International Journal of Navigation and Port Research
Vol.29, No.4 pp. 349~355, 2005 (ISSN-1598-7701)

# A Study on Building B2B EC Business Model for The Shipping Industry Using Expert System

*Song-Jin Yu**

**Division of Shipping Management, National Korea Maritime University, Busan 606-791, Korea*

**Abstract** : *The use of the internet to facilitate commerce among companies promises vast benefits. Lots of e-marketplaces are building for several industries such as chemistry, airplane, and automobile industries. This study provides the new B2B EC business model for the shipping industry which concerns relatively massive fixed assets to be fully utilized. To be successful the proposed model gives participants useful information. To do this the expert system is constructed with the hybrid prediction system of neural network (NN) and memory based reasoning (MBR) with self-organizing map (SOM) and knowledge augmentation technique using qualitative reasoning (QR). The expert system supports participants useful information coping with dynamic market environment. with this shipping companies are induced to participate in the proposed e-marketplace and helped for exchanges easily. Also participants would utilize their assets fully through B2B exchanges.*

**Key words** : *Shipping industry, B2B EC, expert system, Neural network, Qualitative reasoning*

## 1. Introduction

Electronic marketplaces are becoming important players in several industries because they promise to greatly improve economic efficiency, reduce margins between price and cost, and speed up complicated business deals. The services they provide will expand many companies' purchasing and selling abilities, and will make prices more dynamic and responsive to economic conditions.

The majority of these sites will be vertical exchanges, which focus on specific types of goods or the needs of particular industries. Several are already functioning in such key areas as metals, plastics, and electronic components. In these market areas there exist huge companies that have sufficient market share and name value as much as overwhelming competitors. Such companies (for example GE, Dell) opened sites in the form of vertical market to procure theirraw material and components or to sell their goods in early EC market for their own profits. However, e-marketplace's advantages cause the range of market to expand from an individual company to same industry and exchanges among different industries to occur naturally.

E-marketplaces are fascinating because they present serious technical challenges. Several vendors offer software and services to support them, but requirements are expanding and shifting as markets develop. E-marketplaces are sensitive to business details, and small changes in the rules of engagement can profoundly alter a marketplace's attractiveness and profitability. A successful exchange can aggregate more activity than an individual buyer's or seller's site, but a marketplace's structure determines whether it is a desirable place to do business or not. E-marketplaces should manage participants, information, and business processes the flow of information and the business transactions that are the heart of the activity. More formally, an exchange should support security, liquidity, transparency, efficiency, and anonymity. Therefore, for the participants of e-marketplace customer relationship management (CRM) is needed.

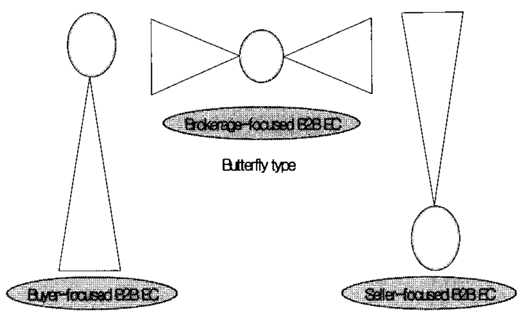


Fig. 1 Types of e-marketplace

This paper suggests business model of B2B EC in the shipping industry. Counter to the common wisdom about B2B today, exchanges are not the primary source of value in markets that are information intensive. It is so important that shipping lines, which are global multinational and forefront of international logistics, persue active e-Business including B2B EC. In the perspective of information

* Corresponding Author : Song Jin Yu, coppers@bada.hhu.ac.kr, 051) 410-4383, 018-562-2960

management, we develop the business model in shipping industry using integration of artificial intelligence tools and qualitative reasoning. Integration of data mining tools may be the best currently for building up knowledge bases in a complex domain such as B2B EC.

This study is organized as follows. In section 2 flaws in traditional B2B model and current states of shipping industry in B2B EC are reviewed. Section 3 describes core systems of the proposed B2B business model which support useful information for decision-making through data-driven approach in dynamic environment. With designed systems in section 3, new B2B business model for shipping industry focused on shipping lines is constructed and described in section 4. And conclusion will be followed.

## 2. Literature Review

Like as Alvin Toffler's forecast, "21th century will be new marine era," the sea is appearing the front of history. Especially, with advent of WTO in 1995 trade barriers among countries are being collapsed and unlimited competition and continuous economic growth with rapid progress of hi-tech change continuously maritime environments.

