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Single and Multiple Sourcing in the Auto-Manufacturing Industry

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***Abstract*—**This article outlines a hybrid method, incorporating multiple techniques into an evaluation process, in order to select competitive suppliers in a supply chain. It enables a purchaser to do single sourcing and multiple sourcing by calculating a combined supplier score, which accounts for both qualitative and quantitative factors that have impact on supply chain performance.

***Keywords*—**Analytic hierarchy process, Data envelopment analysis, Neural network, Supply chain management.

I. INTRODUCTION

THE win - win strategies are more important to strategically-related firms, which conduct direct commercial transactions in an industrial network. Manufacturing firms, which face a competitive environment, should seriously consider win–win strategies, as customer needs vary over time and technology changes rapidly. Firms begin to focus on strategic business partners in the production process and recognize the significance of a supply chain and supply chain management, in order to actively cope with such environmental changes.

In order to gain competitive advantages in markets, manufacturers must collaborate, not only with component or raw material suppliers, but also with wholesalers/distributors, retailers, and customers, who all participate in a supply chain, directly or indirectly, in order to fulfill customer requests.

Supply chain management (SCM) involves the management of transaction flows among players in a supply chain so as to maximize total supply chain profitability. Firms within a supply chain can achieve sustainable competitive advantages through developing much closer relationships with all companies, and they can significantly reduce time and costs depending on the appropriate management of the supply chain, while serving customer needs at the same time. In a competitive environment, successful SCM is much helpful in strengthening the competitive edge of firms [8].

Among a variety of available suppliers, manufacturers must choose more collaborative ones who are able to develop long-term relationships. Especially, as purchasing activities within a supply chain play a more strategic role and trends include the movement from spot purchasing to long-term contractual relationships, sound supplier selection has become a strategic decision, meaning that it has become a vital source for adding strength to value proposition and for improving the competitiveness of manufacturers [18].

This paper, therefore, focuses on the selection of competitive suppliers in order to develop an efficient supply chain. The organization of this paper is as follows. The second section provides the various performance categories that are considered while evaluating and selecting the supplier, and it provides an overview of existing methods. The next section presents a hybrid method, incorporating *analytic hierarchy process* (AHP), *data envelopment analysis* (DEA), and *neural network* (NN) into the evaluation process. The fourth section exhibits the results from the new method by using actual data. Finally, concluding remarks and discussions follow.

II. LITERATURE REVIEW

Manufacturers usually evaluate potential suppliers across multiple performance categories, using their own selection criteria with assigned weights. These evaluation factors are mainly classified into qualitative and quantifiable measures.

A. Supplier Selection Criteria

According to literature, some supplier selection criteria are found to vary in different situations, and experts agree that there is no one best way to evaluate, select suppliers and that organizations use a variety of different approaches in their evaluating processes.

A study carried out by Dickson [4] surveyed buyers in order to identify factors they considered in awarding contracts to suppliers. Out of the 23 factors considered, he concluded that quality, delivery, and performance history are the three most important criteria.

Another study conducted by Weber, Current, and Benton [15] derived key factors that were thought to affect supplier selection decisions. Based on a comprehensive review of vendor evaluation methods, they summarized that price was the highest-ranked factor, followed by delivery and quality. These empirical researches revealed that the relative importance of various selection criteria such as price, quality, and delivery performance is similar. More emphasis on just-in-time manufacturing strategies since the 1980's has placed an increasing importance on strategic vendor evaluation and multiple vendor criteria. For example, the study of Weber, Current, and Desai [16] considered factors, including geographical location, which he regarded as being more important than Dickson's.

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After Weber's work, most researchers focused on supplier-selection criteria in either specific industries or specific countries. Especially, since Internet-based businesses have grown rapidly since 1995, vendor criteria have changed a great deal, thus corresponding to the business environmental changes [12].

B. Analytical Methods used in the Vendor Selection Process

De Boer, Labro, and Morlacchi [2] performed an extensive review of decision methods, reported in literature, for supporting supplier selection processes since previous reviews conducted by Weber, Current, and Desai [15], Holt [7], Degraeve, Labro, and Roodhooft [3]. Unlike the other reviews, De Boer, Labro, and Morlacchi [2] covered all phases in the selection process from initial problem definition, the formulation of criteria, the pre-qualification of potential suppliers, to the final choosing of the best suppliers.

