

# **SELECTING SUPPLY PARTNERS FOR E-COLLABORATION IN SUPPLY CHAINS**

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**Abstract:** The system we propose supports a partner selection process in an e-business environment. The system evaluates partners' supply capabilities and market conditions changed over time with multi-criteria, including quantitative and qualitative criteria. It helps selecting the optimal partners for maximizing revenue under a level of supply risk. The proposed system has been applied to partner selection problem under the supply chain of an agriculture industry.

**Key words:** Supply chain; e-collaboration; supplier selection; e-business.

## **1. INTRODUCTION**

In industrial companies, as procurement activities account for the 50-90% of the whole business activities, the direct and indirect consequences of poor partner selection become more severe, making decisions of purchasing strategies and operations primary determinants of profitability.

Companies have more chances for selecting more effective partners due to the globalization of trade and the prevalence of the Internet. They can purchase better quality goods at a cheaper price and with better delivery conditions. However, there exist complicated issues, including the increasing number of available suppliers and the market conditions which have changed over time.

The research fields of partner selection are divided into four parts: problem definition, formulation of criteria, pre-qualification, and final selection (Boer et al., 2001). Especially, pre-qualification and final choice

parts are currently being actively pursued. We have come up with the following conclusions by examining the existing research results: When selecting supply partners, we should consider changes of supply capabilities and supply market conditions over time; Partners should be evaluated with both quantitative and qualitative criteria (e.g. price, quality, or delivery performance); We must select suppliers which maximize the revenue of a purchasing company and satisfy the procurement conditions as well which the purchasing company wants to impose.

## **2. SUPPLY PARTNER SELECTION METHODS**

### **2.1 Existing literature review**

In a review of supplier selection methods by Boer et al. (2001), the authors divided the supplier selection process into two steps of pre-qualification and final choice. The pre-qualification step can be defined as the process of reducing the set of all suppliers to a smaller set of acceptable suppliers. They pinpointed four categories of methods: Categorical methods, data envelopment analysis (DEA), clustering analysis (CA), and case-based reasoning (CBR).

Holt (1998) reviewed and compared several decisional methods (CA, bespoke approaches, multi-attribute analysis, multiple regressions, and multivariate discriminant analysis) which have been applied in supplier selection. He suggested that CA offers the greatest potential for pre-qualifying all suppliers. CA reduces the probability of rejecting a good supplier too early in the process via subjective reduction of the often large original set. CA can enlarge the scope for rationalization of the selection process by identifying the criteria involved. Because of these merits, we use a CA method for evaluating all available suppliers in the pre-qualification stage.

Methods suggested in final choice step are categorized into linear weighting, total cost of ownership, mathematical programming, statistical, and artificial intelligence models. Most methods belong to linear weighting and mathematical programming models (MP). MP allows a decision-maker to formulate a decision problem in terms of a mathematical objective function that subsequently needs to be maximized or minimized by varying the values of variables in the objective function. Weber and Desai (1996) illustrated how parallel axis analysis can be used to identify alternative paths in which inefficient vendors can become efficient providers of a product. Weber et al. (1998) expanded their models to negotiate with suppliers

selected by multi-objective programming models under non-cooperative negotiation strategy. Especially, they showed that the values of supplier selection change according to the number of suppliers.

In linear weighting models, weights are given to the criteria, and the biggest weight indicates the highest importance. Ratings of the criteria are multiplied by their weights and summed in order to obtain a single figure for each supplier. The supplier with the highest overall rating can then be selected. Lee et al. (2001) suggested a supplier selection and management system (SSMS) which uses the linear weighting model to calculate the weights of tangible and intangible criteria and to rank the supplier's performance. Characteristic of the system resides in the process which identifies the weak criteria of selected suppliers by comparison with alternative suppliers. The SSMS informs us of the directions improving supplier performance.

## **2.2 Problems to solve**

The static assessment for partner selection in the current research results does not cope with changes in supply capabilities and supply market conditions over time. It can be difficult for a supplier to maintain the same capability conditions during all supply periods depending on types of industries. Especially, it is very serious when we select a partner for agriculture products which have seasonal availabilities and have a wide fluctuation of capability over time. All partners can not maintain the same capabilities during all analysis periods because of changes in the delivery condition, inventory level, and market environments. Even if a partner maintains a constant supply capability, the risk level of the supply market can change over time. We can not evaluate these capability condition changes if we use the average values of criteria during the total periods of analysis. We can lose a chance to find the better solution. Thus, it is important that we divide all periods of analysis into several meaningful period units, evaluate supply conditions of each period unit, and put the results together (Talluri and Sarkis, 2002).

