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Analysis of Optimized Logistics Service of 3C Agents in Taiwan Based on ABC-KMDSS

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Abstract: 3C (computer, communication, and consumer electronics) distributors in Taiwan provide world-class logistics service quality, as enterprises can provide logistics services for customized products (products with segmented standardization and customized standardization) in the value chain that meet individual customer needs. If enterprises can achieve the objective of providing customers with services in accordance with their individual needs, they are more likely to obtain high customer satisfaction. This study selected multinational 3C distributors in Taiwan as the subjects and their internal MIS (management information system) databases as data sources. Data mining was employed to screen important and relevant information from the MIS databases. The key factors affecting the service quality of customized logistics, as obtained from the benchmarking platform of cost information, were used as the contents of a hierarchical structure. After the information was input into the linear planning model, better solutions were obtained. Moreover, the results were saved in the ABC (activity based costing)-KMDSS (knowledge management decision support system) database. The rules for enterprise operation in the knowledge database, together with data from the ABC-KMDSS database, were used for the CBR (case-based reasoning) method of knowledge reasoning to determine the proper decision-making for logistics services of relevant customized products.

Keywords: 3C distributors, Logistic service for customized products, ABC-KMDSS, CBR

1 Introduction

To meet the diverse needs of customers, in recent years, many electronics manufacturers have been expanding and linking their sales offices worldwide; however, the outcome of expansion is often unsatisfactory, due to limitations from differences in cultures, lifestyles, etc. For cost-based and professional considerations, enterprises depend on retail distributors for sales through the international division of labor to save costs and enhance business performance. In recent years, due to the rapid development of digital technology, numerous technological products have been created, other than general household appliances, and such types of goods are collectively known as 3C (computer, communication and consumer electronics) products. In the current era of efficiency and novelty, the sales volume of 3C products has been dramatically increasing. At present, information and communication products are the mainstay of 3C product development. 3C distributors have to create innovative business models, which indirectly leads to changes in the response to consumer needs and the business models of 3C distributors. Due to this situation, 3C distributors in Taiwan have evolved. With the rise of domestic chain sales channels, consumers that purchase 3C products are paying increased attention to distributors' brands, in addition to consideration of the product brand, as both the brand and the reputation of the distributors will directly affect the related logistics service quality. In an era of customized sales, the marketing strategies of the retail channels are attracting the attention of many customers. With innovative marketing strategies, 3C distributors are striving to enhance consumer post-purchase satisfaction in order to maintain customer loyalty and turn one-time consumers into regulars, thus stabilizing corporate profit. The retail channel of consumer electronic products is one of the major channels for 3C products. The development of 3C distributors and research results of related studies in Taiwan have suggested that Taiwan's entry into the WTO will have a

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great impact on 3C distributors. It is clear that 3C distributors have gradually become a major 3C retail channel. This is one of the motivations for selecting the research subjects. This study aims to discuss products with segmented standardization and products with customized standardization. Products with segmented standardization begin providing customized service in the marketing and distribution links at the back-end of the value chain (e.g., replacing mobile phone casings and external hard drive enclosures). Customized standardization extends the customization to the assembly stage. In this case, the customization service is in a modular or structured form (e.g., the selection of the motherboard, memory, hard disc and other computer components needed to assemble a PC according to the customers' needs [1]. This study used the contents of the firms' internal MIS (Management Information System) databases as the basis for data reasoning. An MIS database keeps a record of daily operating data; however, such unprocessed data are inappropriate for making direct decision-making inferences. Therefore, relevant data mining technology is applied to the data to select important information from the MIS database. The data are then used to find better solutions using the linear planning model of the cost information benchmark-learning platform, and the results are stored in the ABC (activity based costing)-DSS (decision support system) database. The knowledge reasoning process of CBR (case based reasoning) is used to carry out knowledge reasoning based on the business rule case from the case knowledge database and data from the ABC-DSS database. The results are used to create customized product service suggestions for the reference of decision-makers [2,3].

2 Research Method

This study treated internationalized 3C distributors in Taiwan as the subjects, and used their internal MIS databases as the basic data source. Although MIS databases keep records of the daily operating data, such unprocessed data are inappropriate for making direct decision-making inferences. Hence, relevant data mining technology was employed to extract the major relevant information from the MIS databases. The data were then used to find better solutions using the linear planning model with the help of the contents of the customized logistics service quality key factor structural hierarchy on the cost information benchmarking learning platform. The results were saved in the ABC-DSS database. The CBR method of knowledge reasoning, together with the business operating rule cases of the case knowledge database and data from the ABC-DSS database for knowledge inference, were used to help provide solutions for relevant customized product logistics service decision-making activities, as shown in the Figure 1 [2,3].