Based on procurement situations and selection process phases, they summarized decision methods that were used for the pre-qualification of suitable suppliers, including categorical methods, DEA, cluster analysis, and case-based-reasoning systems. Decision models for the final choice phase comprehended the linear weighting, total cost of ownership, mathematical programming, statistical, and artificial intelligence-based models.

Morlacchi [10] developed a model that combines the use of a fuzzy set with an AHP and implemented it in order to evaluate small suppliers in the engineering and machinery sectors. Ghodsypour and O'Brien [6] proposed an integration of an AHP and linear programming to consider both tangible and intangible factors in choosing the best suppliers and giving them optimal order quantities so that the total purchasing value is maximized.

Weber, Current, and Desai [17] combined a multi-objective programming and DEA method to provide buyers with a tool for negotiating with vendors that were not selected right away, as well as to evaluate potential suppliers.

Wang, Huang, and Dismukes [14] developed an integrated AHP and preemptive goal programming (PGP) methodology to take into account both qualitative and quantitative factors in supplier selection. While the AHP process matched product characteristics with supplier characteristics in order to qualitatively determine supply chain strategy, PGP mathematically determined the optimal order quantity from the chosen suppliers.

III. Hybrid Method for Supplier Selection

The hybrid method uses an AHP to assign weight to the qualitative selection criteria, and it uses a DEA or NN in order to choose efficient vendors in the final selection process.

Some attempts, combining an AHP and a DEA, have been made in other areas. Sinuany Stern, Mehrez, and Hadad [11] extended the DEA analysis beyond the mere classification of efficient/inefficient to a full ranking, by incorporating an AHP. Since layout design has a significant impact on the performance of a manufacturing or service industry system, Yang and Kuo [19] proposed a hierarchical AHP and DEA to solve plant layout design problems.

Takamura and Tone [13] solved a site-selection problem by deciding on the relocation of several government agencies from Tokyo. Based on an AHP and DEA, the best two sites were chosen from ten contenders.

The best of multiple models can be applied to vendor evaluation when using a hybrid approach of techniques (i.e., AHP, DEA, or NN) by avoiding the pitfalls of each.

The hybrid method adopts multiple techniques, including the AHP and DEA. It aims to determine the performance frontiers from a set of potential vendors, considering both quantitative and qualitative data. Fig. 1 shows a procedure that generates a combined supplier score (CSS) and cluster analysis.

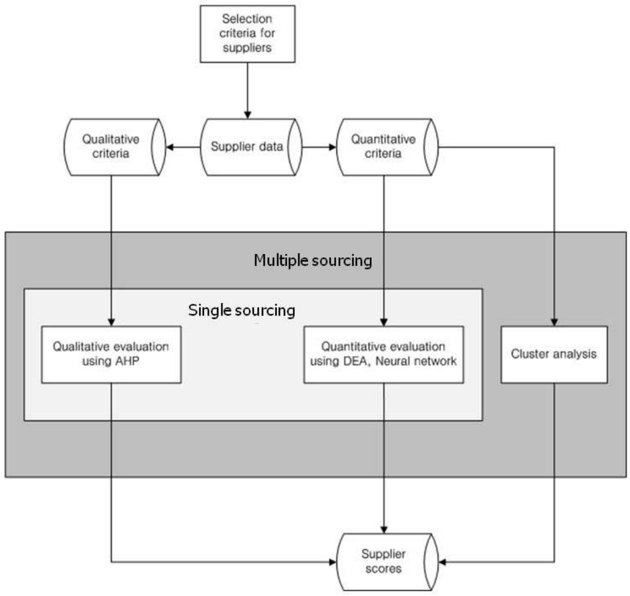

Fig. 1 Procedure for single and multiple sourcing

A. Determining Vendor Selection Criteria

The effective criteria for assessing and scoring supplier result from multifunctional collaboration within a firm. Collaboration must continue beyond criteria formulation, to the procurement of material and, to the evaluation of supplier performance. Vendor selection coordination will improve if all personnel take action, whereby together, they choose efficient supply chain partners [1].

Good criteria should account for all factors that impact supply chain performance and they should be designed to increase supply chain profits. A good supplier assessment process must identify and track performance along all dimensions that affect supplier selection. When comparing suppliers, price has traditionally been the only factor used. However, there are many other characteristics to consider, as shown in Table I.

The overall performance of each supplier can thus, be characterized in terms of a rating of these quantifiable and non-quantifiable factors, since suppliers may differ on other important dimensions. The factors allow a purchaser to rate and compare various suppliers, regarding their performance, on each dimension.