We consider multi-criteria (quantitative and qualitative criteria) to evaluate suppliers' capability conditions. In an early study on partner selection criteria, Dickson (1966) identified 23 criteria that have been considered by purchasing managers in various partner selection problems. Since the Dickson's study, many researchers have identified important criteria varied by industry and buying situation, and have suggested multi-criteria models. In his portfolio approach, Kraljic (1983) identified the purchasing situation in terms of two factors: profit impact and supply risk. Profit impact includes such elements as the expected monetary volume

involved with the goods or services to be purchased and the impact on future product quality. Indicators of supply risk may include the availability of goods or services under consideration and the number of potential suppliers. Therefore we decide to consider such criteria as price, delivery, quality, quantity, reputation and position, warranties and claim, and information share together. By applying these criteria, we can identify several groups of partners who have low supply risk and above the needed profit. Then, we select the optimal partners, which maximize the revenue within the groups.

### **3. DYNAMIC PARTNER SELECTION IN A SUPPLY CHAIN**

The dynamic partner selection system consists of five major modules, as shown in Figure 1: *Prediction Module*, *Segmentation Module*, *Pre-Qualification Module*, *Optimization Module*, and *Update Module*. After building a long-term purchasing plan, a purchaser company searches for partners who can deliver a product or a service, assesses them, and selects the optimal ones. As described in the previous sections, the supply market conditions and the capabilities of partners change over time. Therefore, the selection system must be able to predict changes of the supply market conditions by period of time and segment the total purchasing period into several meaningful periods according to the changes. The system must select optimal partners who can not only deliver their products or services stably, but also maximize the revenues under changed market conditions within each meaningful period. We will describe the system's modules in detail in the following subsections.

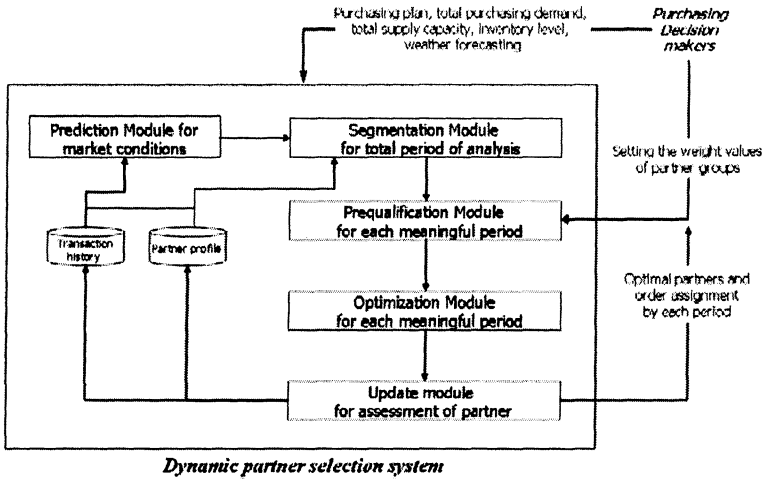


Figure 1. The architecture of dynamic partner selection system.

### 3.1 Prediction Module (PM)

The Prediction Module (PM) predicts the total size of a supply market during the total purchasing period and the market size by period. The total supply capacity of all partners, total inventory level, and operation rate (e.g. weather in an agriculture industry) are used as prediction factors. A purchaser investigates values of the prediction factors and inputs these values to the selection system. The PM retrieves, then, the most similar cases from past cases. A case is defined as a record which consists of the supply condition fields (total supply capacity, total inventory level, and operation rate) and supply market fields (total size, size by period) in a transaction history database. For finding the cases which are most similar with values of the prediction factors, we use a hybrid approach of Memory And Neural Network-based learning (MANN) (Shin et al., 2000). The MANN method is one of the feature weighting methods for overcoming weakness of k-NN method, meaning that all features of k-NN have the same weight.

As shown in Figure 2, the PM calculates the weight of each prediction factor from the neural network. Because an important factor has a greater effect on prediction than others, we give it a higher weight when finding a similar case.