Recently B2B EC is going to be introduced and boosted in maritime industry. Dominant maritime portal sites are INTTRA and GTN. Maersk Sealand, P&O Nedlloyd, Hamburg Sud, MSC Mediterranean Shipping Co, CMA, CGM, and Hapag-Lloyd and main logistics companies in Europe are paricipated in INTTRA. Service areas of INTTRA are on-line booking, seaborne goods tracking, shipping line and schedule inquiring, drawing B/L, statistics about shipping and so on. It aims to provide global integrated logistics services. APL, CP Ships, Yang Ming, MOL, K-line, Senator, ZIM, Hanjin Shipping, and Hyundai Merchant Marine Co. are participated in GTN. GTN provides services of on-line booking, shipping schedule inquiring and booking, shipping cost inquiring, seaborne goods tracking, ship dealing information, and so on. As GTN integrates and operates information system of its member companies, it provides one-stop service from inquiring services of member companies to concluding contracts via access to GTN.

In Han's research (2000) B2B EC of shipping industry categorized into online aggregator, shipping service referral, online B&M carrier, after market service provider. And he pointed out most of domestic B2B companies in shipping industry receive benefits from advertizing or providing solutions to later-opened sites on the contrary to innate goals. Most web sites of shipping companies also provides only introduction of their companies or services.

On the other hand, most of B2B activity to date has centered on online exchanges and auctions, and most observers have assumed that these e-marketplaces would come to dominate the B2B landscape. However, they suffer from meager transaction volume and equally meager revenues, and they face a raft of competitors.

Richard Wise and David Morrison (2000) pointed out that the current B2B model has three fatal flaws. First, the value proposition offered by most exchanges competitive bidding among suppliers allows buyers to get the lowest possible prices runs counter to the best recent thinking on buyer-supplier relations. Second, the exchanges deliver little benefit to sellers. Finally, the business models of most B2B exchanges are, at best, half-baked.

The current B2B model, propped up by cheap investment capital, is not sustainable. As the markets mature, they will have to evolve in ways that solve the problems of the existing system. New structures will enable buyers and suppliers to form tight relationships while still enjoying the reach and efficiency of e-commerce.

## 3. Design of Expert System Using AI Tools

### 3.1 MBR- and Neural Network-Based Expert System

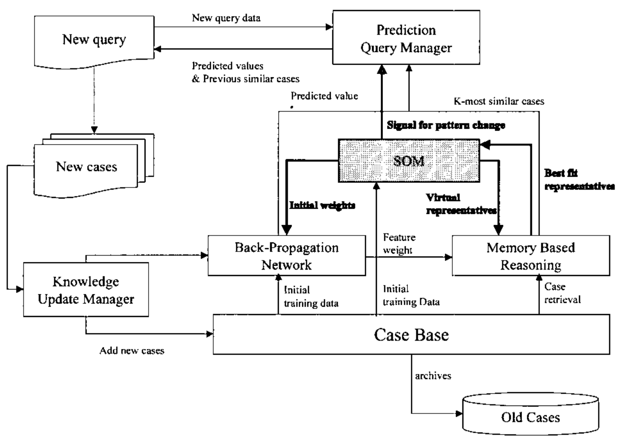


Fig. 2 Framework of memory- and neural network- based expert system with a unified approach

While it is important that general B2B EC business models give a relevant service for buyers according to their needs, it is important that B2B EC business model for shipping industry helps suppliers to fully utilize their assets. Therefore, in a proposed business model building up knowledge bases for supplier is the core.

In developing and refining knowledge base, pattern analysis of input data using SOM(Self-Organizing Map) is performed at first as shown in Fig. 2.

SOM gives us useful information in two ways. At first, we can discriminate using SOM whether several sets of data have same distribution. With the theoretical background of Shannon's information theory, we can compare whether feature maps of them are the same or not and infer that different maps mean different data sets. We can also do it indirectly by mapping onto discrete output space for several sets of data using a same feature map. If the results of mapping are different, they have different distribution functions. This ability of SOM helps expert system to adapt in dynamic environments.

