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Full Length Research Paper

Development and application of an integrated multi-objective methodology for supplier selection

Z. H. Che[1], Tzu-An Chiang[2], H.S. Wang[1] and Y.F. Chang[1]

[1]Department of Industrial Engineering and Management, National Taipei University of Technology, 1, Sec. 3, Chung-Hsiao E. Rd., Taipei 106, Taiwan, ROC.
[2]Department of Business Administration, National Taipei College of Business, 321, Sec. 1, Jinan Rd., Taipei 100, Taiwan, ROC.

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This study developed a hybrid supplier selection model, which combines multi-objective data envelopment analysis (MODEA) and multi-objective genetic algorithm (MOGA), called as MODP. MODEA involved the consideration of several supplier selection factors. In addition to maximizing the efficiency of the decision making unit (DMU) itself, the approach also took into account other DMUs, enabling minimization of the total deviation and minimization of the maximal deviation. Besides, to solve the MODEA model efficiently, this study applied non-dominated sorting genetic algorithm II (NSGA-II) to problem solving. Finally, the proposed MODP methodology was introduced in a hemadynamometer supplier selection case, and results suggested the proposed MODP methodology is effective for supplier selection.

Key words: Multi-objective data envelopment analysis, multi-objective genetic algorithm, supplier selection.

INTRODUCTION

Supplier selection is a key issue for business management in an enterprise. Chen et al. (2006) argued that good supplier management and a well-established supplier chain system will have a profound impact on overall competitiveness for enterprises. Wang and Che (2007) figured out that selecting a proper supplier may help reduce risk in the industry. Sha and Che (2005) indicated that it is important to search for the optimal partner for production and assembly in a collaborative manufacturing environment. Kokangul and Susuz (2009) and Sha and Che (2006) also listed supplier selection as one of the important functions for business management. In addition, Şenyigit and Göleç (2010) pointed out that supplier selection in the supply chain system is an important matter for an enterprise in today's competitive intensive commercial environment. Therefore, developing a suitable methodology for supplier selection is an essential task for promotion of business competitive advantage. This study will propose MODP, a supplier selection model mainly composed of multi-objective data envelopment analysis (MODEA) and multi-objective genetic algorithm (MOGA). It is hopeful that the proposed MODP can help enterprises select good suppliers to reduce operating costs.

Supplier selection is a multi-criterion decision making (MCDM) problem (Xia and Wu, 2007; Ustun and Demirtas, 2008; Che, 2010a; Che, 2010b; Che, 2010c). There are many indicators available for supplier selection. Weber et al. (1991) point out that each industry has its unique supplier selection criteria. According to literature by Dickson (1966), Ustun and Demirtas (2008), Wadhwa and Ravindran (2007) and Liao and Rittscher (2007), cost, delivery time and quality are the main performance indicators to be considered for supplier selection. In

*Corresponding author. E-mail: zhche@ntut.edu.tw. Tel: +886-2-771-2171 ext. 2346.

Abbreviations: MODEA, multi-objective data envelopment analysis; **MOGA,** multi-objective genetic algorithm; **DMU,** decision making unit; **NSGA,** non-dominated sorting genetic algorithm; **MCDM,** multi-criterion decision making; **CROs,** contract research organizations; **STB**, smaller-the-better; **BTB,** bigger-the-better; **ER,** error ratio; **DEA,** data envelopment analysis; **CEO,** chief executive officer.

Table 1. Notations for the MODP methodology.

Notation	Description
x_{ij}	the evaluation value of the *j*th DMU of the *i*th input
y_{rj}	the evaluation value of the *j*th DMU of the *r*th output
Z_k	the relative efficiency of the *k*th DMU
v_{ik}	the weight of the *k*th DMU of the *i*th input
u_{rk}	the weight of the *k*th DMU of the *r*th output
d_j	the waste of the *j*th DMU
M	the maximum waste of DMUs
$f_m^{\max}$	the maximum value of the chromosomes for Level s at objective m
$f_m^{\min}$	the minimum value of the chromosomes for Level s at objective m

addition, the data envelopment analysis (DEA) is a well-known MCDM approach. It is a method for comparing different decision making units (DMUs) productivity based on multiple inputs and outputs. The DEA can not only identify efficiency value of each DMU but also suggest how to adjust the portfolio of inputs and outputs for each DMU to achieve higher efficiency. MODEA, a model derived from the DEA, is mainly used to improve DMU problems that the DEA cannot effectively address. Zerafat et al. (2009), Wei et al. (2008) and Lozano and Villa (2009) applied MODEA to resource planning and program evaluation and obtain favorable planning outcomes. For this reason, this study uses MODEA to construct an optimized multi-criterion supplier selection model.