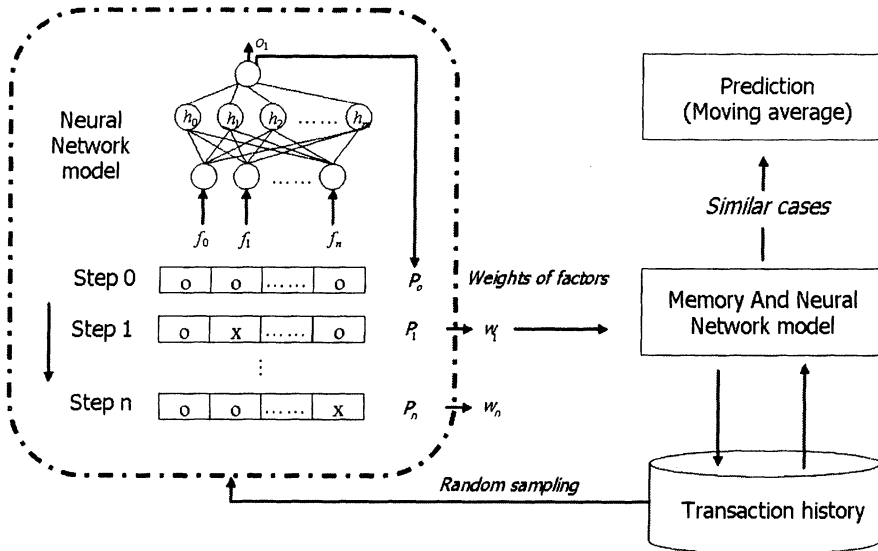


Figure 2. The procedure for calculating the weight of each factor.

The process for calculating the weight of each factor is as follows: First, we build a neural network having an input layer (total supply capacity of all partners, total inventory level, and operation rate), an output layer (total size of supply market), and one hidden layer with  $m$  nodes. Then, we train the neural network with a training set of  $k$  cases which are randomly sampled from the transaction history database.

Second, we use a sensitivity method to calculate the degree of importance of each factor: 1) A factor is selected and removed from the trained neural network, as shown in step 1 of Figure 2; 2) The weights of all nodes are set at zero and a new result is predicted from the modified neural network model; 3) The new result is compared with the initial result obtained from step 0. For comparison, we use the following sensitivity function:

$$w_i = \frac{(\sum_L \frac{|p^0 - p^i|}{p^0})}{n} \quad (1)$$

where  $p^0$  is an initial result and  $p^i$  is the new result calculated when  $i$ th factor is removed.  $L$  is a set of all  $n$  cases used for calculating the sensitivity of each factor. The new result is compared with the initial result obtained from step 0; 4) The degree of importance of all factors is calculated.

Third, we calculate the similarity between each case ( $x$ ) and the query ( $q$ ), the expected values for predicting a coming supply market condition with the weights of the prediction factors. The similarity is obtained by using the weighted Euclidean distance equation.

$$D(x, q) = \sqrt{\sum_{f=1}^n w_f \times \text{difference}(x_f, q_f)^2} \quad (2)$$

where  $w_f$  is the weight value assigned to factor  $f$ , and  $\text{difference}(x_f, q_f)$  is calculated from  $|x_f - q_f|$ . The higher the similarity of a case, the greater weight the case has.

After calculating the similarity values of all cases, we finally select  $K$  cases having higher similarity of all cases and calculate the total size of the supply market and the market size by period by averaging out  $K$  cases.

### 3.2 Segmentation Module (SM)

After predicting the total size of the supply market and the market size by period, we compare those with a predicted purchasing demand (how much quantity competitor companies of the purchaser will purchase). The supply and the demand change over time. The difference between supply and demand may become smaller in any period and the difference may become larger in another period. The former is a case having a low risk because the purchaser can find alternatives easily and pay a low switching cost even if a partner does not deliver products or services to him. The latter is, however, a case having a high risk.

Therefore, we consider a supply risk of the market to assess partners effectively under these market conditions, and divide the total purchasing period into several meaningful periods according to the supply risk. Park and Park (2003) suggested a method for dividing the whole period into several meaningful period units. They segmented sales records for the total period with a genetic algorithm and a linear regression model. We adopt this method in our system to divide the total period, as shown in Figure 3.