TABLE I
VENDOR SELECTION CRITERIA

Criteria	Type	Details
Quality	Qualitative	Production facilities (PF)
		Quality management intention (QMI)
	Quantitative	Quality system outcome (QSO)
		Claims (CL)
		Quality improvement (QI)
Delivery	Quantitative	Response to claims (RC)
		On-time delivery (OD)
Management and Organization	Qualitative	Organizational control (OC)
		Business plans (BP)
		Customer communication (CC)
	Quantitative	Internal audit (IA)
		Data administration (DA)

B. Using AHP for Qualitative Data Evaluation

The AHP is a multi-criteria decision making process that helps decision makers set priorities and arrive at the best decisions when the qualitative aspects of vendor selection decision need to be considered. The AHP structures a decision into smaller parts, by proceeding from the goal to objectives to sub-objectives, down to alternative courses of action. Decision makers make pair-wise comparisons throughout the hierarchical structure in order to arrive at overall priorities for a set of alternatives. The AHP makes some calculations to determine the overall weight that the decision makers assign to each criterion: this weight is between zero and one, and the total weight adds up to one.

The AHP procedures are applicable to facilitating individual and group decision making. In a group setting, many methods can be used to accommodate the views and judgments of group participants in a priority-setting process. Many researchers consider the AHP technique to be well suited for group decision making due to its role as a synthesizing mechanism [5][9].

C. Using DEA and NN for Measuring Performance Efficiency

Since a DEA and a NN can complement each other, using the two techniques is helpful to get a more accurate efficiency index. The DEA is a nonparametric approach that does not require any assumptions about the production function. The DEA usually deals with a *decision-making unit* (DMU) k, which has multiple inputs X_{ik} where $i = 1, . . . , n_1$ and multiple outputs Y_{ok} where $o = 1, . . . , n_2$, which can be incorporated into an efficiency measurement: where u_o and v_i are a set of factor weights.

$$h_k = \sum u_o Y_{ok} / \sum u_i X_{ik} \qquad (1)$$

In choosing the optimal weights for the input and output, each DMU k is assigned the highest possible efficiency score that the constraints allow from the available data. Through this procedure, the DEA divides the DMUs into two groups, efficient ($h_k \geq 1$) and inefficient ($h_k < 1$), by identifying the efficient frontier of the data. As an efficiency evaluation technique, the DEA is useful especially when there are various selection criteria and measurement units.

A NN is composed of a set of neurons, connected together through weighted connections. The neurons of a NN are organized in layers: input, output, or hidden. The neurons of the output layer receive the outputs from the hidden layer, which are weighted by the weights z_{kj}, and produce the final network outputs $y_j = g(h, z_j)$. The output of neuron j in the output layer is where x is n input signals and consists of $[x_1, x_2, . . . , x_n]$, and each signal is attached with a weight $w_j = [w_{1j}, w_{2j}, . . . , w_{nj}]$.

$$y_j = g\left(\sum_k h_k z_{kj} \right) = g\left(\sum_k z_{kj} f(X, W_k) \right) \qquad (2)$$

In learning weights in a NN, the error functions between the observed and fitted values should be considered. For a given training data set $D = \{(x_1,t_1), . . . , (x_n,t_n)\}$, the objective of learning is to minimize error function in terms of weights,

$$E(W) = \sum_{i=1} \sum_{k=1} (t_{i,k} - y_{i,k})^2 \qquad (3)$$

After evaluating efficiency by using the DEA and NN, the results of each technique are compiled into one efficiency index. A simple average method can be used.

D. Cluster Analysis

When a firm wishes to choose multiple sourcing, a portfolio of suppliers should be determined by supplier performance which measures all dimensions, and the demand of a purchaser should be allocated among the chosen suppliers. That is because the portfolio consists of different suppliers, such that one supply source performs well on one dimension (efficiency), whereas other sources perform well on a complementary dimension (responsiveness). The combination of suppliers results in a better matching of supply and demand at lower costs. Given the heterogeneous nature of suppliers, we decide to perform a cluster analysis in order to find homogeneous clusters and to compose a portfolio of suppliers.

Even with single sourcing, cluster analysis can be important. More opportunities for the buyer and supplier to work together are generated which can provide solid cooperation for maintaining stable production capability. This results in a long-term relationship and a degree of trust, which encourages the supplier to expend effort on investment in buyer-specific technology and design collaboration.