Secondly, an analysis of feature map itself diminishes learning burden of BPN(Back-Propagation Network) and gives MBR(Memory Based Reasoning) virtual cases that are meaningful features of data. Since there is no formal method to settle the network architecture of BPN, exploratory experiments are performed iteratively until the proper network is obtained. Since initial weights of network are randomized values near zero in training, more experiments are required to avoid local minimum. Features of input patterns can help to setup initial weights and threshold values of BPN, and inform whether training of partial data divided by features of input patterns is more efficient for acquiring good knowledge than training of whole dat

For the development of a knowledge base, BPN and MBR can be used for both of classification and regression tasks without any converting mechanism. BPN generally generates one real-valued output per output node. One can set some threshold values to interpret the value as a predicted class for classification tasks. MBR retrieves a set of $k$ most similar previous cases and assigns the class that is most frequent in the set. As for regression tasks, the output of BPN can be directly interpreted as the predicted value. MBR generally averages the target value of similar cases. Both of methods can easily refine their knowledge as new cases are appeared. BPN can modify the weight set as more data are newly introduced. On-line learning is possible for the memory-based reasoning. One can update the case base with new and fresh data and exclude old data from the case base whenever SOM warns that the features of new data are different from them of old.

In our architecture of memory- and neural network-based prediction system, integration of prediction result is carried by the Prediction Query Manager (PQM). PQM receives new data and consult to BPN and MBR concurrently. When both predictors coincidein prediction, PQM answers with predicted values. When the results are different largely from each other, PQM answers the suspicious result with most similar previous cases. When disagreement of both methods occurs frequently, PQM might sent a warning signal which indicates that the knowledge base may not cover the whole space of data or that something wrong is going on the prediction system itself. Knowledge Update Manager (KUP) takes the role of providing new cases for knowledge refinement. For MBR old cases may just take unnecessary storage space in a case base and delay searching similar cases, and they may even hinder MBR from correct prediction in a dynamic situation like semiconductor industry. Besides, old knowledge of BPN may not fit new cases of current environments or processes. Whenever SOM module catches a signal of any change about application areas, KUP provides new cases for retraining of BPN and adjusting a case base of MBR.

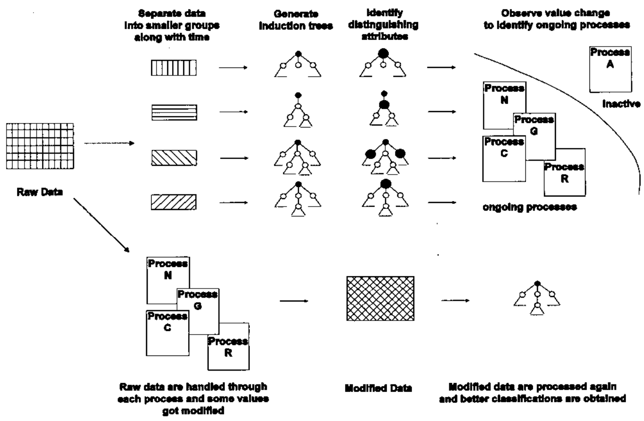


Fig. 3 Data and control flow of Decision Support System

### 3.2 Decision Support System Using Qualitative Learning

The proposed expert system mentioned above has a good capability for prediction adapting to highly dynamic environment such as shipping industry. But expert systems have limitation that their prediction abilities are good only in definite time period. It is difficult that the knowledge base built up with the existing data have long-term knowledge and qualitative knowledge. To overcome these limitation, the decision support system using qualitative reasoning is introduced.

General data and control flows are illustrated in Fig. 3. The data and control flow can be traced in two separate paths. Following the upper path, it is the *analysis mode;* and the one in the bottom of the figure is called the *application mode.* In the analysis mode, we look at the data and pay attention to the changes among data values. These changes will serve as a clue during the procedure of identifying which processes are currently active. Once the active processes are identified, we then proceed to the application mode. In this mode, the effects due to any active process will be applied to the data samples and some attribute values will be modified. The modification is aiming at making the existing phenomena more prominent so that they can be captured by the concept classification system.

In identifying the underlying processes which are affecting the values of each company's data, we need to pick distinguishing attributes from among the attributes to be observed. These attributes are determined by comparing decision trees obtained from different subgroups of the data. In the following, we present out method of identifying the distinctive attributes from the attributes of an entire data set. In general, it takes two stages to complete the task. The first is to compare, and the second to verify. In the first stage we make up two less general yet contrasting concepts and represent these two concepts in the form of decision trees. In generating the decision trees, we may need to feed in all or only a portion of the entire data set, depending on the characteristics of the concept in question. After the trees are generated, we then look closely at the attributes that constitute each tree. Since each tree is made up of different attributes, the comparison of the presence and absence of each attribute in each decision tree, and of the ranking of those attributes appearing in a tree will help us identify what attributes play a more significant role in a decision tree.