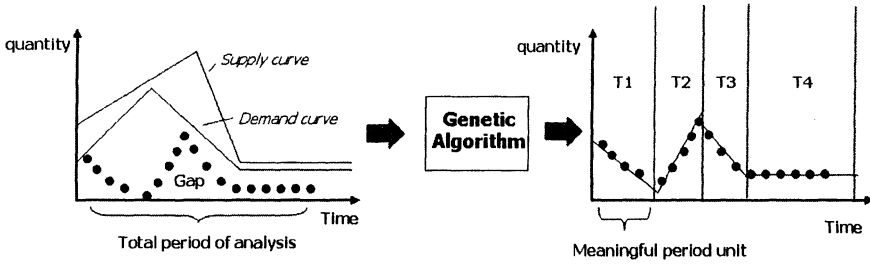


Figure 3. Dividing total analyzing period into several meaningful period units

We calculate the difference (gap) between supply and demand in each period to measure a level of risk and plot the differences in the graph. The plotting points are represented by binary codes, such as (1,0,0,0,1,0,0,0,0,1,0,0,1,0,0,0,0,0). The starting point of each period is 1; otherwise, it is 0. We find the best segmentation of periods by using a genetic algorithm with the following fitness function and binary representation.

$$\text{Fitness function} = \alpha \sum_{i=1}^N R_i^2 w_i + \beta F(N), \quad (3)$$

Where  $N$  is the number of intervals,  $w_i$  is the ratio of periods in the  $i$ th interval to the whole periods,  $R_i^2$  is the residual error of the  $i$ th interval,  $0 \leq \alpha \leq 1$ ,  $0 \leq \beta \leq 1$ , and  $\alpha + \beta = 1$ .

We can obtain four meaningful periods, as shown on the right of Figure 3. When the total purchasing period is defined as one year, the risk level of the market in the first and second meaningful periods is relatively lower than that in other periods because the gap is increased or decreased slowly. However, the risk level of the market in the third and fourth periods is very dangerous if a purchaser manages his partner loosely.

### 3.3 Pre-Qualification Module (PQM)

In the previous sections, we described the importance of an assessment model considering both quantitative criteria and qualitative criteria. The proposed system implements this assessment by aid of two modules, pre-qualification and optimization.

After dividing the total period into several meaningful period units, in the pre-qualification phase we segment partners into several groups which have



similar supply conditions in each meaningful period. We use Self-Organizing Map (SOM), a clustering tool using an unsupervised learning scheme, to train the neural network. Unsupervised learning comprises those techniques for which the resulting actions or desired outputs for the training sequences are unknown. The network is only given the input vectors, and then self-organizes these inputs into categories (Ha and Park, 1998).

The SOM is designed as follows: 1) Normalization: we normalize values of supply conditions into 0 ~ 1; 2) Clustering: we design a SOM which has 7 inputs and 9 outputs. The inputs include quantitative criteria (quality, frequency, price, and quantity) and qualitative criteria (reputation and position, warranties and claim, and information share). Outputs are the number of clusters to which a supply partner belongs. The SOM segments the partners into several groups with similar characteristics; 3) Pre-qualification: The system compares the characteristics of each group with the purchaser's needs in each meaningful period. For comparison, the system measures the distance between partner groups and needs of the purchaser, and selects groups which are close to the needs.

$$Distance(G, I) = \sqrt{w_d \times x_d + w_p \times x_p + w_q \times x_q + w_{qly} \times x_{qly} + \dots} \quad (4)$$

In the case of a high risk level, we assign higher weights to the criteria such as frequency, quantity, reputation and position, and warranties and claim. In the case of a low risk level, however, we assign higher weights to the criteria such as price, quality. Weights difference among criteria changes according to the gradient of gaps between demand and supply within each period (see Figure 4).