2.1 Architecture of the Activity-based Cost Knowledge Management Decision-making Support System

This study used the internal MIS databases of the case company as the basis for data inference. Although MIS databases keep records of the daily operating data, such unprocessed data are inappropriate for making direct decision-making inferences. Hence, relevant data mining technology was employed to extract the major relevant information from the MIS databases. The data were then used to find better solutions using the linear planning model with the help of the contents of the logistics service quality key factor structural hierarchy on the cost information benchmarking learning platform. The results were saved in the ABC-DSS database. The CBR method of knowledge reasoning, together with the business operating rule cases of the case knowledge database and data from the ABC-DSS database for knowledge inference, were used to help provide solutions for relevant customized product logistics service decision-making activities. The findings could serve as references to decision makers [2,3].

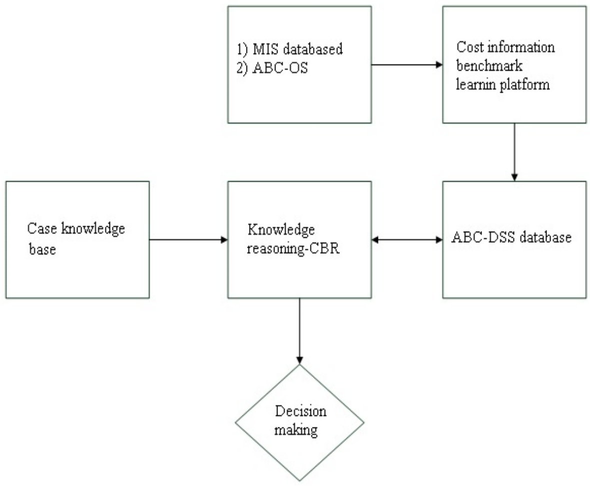

Fig. 1 Activity-based cost knowledge reasoning architecture [2, 3]

2.2 Illustrations of the ABC-KMDSS and Multiple-agent Programming System Architecture

The activity-based cost knowledge management decision-making support system is a multiple-agent programming system architecture, which is based on case rules and corporate internal data. The system processes a variety of relevant data from each agent according to the needs of the tasks. Front-end users can input problems related to decision-making through the terminal computer and the system will automatically extract rules of reasoning for the desired corporate case from the knowledge database and the ABC-DSS database data for reasoning comparison. After the comparison, the new facts that have been generated are then sent back and saved in the ABC-DSS database. CBR reasoning is repeatedly conducted until the results are produced and displayed for decision-makers as a reference. The implementation steps of CBR are as shown below [2–4].

2.3 Knowledge Reasoning-CBR Expert System

This study categorized the search conditions of the CBR reasoning process into explicit indicators and implicit indicators. The explicit indicators are employed to compare all the cases in the case database and generate the indicator values of the cases. The indicator values are then used to retrieve the supplier database and find similar maintenance cases. However, since the supplier database is quite large, the retrieved cases may be unable to satisfy the current inquiry. In other words, cases with similar index values may be found during the comparison process. To acquire more accurate comparison information, during the retrieval process, the sub-sequence of inexplicit indicators is added to put the retrieved cases more in line with the supplier database, the customer background, the industry, and technological capabilities. The explicit indicators refer to the significant indicators of the current problems to be estimated. For example, the key case indicator values for consideration include the immediate response capabilities of 3C distributors, the supplier product quality and the electronization level of the suppliers. The processing of the explicit indicators in the CBR method is as illustrated below:

(1)Summarize the relevant elements of the items to be processed through experience-based interviews and judgment, as well as the integration of maintenance manuals and references.

(2)Determine the weights of the various indicators and the similarity values in between the attributes of various indicators. During this process, the value determination mainly depends on expert-based rules of thumb or upon group consensus on the weight and relevance. Traditional decision-making methods use accurate values to represent the evaluated values of a decision-making matrix. However, the evaluation values are often obtained on the basis of incomplete information and depend on the experience of experts for judgment. As a result, such evaluation values have high subjectivity and fuzziness. Therefore, fuzzy theory principles are employed to express expert or decision-making views.

The inexplicit indicators refer to an evaluation of the scores of various cases through learning the customers' needs and gaining the required professional technological capability support. In this way, case retrieval can consider the gap in educational backgrounds, education levels and professional technological capabilities of different customers. When evaluating the cases, qualitative comparisons should be quantified. Hence, semantically fuzzy rules are employed to quantify each factor before integrating expert experience to give different levels of weight to each factor. The multiplication addition results are the index values of the inexplicit indicators. Regarding the processing of inexplicit indicators by the CBR method, the operations of explicit indicators and inexplicit indictors can determine the similarity values between the inquiry case and each case in the database. Through the comparison ranking method, the total similarity value of the explicit indicators can be used for making priority selections before using the inexplicit indicators to implement the sub-rankings of the total similarity value in each level. The inquiry results can better satisfy the inquiry case by comprehensively calculating the explicit and inexplicit indicators.