Once suppliers have been selected, supply contracts could be structured between the buyer and each supplier. At this time, different vendor clusters can specify different parameters governing the buyer-supplier relationship on the contract. The differences in performance along key dimensions such as price, quality, and delivery can lead to significant discrimination among suppliers. Therefore, cluster analysis can provide the buyer with more flexible strategies when designing contracts.

IV. IMPLEMENTATION

To see how the model works in practice, the hybrid framework was applied to an auto company which manufactures auto parts (mainly used in automatic transmission drive). The company maintains explicit management policies about outsourcing evaluation and selection. Twenty-seven

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vendors are involved in the study; the number of qualitative factors is five; and the number of quantitative criteria is seven.

A. Evaluating Qualitative Criteria

In the hybrid method, the purpose of utilizing an AHP model lies in considering the qualitative aspects of decisions associated with corporate goals and long-term objectives for supply sourcing. The AHP converts the qualitative criteria (i.e., product facilities, quality management intention, organizational control, business plans, and customer communication) into a single quantitative measure. We use a single level AHP, where the elements for the evaluation are the suppliers. Both relative scores for each supplier calculated by the AHP and quantitative criteria are fed into a DEA and a NN. Each supplier's performance can then be evaluated.

B. Measuring the Performance Efficiency of Suppliers

We use two techniques in order to measure performance efficiency: DEA and NN. Table II shows the efficiency scores and references obtained for each supplier. A column AHP contains the relative scores derived by the AHP. The DEA generalizes the efficiency of a single supplier in eight inputs and one output (i.e., the factor Quality System Outcome) setting. Each supplier constitutes a DMU. A supplier is termed efficient if its efficiency rating from the DEA is greater than 100%. It is because the output produced is greater than the input consumed in computing the technical efficiency of a DMU. Otherwise, the supplier is considered inefficient. As shown in Table II, among the seven efficient suppliers (including C2, C3, C4, C7, C9, C12, and C17), C3 is the most efficient and it constitutes the benchmark for the inefficient ten DMUs.

The second technique in measuring performance is to use a NN. To build a NN model, the decision maker gathers real data and synthesizes hypothetical data. Sixty percent of data comprise a training set which is used to fit the NN model, and the rest of the data comprise a test set used to assess the model's accuracy. The training parameters include the following: The number of input neurons is set to seven; the number of hidden neurons is four; the number of output neurons is one. The prediction accuracy of the trained model associated with the test set, reached 78.87%. Table III examines the suppliers' performance, which is measured by using the DEA and is compared with that of the NN model.

After measuring efficiency, both results were compiled into one efficiency index. We used a simple averaging method. Since both results have very weak correlation relationships (–0.234 of correlation coefficient), this compilation can diminish the bias associated with using only a single technique.

Table IV summarizes the compilation results. According to the compiled results of the DEA and NN, C3 is the most efficient supplier and C6 is the least efficient one.

TABLE II
EFFICIENCY SCORES AND REFERENCES FOR EACH SUPPLIER

Supplier	AHP	DEA efficiency score (%)	Reference
C1	0.039	86.58	C3, C9, C12, C17
C2	0.034	113.10	
C3	0.035	155.17	
C4	0.041	111.11	
C5	0.037	98.39	C2, C17
C6	0.029	60.85	C3, C9, C17
C7	0.040	100.00	
C8	0.036	92.31	C2, C12
C9	0.039	111.11	
C10	0.038	72.91	C2, C12, C17
C11	0.040	90.57	C2, C3, C12, C17
C12	0.039	126.82	
C13	0.033	65.93	C3, C12, C17
C14	0.041	89.71	C2, C3, C12, C17
C15	0.040	90.57	C2, C3, C12, C17
C16	0.041	92.34	C3, C9, C12, C17
C17	0.030	116.13	
C18	0.027	86.42	C17
C19	0.030	94.46	C9, C17
C20	0.038	84.21	C3, C4, C17
C21	0.038	100.00	C2
C22	0.036	92.31	C2, C7, C12, C23
C23	0.040	100.00	C7, C12
C24	0.041	89.26	C2, C12, C17
C25	0.041	90.16	C2, C3, C12, C17
C26	0.038	72.91	C2, C12, C17
C27	0.038	78.56	C2, C3, C17

TABLE III
THE CORRELATION BETWEEN THE DEA AND NN

		DEA	NN
DEA	Pearson correlation	1	-0.234
	Sig. (2-tailed)	–	0.241
	N	27	27
NN	Pearson correlation	-0.234	1
	Sig. (2-tailed)	0.241	–
	N	27	27

C. Clustering Analysis of Suppliers

The clustering variables (factors) consist of the seven quantitative criteria. Some robust algorithms used to perform clustering include a Self-Organizing Map (SOM), a neural clustering method which performs unsupervised learning. It divides suppliers into a variety of groups and allocates each supplier into one of the resulting segments.