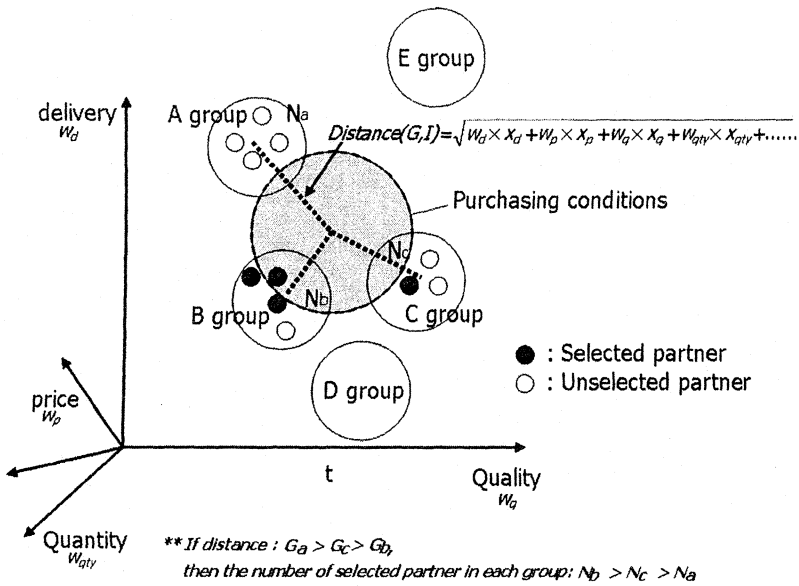


Figure 4. Selecting suppliers which maximize revenues under supply risks.

### 3.4 Optimization Module (OM)

After the pre-qualification stage, we decide on a final partner who can maximize revenue and satisfy the procurement conditions which the purchasing company wants. The following mixed integer model is designed to satisfy the procurement conditions.

$$Max Z = \sum_{i=1}^I \sum_{k=1}^K \sum_{t=1}^T R_{ikt} \times x_{ikt} \tag{5}$$

subject to

$$\sum_{i=1}^I \sum_{k=1}^K x_{ikt} \leq D_t, \text{ for all } t \tag{6}$$

$$x_{ikt} \leq \min(S_{it}^u, L_{it}^l) Y_{ikt}, \text{ for all } i, k, t \tag{7}$$

$$x_{ikt} \geq \max(S_{it}^l, L_{it}^l) Y_{ikt}, \text{ for all } i, k, t \quad (8)$$

$$\sum_{i=1}^I \sum_{k=1}^K y_{ikt} \leq N_t, \text{ for all } t \quad (9)$$

$$\sum_{i=1}^I y_{ikt} \geq \rho_{k+1,t} \sum_{i=1}^I y_{i(k+1)t} \geq \dots \geq \rho_{k+K,t} \sum_{i=1}^I y_{i(k+K)t}, \text{ for all } t \quad (10)$$

$$x_{ikt} \geq 0, \text{ for all } i, k, t \quad (11)$$

$$y_{ikt} \in (0,1), \text{ for all } i, k, t \quad (12)$$

where  $x_{ikt}$  is quantity ordered from the supplier  $i$  who belong to cluster  $k$  in period  $t$ ,  $R_{ikt}$  is revenue per unit made from the supplier  $i$  who belongs to cluster  $k$  in period  $t$ ,  $D_t$  is purchasing demand in period  $t$ ,  $S_{it}^u$  is maximum order quantity available from supplier  $i$  in period  $t$ ,  $S_{it}^l$  is minimum order quantity available from supplier  $i$  in period  $t$ ,  $L_{it}^u$  is maximum amount of business to be given to supplier  $i$  in period  $t$ ,  $L_{it}^l$  is minimum amount of business to be given to supplier  $i$  in period  $t$ ,  $N_t$  is the number of supplier to be selected in period  $t$ ,  $\rho_{k+n,t}$  is ratio of number of supplier selected in cluster  $k+n$  to number of supplier selected in cluster  $k$  in period  $t$ ,  $y_{ikt}$  is 1 if supplier  $i$  of cluster  $k$  is selected in period  $t$ ; 0, otherwise.

Objective function (5) shows the maximization of revenue during total planning periods under following constraints: Constraint (6) shows a purchasing demand in period  $t$ . Total order quantity of all suppliers cannot exceed the purchasing demand in period  $t$ . Constraints (7) and (8) show potential constraints of suppliers and policy constraints of a purchaser.

Constraint (9) is a limitation of the number of suppliers who are selected in period  $t$ . It can be a policy of purchaser. As the number of suppliers increases, the management cost increases and supply risk decreases. Constraint (10) shows a limitation for selecting suppliers in terms of the supply risk of cluster. If cluster 7 is superior to cluster 1, for example, the number of cluster 7 is  $\rho$  times as large as the number of cluster 1. The suppliers who have a low supply risk are finally selected more than other suppliers as maximizing the revenue. We choose the final suppliers and their supply quantities by using the mathematical model and determine other supply conditions from the cluster features.