MODEA is a multi-objective optimization model that consumes more computation time for problem solving, while a MOGA has been widely and effectively applied to various multi-objective optimization problems. We may refer to literature reports by Srinivas and Deb (1994), Zitzler and Thiele (1999), Knowles and Corne (2000) for details. Deb et al. (2002) proposed a non-dominated sorting genetic algorithm (NSGA-II), which improves the non-dominated comparison operator to enhance operating efficiency of the algorithm. They also propose a crowded-comparison operator to determine the new population for follow-up evolution by calculating the crowding distance between non-dominated solutions of the same level, making the obtained Pareto optimal solutions evenly distributed in the Pareto front. Shi et al., (2005), Guo and Ning (2005) and Gao et al. (2008) have successfully applied NSGA-II to multi-objective optimization problems. In view of the argument stated above, this study uses NSGA-II to solve the multi-objective optimization supplier selection model.

There are three major focus in this study: (1) Proposing a methodology combining MODEA and MOGA – MODP – and applying this methodology to supplier selection. As far as we know, there has been no paper involving the application of a methodology combining MODEA and MOGA to supplier selection. (2) Using MODEA to develop a multi-objective optimization supplier selection model and applying NSGA-II to solve the multi-objective optimization model. When carrying out NSGA-II, we proceed with parameter setup to obtain better parameter combinations, ensuring acceptable outcomes when NSGA-II is used to solve the MODEA model. (3) Illustrating and examining the applicability of the MODP using a real case – choosing hemadynamometer suppliers.

This paper consists of the following sections. The second section gives the structure of the MODP methodology and explains the way to determine supplier selection criteria, data normalization, construction of an MODEA model and NSGA-II algorithmic process. The third section explains and verifies significant benefits of the proposed methodology using hemadynamometer – a health care related product – as a case study. The fourth section shows conclusions and suggestions.

MODP METHODOLOGY FOR SUPPLIER SELECTION

This study proposed a supplier selection methodology – MODP, which combines MODEA and MOGA. The MODP methodology is built on the following assumptions:

(1) The value of each evaluation criterion is crisp.
(2) All objectives in MODEA model have equal weights.
(3) The weight of each input/output criterion is >0 and the MODEA model does not impose other restrictions on the weight scope of inputs and outputs.

Notations for the MODP methodology are shown in Table 1 and procedures for the MODP methodology are described in the following subsections.

Determine criteria for supplier selection

To establish selection criteria is the first task for supplier selection. By referring to literature such as related journals and study reports, this study summarizes critical reference criteria that will influence supplier selection. And then we collect rating data of the reference criteria from experts via questionnaire survey. Experts are professionals in relevant industries, e.g. procurement managers, CROs. Regarding the rating method for the reference criteria, we use the 5-point Likert scale originally proposed by Likert (1932). In the 5-point Likert scale, items are grouped into five scales: “extremely unimportant”, “unimportant”, “neutral”, “important” and “extremely important”. Scores are given from 1 to 5; the higher the score that the experts give, the more important the reference criteria will be. The reference criteria with lower total scores given by experts will be deleted; otherwise, the criteria will be included in criteria for supplier selection.

Data normalization

To avoid deviation due to different units of inputs and outputs, we normalize all inputs and outputs. Regarding the input/output setup, we use the Smaller-The-Better (STB) as input and Bigger-The-Better (BTB) as output. The normalization method is listed as in Formula (2):

$$x_{ij}^{'} = \frac{x_{ij}}{\max\{x_{i1}, x_{i2}, ..., x_{in}\}}, i = 1...I \quad (2)$$

$$y_{rj}^{'} = \frac{y_{rj}}{\max\{y_{r1}, y_{r2}, ..., y_{rn}\}}, r = 1...R$$

Construction of MODEA model

This study uses the MODEA model proposed by Li and Reeve (1999), as shown in Formula (3):

$$f_1 : Max \quad Z_k = \sum_{r=1}^{R} u_{rk} * y_{rk}$$

$$f_2 : Min \quad M$$

$$f_3 : Min \quad \sum_{j=1}^{J} d_j$$

$$s.t. \quad \sum_{r=1}^{R} u_{rk} * y_{rj} - \sum_{i=1}^{I} v_{ik} * x_{ij} + d_j = 0, j = 1...J \quad (3)$$