The attributes being identified as distinctive in the first stage are only good when considering each decision tree alone. Furthermore, as we mentioned above, each of the trees represents nothing but a less general concept, or a sub-concept, of the final concept in which we are interested. Thus in the second stage, we will need to verify that those attributes selected in the first stage are important for the final concept as well. To do so, we compare the trees for sub-concepts with the decision tree generated for the final concept. The idea is that some attributes, while being distinctive for an individual decision tree, may provide conflicting information when considered collectively with attributes present in other decision trees. The purpose of conducting the comparison in the second stage is to guard against this kind of side effect. More detail description about the second stage is as following.

Fig. 4 describes a knowledge augmentation procedure from static-valued data using QR we call it the *application mode*. First the same company's data at different times are checked to see whether they were activating a certain ongoing process or not, which describes qualitative changes during the time unit. When the whole activation condition of the process was satisfied, an activated process was fired. This means that the next financial data will be changed following it, and it is proposed that the company's strategy not be changed. But it will not tell how much it is changed. So we modify the related attributes of the financial data with a meaningful amplification rate. Modified data are inputs in a decision tree and give us the decision information. Here the decision tree is the concept by which companies are more likely to make claims at current time. We repeat the above process with various amplification rates and settle on the appropriate value that gives the best correct prediction ratio (CPR).

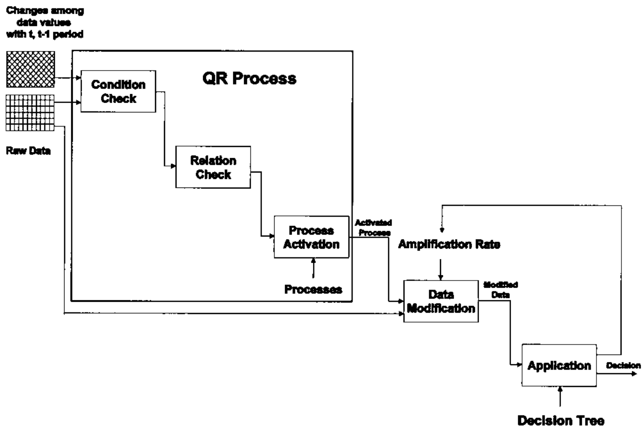


Fig. 4 Knowledge augmentation procedure using QR

## 4. New B2B EC Business Model For The Shipping Industry

Shipping business is too much broad to cover in this research. In the paper shipping business is defined in narrow sense as works that ships transport seaborne goods ship via ocean. Shipping companies are categorized into liner and tramper ones and types of decision-making are too different between them. Liner is large merchant ship that visits designated ports on a regular schedule, carrying whatever cargo and passengers are available on the date of sailing. Most of major global shipping companies focus on managing liners. Therefore the proposed B2B EC business model is focused on liner companies.

Many B2B transactions will be consist of sell-side asset exchanges, in which suppliers will trade orders among themselves, sometimes after initial transactions with customers are made on general B2B sites. Sell-side swapping will be most valuable where markets are highly fragmented, both on the buyer and seller sides where, for geographic or information reasons, demand and supply are often mismatched and where suppliers can benefit greatly from keeping expensive fixed assets fully utilized. Industries with these characteristics include transportation, metalworking, plastic molding, farming, and construction. Shipping Industry also have these characteristics. Furthermore it is capital-intensive industry and has strong competition among shipping companies.

A company seeking to pursue the asset-exchange model will need to have strong relationships with the supplier community, since success will hinge on its gaining a critical mass of supplier transactions. It will also need to be adept at understanding supplier problems; sales of products and services that solve them will likely be an important source of profits.

The business model for shipping industry is depicted in Fig. 5. While it is important that a traditional model give a relevant service for buyers according to their needs, it is important that the proposed model helps shipping companies to fully utilize their assets. Therefore, in the proposed model building up knowledge bases for shipping lines is the core.