Several techniques speed up this self-organizing process and make it more reliable. One technique to improve the performance of the SOM during training is to vary the size of the neighborhoods: from large (one, in our case) to small (it could include only the winning neuron). The learning rate also varies over time. An initial rate of 0.3 allows neurons to learn input vectors quickly. It then shrinks asymptotically toward zero, so that learning becomes stable. Another technique that speeds up self-organization is to have the winning neuron use a larger learning rate than that of the neighboring neurons. In training the SOM, output nodes are restricted to ten or fewer for managerial convenience. One-hundred fifty (150) epochs

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TABLE IV
SUPPLIER RANKING, COMBINED SCORE, AND CHARACTERISTICS OF THE SUPPLIERS

Rank	Supplier	DEA	NN	CSS	Characteristics						
					QSO	CL	QI	RC	OD	IA	DA
1	C3	1.552	0.640	1.096	4.5	5.0	8.0	1.0	1.0	2.0	22.6
2	C12	1.268	0.689	0.979	5.0	1.0	10.0	2.0	2.0	2.5	22.5
3	C9	1.111	0.694	0.903	5.0	5.0	10.0	3.0	3.0	1.5	27.5
4	C17	1.161	0.632	0.897	4.5	5.0	8.0	1.0	1.0	3.5	22.0
5	C4	1.111	0.667	0.889	5.0	5.0	9.0	1.0	1.0	5.0	28.5
6	C2	1.131	0.636	0.884	4.0	1.0	7.0	2.0	2.0	2.5	26.0
7	C7	1.000	0.691	0.846	5.0	1.0	10.0	2.0	2.0	4.0	24.5
7	C23	1.000	0.691	0.846	5.0	1.0	10.0	2.0	2.0	4.0	24.5
9	C21	1.000	0.668	0.834	4.0	5.0	7.0	3.0	3.0	4.5	26.5
10	C5	0.984	0.673	0.828	4.3	5.0	7.7	3.0	3.0	4.0	25.4
11	C16	0.923	0.699	0.811	5.0	5.0	10.0	3.0	3.0	3.0	28.0
12	C11	0.906	0.699	0.802	5.0	5.0	10.0	3.0	3.0	3.5	27.5
12	C15	0.906	0.699	0.802	5.0	5.0	10.0	3.0	3.0	4.0	28.0
14	C25	0.902	0.701	0.801	5.0	5.0	10.0	3.0	3.0	4.0	28.0
15	C14	0.897	0.699	0.798	5.0	5.0	10.0	3.0	3.0	4.0	30.0
16	C24	0.893	0.701	0.797	5.0	5.0	10.0	3.0	3.0	4.5	29.0
17	C19	0.945	0.647	0.796	4.0	5.0	8.0	2.0	2.0	3.0	22.5
18	C22	0.923	0.659	0.791	4.0	1.0	8.0	2.0	2.0	4.0	24.5
19	C8	0.923	0.652	0.788	4.0	1.0	8.0	2.0	2.0	2.5	27.9
20	C1	0.866	0.692	0.779	4.5	5.0	9.5	3.0	3.0	3.0	27.5
21	C18	0.864	0.640	0.752	3.5	5.0	7.5	2.5	2.5	3.5	24.0
22	C20	0.842	0.653	0.748	4.0	5.0	8.5	1.0	1.0	3.5	26.3
23	C27	0.786	0.686	0.736	4.0	5.0	9.0	3.0	3.0	4.0	29.0
24	C10	0.729	0.697	0.713	4.0	5.0	10.0	3.0	3.0	4.5	27.5
24	C26	0.729	0.696	0.713	4.0	5.0	10.0	3.0	3.0	5.0	29.5
26	C13	0.659	0.689	0.674	3.0	5.0	10.0	3.0	3.0	3.0	22.5
27	C6	0.609	0.625	0.617	2.5	5.0	8.0	1.0	1.0	3.0	23.7