The case similarity equation is the similarity algorithm used in this study. It compares the total similarity value of the input indicators with each case in the database and sorts out the comparison results by order. The calculation steps are as shown in the Figure 2 [5]:

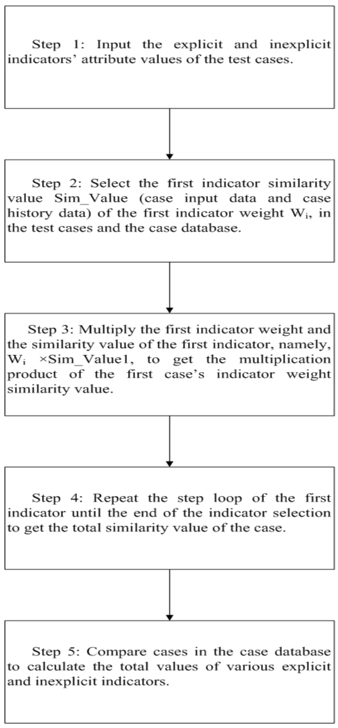

Fig. 2 The calculation steps of CBR [5]

2.4 Multiple Agent System

The multiple agent system can be divided into the website management agent, the assignment control management agent, the MIS agent, the database agent, the case knowledge agent and the rule model agent. The following is an illustration of the functions of various agent programs are as shown in the Figure 3 [6,10–15]:

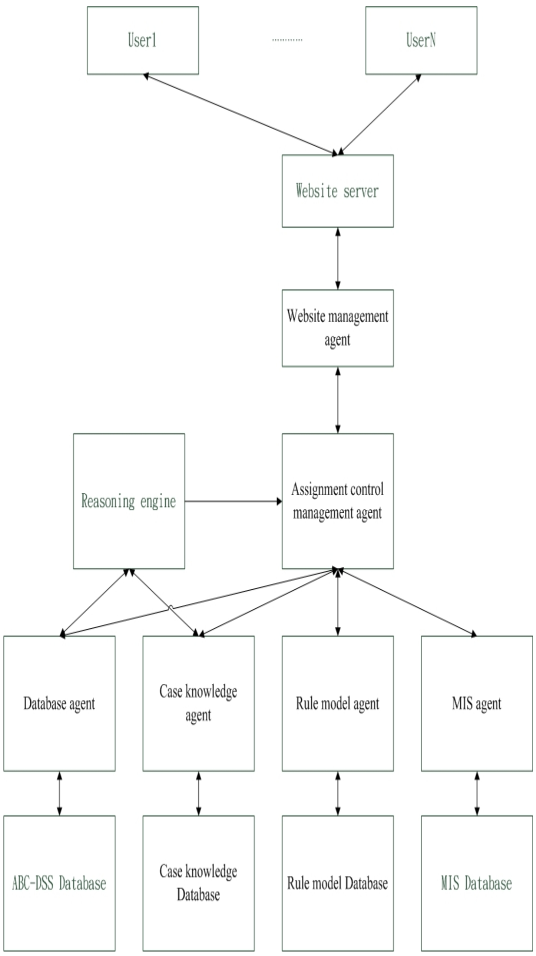

Fig. 3 Multiple Agent System [6,10–15]

(1)Website management agent: this is used to establish the user-system interface. The user executes system operations through the website agent program.
(2)Assignment control management agent: this is used to assign the user needs to the knowledge agent program, the MIS agent program and the database agent program for service.
(3)MIS agent: this is used to execute the data mining functions of the MIS database, including production management, raw material management, and sales management, according to the rules of the knowledge database, and then save the results in the ABC-DSS database through the database agent.
(4)Database agent: this is used to provide already-existing facts to the knowledge agent program for rule reasoning comparison, and then save the newly generated facts in the ABC-DSS database, Integration of ABC and ABM(Activity-Based Management) are as shown in the Figure 4[16].