$$\sum_{i=1}^{I} v_{ik} * x_{ik} = 1$$

$$u_{rk} \geq \varepsilon > 0, r = 1...R \; ; \; v_{ik} \geq \varepsilon > 0, i = 1...I$$

$$M - d_j \geq 0, j = 1...J \; ; \; d_j > 0, j = 1...J$$

v_1	v_2	$\dots$	v_I	u_1	u_2	$\dots$	u_I

Figure 1. Chromosome structure.

NSGA-II computational procedure for solving MODEA model

Step 1: Chromosome coding

Each chromosome represents a set of feasible solutions, including the weight of input (symbolized by $v_i, i = 1...I$) and the weight of output (symbolized by $u_i, i = 1...I$), as shown in Figure 1.

Step 2: Generation of initial population

Initial population P_0 is randomly generated with the population size of N. The range of initial weights of input and output is set to be (0, 2).

Step 3: Calculating objective function value

According to Formula (3), we calculate objective function values f_1, f_2 and f_3 in relation to each chromosome in the population and rank f_1, f_2 and f_3.

Step 4: Non-dominated solutions sorting

Sorting of non-dominated solutions is intended to divide the initial population P_0 into some sets of non-dominated solutions based on the objective function value of each chromosome. We calculate the number dominated by other chromosomes for a certain chromosome; if the number is 0, it means the chromosome is not dominated by other solutions, in which case we define it as level 1 and remove it from the population. Again, we calculate the number dominated by other chromosomes for another chromosome from the remaining population; if the number is 0, we define it as level 2. In this way we screen chromosomes and increase the level by sequence until all chromosomes in the population are sorted.

Step 5: Mechanism of exclusion comparison

The mechanism of exclusion comparison is mainly used to calculate the exclusion distance. The exclusion distance is calculated as in Formula (4); the exclusion distance between chromosomes for level S is calculated as CD_i. With S as Level 1, the distance between solutions is calculated till the maximal level of the population by sequence. Besides, the exclusion distance between two chromosomes at the boundary is directly set as infinite. The concept is described in Figure 2.

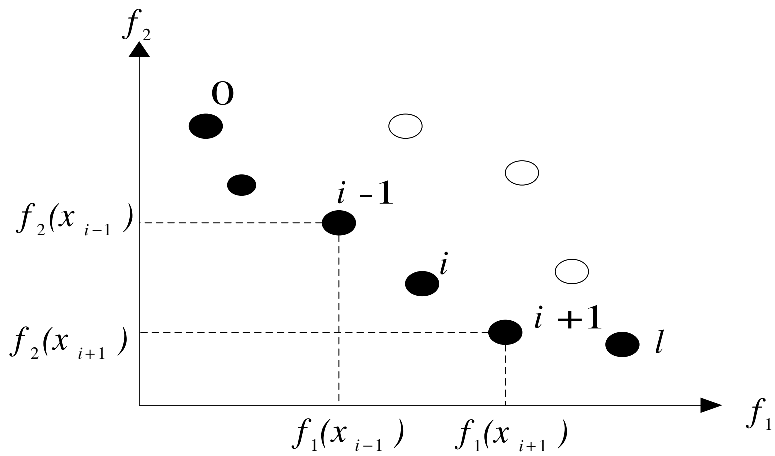

Figure 2. Mechanism of exclusion comparison.

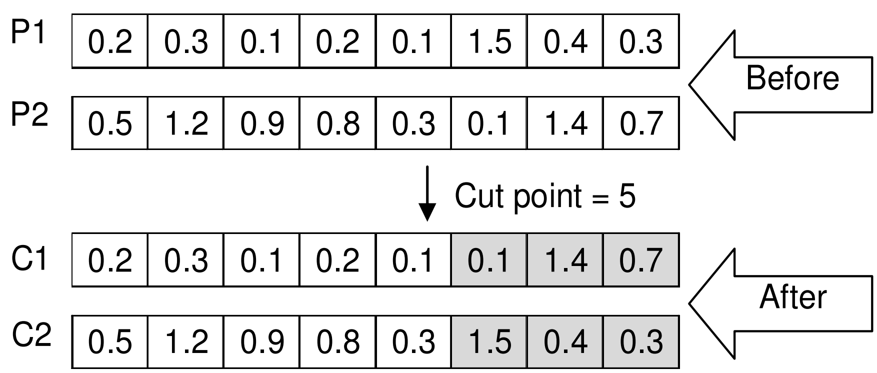

Figure 3. Single-point crossover.