TABLE V
SUPPLIER SEGMENTS AND THEIR CHARACTERISTICS

Segment	Characteristics of each segment									Member supplier
	QSO	CL	QI	RC	OD	IA	DA	AHP	(DEA+NN)/2	
	Avg	Avg	Avg	Avg	Avg	Avg	Avg	Avg	Avg	
	Std	Std	Std	Std	Std	Std	Std	Std	Std	
A	4.10	5.00	8.30	1.00	1.00	3.40	24.62	0.035	0.80	C3, C4
	0.96	0.00	0.45	0.00	0.00	1.08	2.72	0.005	0.18	C6, C 17, C20
B	4.50	1.00	8.83	2.00	2.00	3.25	24.98	0.038	0.81	C2, C7
	0.55	0.00	1.33	0.00	0.00	0.82	1.81	0.003	0.07	C8, C 12, C22,C23
C	4.00	5.00	8.00	2.00	2.00	3.00	22.50	0.030	0.733	C19
D	3.93	5.00	7.40	2.83	2.83	4.00	25.30	0.034	0.76	C5, C18
	0.40	0.00	0.36	0.29	0.29	0.50	1.25	0.006	0.05	C21
E	3.83	5.00	9.50	3.00	3.00	3.33	26.33	0.037	0.66	C1, C13
	0.76	0.00	0.50	0.00	0.00	0.58	3.40	0.003	0.06	C27
F	4.78	5.00	10.0	3.00	3.00	3.78	28.33	0.040	0.73	C9, C10
	0.44	0.00	0.00	0.00	0.00	1.03	0.94	0.001	0.06	C11,C14, C15,C16, C24,C25, C26

continue through the training data, which consist of seven input variables and 27 input patterns.

Using a three-by-three SOM, six dominant supplier segments are apparent. Table V describes each segment's characteristics, including an average value and a standard deviation of quantitative factors, the AHP, and an average value of the DEA and NN.

D. Selecting Multiple Suppliers

When looking at the characteristics of segments, suppliers in segment *A* deliver auto parts on-time, but they receive many claims from the purchaser and respond promptly to resolve them. Segment *B* obtains a low number of claims and deals with them quickly (above average). Segment *C* that consists of a single supplier is unremarkable for most factors, and it is below average in organizational management, including internal audit and data administration.

Although it has a strict internal audit, segment *D* is weak in improving quality. Segment *E* accepts a lot of claims and has low scores in response to such claims, on-time delivery, and quality system outcome. Segment *F* receives many claims, has low scores in response to the claims and on-time delivery, but it has high scores in qualitative factors and in most quantitative factors.

If the purchaser needs supply sources that perform well in terms of responsiveness, it can select a supply source from either segment *A* or *B*; whereas, the purchaser can target segment *F* that performs well on a complementary dimension (efficiency). When sorting suppliers according to the CSS, C3 is the best supplier within segment *A*, C12 within segment *B*, C21 within segment *D*, C9 within segment *F*, and C1 within segment *E*.

The criteria for a decision are determined by the decision maker. When the base criteria is established at 0.033 of the qualitative factors and 0.72 of the quantitative factors, two suppliers in segment *A* (C3, C4), six suppliers in segment *B* (C2, C7, C8, C12, C22, C23), two suppliers in segment *D* (C5, C21), and seven suppliers in segment *F* (C9, C11, C14, C15, C16, C24, C25) exceed the base criteria. They can be selected as sources of supply. When the base criteria are intensified to 0.035 of the qualitative factors and 0.8 of the quantitative factors, only four suppliers pass the base criteria (C3 and C4 in segment *A*, C12 in segment *B*, C9 in segment *F*). As the base criteria are intensified, the smaller number of suppliers is chosen.

V. Conclusion

This article outlined a hybrid method, which incorporates multiple techniques (i.e., AHP, DEA, and NN) into an evaluation process, in order to select competitive suppliers in a supply chain.

This hybrid method emphasizes the following characteristics:

- It accounts for both qualitative and quantitative factors that have an impact on supply chain performance.
- It adopts multiple techniques, including AHP, DEA, and NN, to find the performance frontiers from a set of potential vendors.
- It enables a purchaser to do single sourcing and multiple sourcing by calculating a combined supplier score and performing a cluster analysis.

A variety of combination of different techniques, however, can produce different portfolios of the suppliers selected. Under different decision situations, supplier selection methods are found to vary. A combination of AHP, DEA, and NN is one possible approach in evaluating and selecting suppliers. However this combination performed well with regard to the target domain.

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