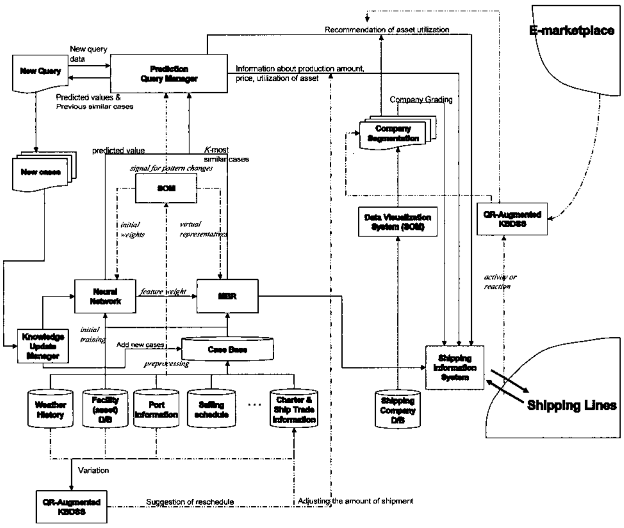


**Fig. 5** Business model of B2B EC for Shipping Industry

The SOM-augmented memory-based and neural network-based expert system is developed for building up knowledge bases. Databases of weather history, facility(ship), sailing status, sailing schedule, port capability information and so on may be useful resources for building up knowledge bases. After these data are preprocessed as relevant forms for neural network training, they are inputted into a neural network. A neural network saves domain knowledge in weights of a trained network. Feature weights of a trained network identify how much impact each variables affects domain knowledge and give MBR the information. The SOM is not a tool that makes a prediction of unseen cases but it supports for building better knowledge bases. Any change of environments or internal processes in an application area induces changes of features of data. With this result, knowledge bases of expert systems have to be refined for accurate prediction.

With appropriate knowledge bases, the expert system supports shipping companies for decision-making. Using data gathered from databases depicted in Fig 5, the expert system estimates the quantity of goods transported in a shipping industry and changes of bottom tonnage that are critical information to every shipping companies for decision-making.

On the other hand, the utilization of fixed assets may be different with each firm for geographic or information reasons. In the case of shipping business, the mismatch of supply and demand is often occurred. The expert system solves these problems with aggregation of data along with regions by building knowledge bases. Using them, the deviation among several regions may be decreased.

However, it is impossible that an expert system build the knowledge base to cope with the variation of all external environment. Qualitative reasoning helps us to infer impacts on transporting schedules in next stage with variations of weather, port & ship status. Data visualization system is also used for company segmentation in a sell-side asset exchange. To keep expensive fixed assets fully utilized, it is desirable that firm communities are composed of firms that have similar characteristics. And these communities would be more active than that consisted of diverse companies. If a small firm community have appropriate portfolio of ships, it can find one or more buyer communities whose demands are matched up with its supplies

## 5. Conclusion

No one deny most of exchanges will be achieved in e-marketplaces in the future. Technical obstacles of building up e-marketplaces were being put away one by one and are nearly vanished. Nevertheless, many companies hesitate to join in exchanges of e-marketplaces although they know advantages of electronic commerce sufficiently. This study proposed new B2B EC business model for the shipping industry which concerns relatively massive fixed assets to be fully utilized. Shipping industry has different characteristics - high fixed costs, relatively fragmented supplier and customer base, and strong competition - in comparison with other industries. So the e-marketplace of the shipping industry should have ability to offer additional relevant services including general services provided by other e-marketplaces and have strong relationships with the shipping lines. The proposed e-marketplace, which gives lots of useful information on every process using data mining approach, is designed to solve these problems. And the model supports realtime information - operation or management information - sharing among ports and combined transport companies and shipping companies including decision supporting from estimating the quantity of goods transported in a shipping industry, changes of bottom tonnage, and so on.

The developed MBR- and NN-based expert system supports information about when and how many shipping lines utilized fixed assets. And it helps one to acquire customer information and to understand the trend of target market. The mature template can be spinning off as an independent system for prediction. The developed knowledge augmentation system supports time-dependent knowledge that gives one the information about future status of interest things or customers or shipping lines.

Whether a company hopes to play a role as a B2B service provider or simply needs to transact business with other companies, it will have to develop a deep knowledge of the emerging landscape and the various business models it will contain. For many companies, traditional skills in such areas as product development, manufacturing, and marketing may become less important, while the ability to understand and capitalize on market dynamics may become considerably more important. The proposed data mining modules help it to have a deep knowledge of its own areas.

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**Received** 4 April 2005
**Accepted** 28 June 2005