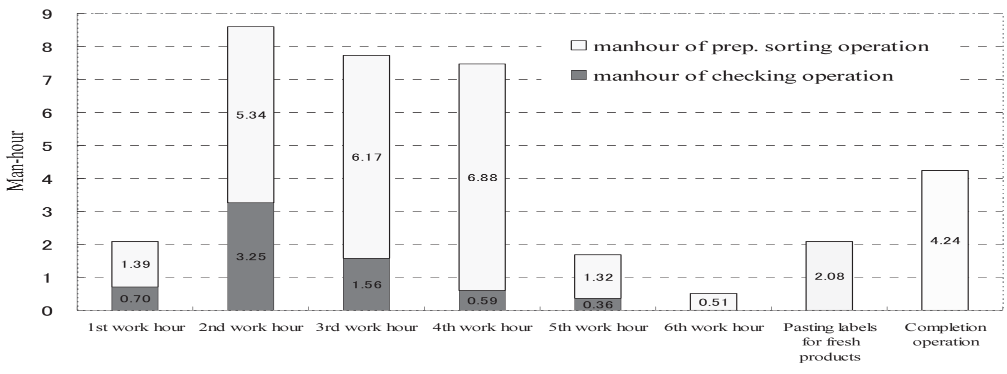

Figure 8. Man-hour requirement

production and logistics systems.

(3) The ICT techniques such as data mining and simulation technology can provide demand forecasting, optimization, and other analytics to empower even more decision flexibility in the production and logistics systems.

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