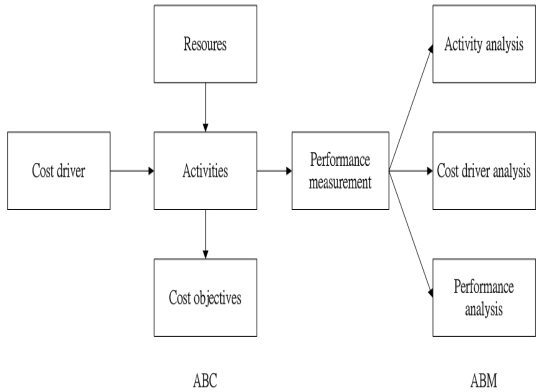

Fig. 4 Integration of ABC and ABM [16]

(5)Case knowledge agent: this is used to execute rule comparisons of the tasks assigned by the user. The case knowledge agent program will receive the request directives sent by the front-end users through the assignment control agent program and then work with the MIS agent program to retrieve cases from the MIS database, while reasoning new facts and decision-making suggestions according to the rules of the knowledge database.
(6)Rule model agent: this is used to read the rule models from the model database and predict future business performance using the knowledge reasoning engine combined with the data mining model, in order to help decision makers conveniently understand the future trends of the enterprises.

One of the decision-making purposes of this study was to discuss the production and distribution problems faced by 3C distributors, and then establish models for the production and distribution of 3C distributors by considering three objectives, including the lowest cost, the maximum service level within the period, and the maximum machine flexibility [7]. The proposed multi-target model established the multi-target production and distribution-planning model according to the characteristics of the 3C distributors for international operations. The MOP (multi-objective planning as illustrated in Eq.(1)-(3), n are variables, m are constrain equations, P are multi-objectives, $Z(X_1,X_2,...,X_n)$ is objective function, $Z_1, Z_2, ..., Z_P$ are single objective function[17, 18].

$$\max Z(X_1, X_2, ..., X_n) = [Z_1(X_1, X_2, ..., X_n)..Z_P(X_1, X_2, ..., X_n)] \quad (1)$$

$$s.t. \sum_{j=1}^{n} a_{ij}X_j \geqslant b_i, \, i = 1, 2, ..., m \quad (2)$$

$$X_j \geqslant 0, \quad j = 1, 2, ..., n \quad (3)$$

The algorithm solution-finding process used the modified multi-objective planning (MOP) algorithm. Its contents included the multi-objective algorithm of NSGA-II (non-dominate sorting genetic algorithm) [8] integrated with PSO (particle swarm optimization). The purpose of the equation was to allow the i-th particle in X_i to move in the direction of the combined vector direction of $Pbest_i$ and Gbest to increase the chances of improving X_i. The position of the particle was then updated by its movement, according to Eq.(4) [9]. After the end of the particle movement, the new fitness value was calculated to update the next generation $Pbest_i$ and Gbest. The updating method was as illustrated in Eq.(5) and (6), where t is the number of evolution generations. According to the comparison of the new fitness value of the particle with the previous $Pbest_i$, if the new fitness value was superior to the original $Pbest_i$, the $Pbest_i$ information would be updated. Gbest was the information of the particle with the optimal fitness value among all $Pbest_i$, the parameter ps referred to the population size, $Pbest_i$ was the best experiential solution of i, and Gbest was the optimal solution of all $Pbest_i$ as well as the global optimal solution. The optimal solution to the problem was thus found through such continuous operation and calculation processes.

$$x_{i,j}(t+1) = x_{i,j}(t) + v_{i,j}(t+1) \quad (4)$$

$$Pbest_i(t+1) = \begin{cases} Pbest_i(t), \, f(X_i(t+1)) \geqslant f(Pbest_i(t)) \\ X_i(t+1), otherwise \end{cases} \quad (5)$$

$$Gbest = \arg\min_{Pbest_i} f(Pbest_i(t+1)), 1 \leqslant i \leqslant ps \quad (6)$$

The implementation of the ABC-KMDSS and the integration of the modified MOP algorithm could save 16.2% of total costs for enterprises, indicating that the method is the best approach for 3C distributors to save relevant costs are as shown in the Table 1.

3 Conclusions

By interviewing experts about 3C distributors, this study learned the obstacles and limitations for the implementation of various decisions of the industry, and further established the activity-based cost knowledge management decision-making support system as expected by 3C distributors in implementation.

The rules for enterprise operation in the knowledge database together with data from the ABC- KMDSS database, were used for the CBR (case-based reasoning) method of knowledge reasoning to determine the proper decision-making for logistics services of relevant customized products [1–5, 14–18]. This study of methods could save 16.2% of total costs for enterprises.

Table 1 Improvement of total costs

Items of costs	Original costs(million/year)	The relational costs of this study(million/year)
Order / Fixed	3.2	2.6
Inventory	0.9	0.75
Transportation	2.6	2.3
Information	1.2	1
Uncertainty	1.9	1.56
Total	**9.8(1)**	**8.21(2)**
Improvement (%)	$\frac{(1)-(2)}{(1)}(\%) = 16.2\%$	

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