### **3.5 Update Module (UM)**

After selecting the optimal partners and collaborating with them during the total purchasing period, the dynamic supplier selection system assesses the transaction history of the partners. The occurrence of the back-order, troubles of information share, and changes in warranty and claim strategy are reevaluated and the result of assessing a partner is updated in the partner profile database. The updated results are applied to the partner selection for the next purchase.

## **4. APPLICATION**

The dynamic supplier selection system has been applied to the partner selection under a supply chain of the agriculture industry. Agricultural products which farmers' associations produce are supplied for purchasers such as wholesalers and manufacturers. Purchasers process or package the produces and deliver them to customers. Because agricultural products are apt to be decomposed and because suppliers have different delivery intervals, harvest quantities and level of inventory facility, and changes of supply conditions by period are larger than other industries. Purchasers are not supplied enough quantities on time and they paid much money for being supplied from other suppliers. It is a very important issue how purchasers select suppliers in this supply environment.

We analyzed the data of the past one year with the proposed model. For comparison, we also applied the revised Weber method (Weber et al., 1998) to the same experimental data. Suppliers could be selected and the order quantities could be assigned to selected suppliers for the next year. The results from two models were compared in terms of revenue, shortages of order, and the number of managing suppliers, as shown in Figure 5.

The findings were: first, the proposed model can manage fewer suppliers than the revised Weber method and the supply risk (i.e., shortage of order) of our model is lower than the revised Weber method. When both models select three suppliers respectively, the suppliers who are selected by our model can fulfill order quantities on time without shortages of order. The revised Weber method, however, produces many shortages of order in all meaningful periods (especially, T2 in which sales are high). The revised Weber method should increase the number of suppliers to resolve the shortages and should pay more cost than our method.

Second, our model creates more revenue than the revised Weber during all periods. The revised Weber method increases the number of suppliers in order to increase revenue. However, revenue in the revised model can not

increase more than that of our model since maximum order quantities assigned to the best supplier are limited by distributing order quantities to other suppliers.

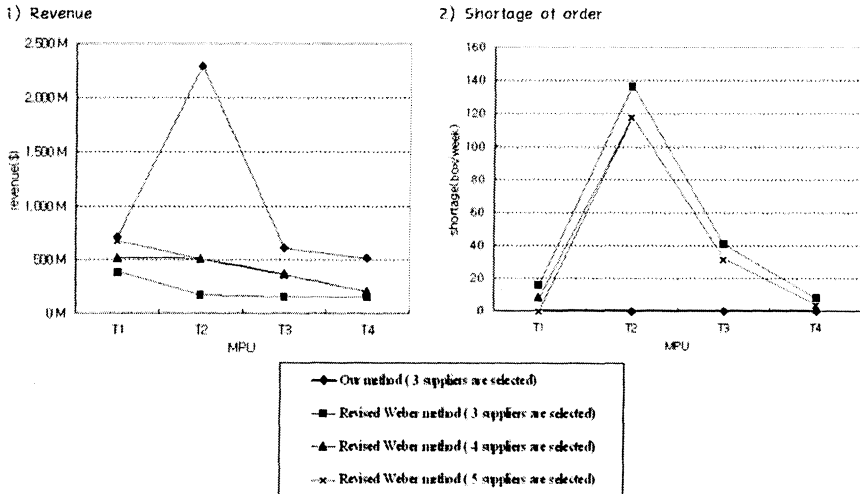


Figure 5. Comparing the proposed method to the revised Weber method

## 5. CONCLUSIONS

A dynamic partner selection system was proposed for supporting a partner selection in an e-business environment. Three problems caused from current selection process were identified and a method was proposed to solve them.

- 1) Evaluating suppliers' capabilities and market conditions over time,
- 2) Considering multi-criteria for evaluating suppliers' capabilities conditions,
- 3) Selecting suppliers to maximize revenue and to satisfy the procurement conditions.

The method was applied to the case of the agriculture industry and was compared to the revised Weber model in terms of the revenue, the shortage of order, and the number of managing suppliers. No shortage of order occurred in the proposed method, while shortages of order occurred except during the first meaningful period in the revised Weber model. Because of

such shortages, the number of managing suppliers is increased and the order amount of each supplier is decreased in the revised Weber model. As a result, the revenue of the revised Weber model was less than that in the proposed method.

Further works can extend the range of application to other industries in which supply conditions change according to time. In addition, because many supplied products are aggregated to one final product in several industries, it is very difficult to measure the profit of final product as an effect each supplied product has.

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