$$CD_i = \sum_{m=1}^{M} \frac{|f_m(x_{i+1}) - f_m(x_{i-1})|}{f_m^{\max} - f_m^{\min}} \quad i = 1,2...,l\text{-}1 \tag{4}$$

In which, $|f_m(x_{i+1}) - f_m(x_{i-1})|$ means the distance between solution x_{i+1} and solution x_{i-1} at objective m.

Step 6: Generate new parent population

It is intended to generate a new population P_{g+1} for the population size of N. The candidate list of P_{g+1} is determined based on the level of solutions and the exclusion distance. Chromosomes of Level 1 in the population are included in the candidate list of P_{g+1} in proper order. If the number of chromosomes of level *s* exceeds the population size N, the exclusion distance between chromosomes of Level *s* should be compared; chromosomes with a larger exclusion distance will be included in the candidate list as priority. Therefore, chromosomes will be included in the candidate list of the new population based on the exclusion distance in a descending order until all of N chromosomes are included.

Step 7: Reproduction, crossover and mutation

This subsection depicts the method for reproduction, crossover and mutation. Binary tournament selection is used for reproduction. Next, we select two chromosomes randomly from the population, determine the levels of these two chromosomes and put the chromosome with better level into the crossover pool; if the two chromosomes have the same level, then we compare their exclusion distances and select the chromosome with a larger exclusion distance into the crossover pool. And then, the genetic algorithm uses single point crossover, where the two mating chromosomes are cut at corresponding points and the sections after the cuts exchanged, as shown in Figure 3. The genetic algorithm also uses a single-point mutation where a chromosome is randomly sampled and a mutation position is generated accordingly; the

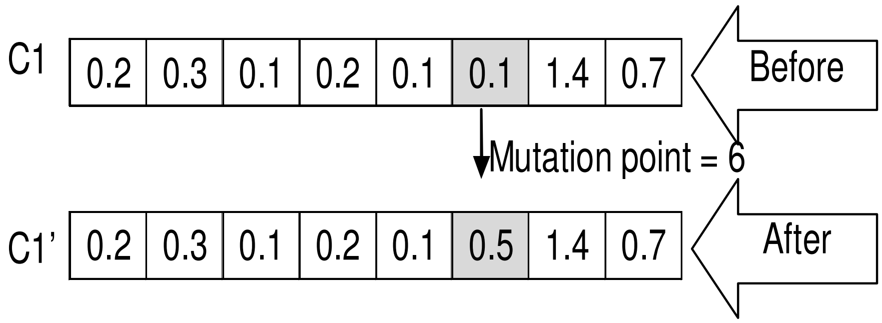

Figure 4. Single-point mutation.

Table 2. Selection criteria.

Criteria	Sub-criteria	Description
Cost	Purchase cost	Cost incurred due to purchase of parts from suppliers by a company
	Transportation cost	Cost arising from delivery of parts from suppliers to the company after purchase
Delivery time	On-time delivery rate	Probability of delivery of parts from suppliers to the company within the delivery time
Quality	Reliability	Probability of effectiveness of parts after a certain period of time after the date of production
	Defect rate	Defect rate of parts purchased from suppliers
Service	Supply capacity	Maximal supply capacity of parts provided by suppliers
	Warranty time	Warranty period of parts provided by suppliers
	Repair turnover time	Processing time required from delivery of repairable malfunctioned parts to suppliers to return of the parts to the company

genetic code of that position is randomly changed within a reasonable range, as shown in Figure 4.

Step 8: Determine termination conditions and obtain the final solution

To determine whether the preset termination conditions are met, we use the number of generations as a stop condition; it stops as soon as the evolution times reach the number of generations; otherwise, the evolution continues. Finally, the set of non-dominated solutions of Level 1 in the population is the final solution.

EMPIRICAL STUDY AND ANALYSIS

To verify the fitness of the proposed methodology, this study uses a real case where Company A, a hemadynamometer manufacturer, has eight major suppliers, and we use the proposed supplier selection model to evaluate the most efficient and feasible suppliers.

Determine supplier selection criteria

By referring to literature such as relevant journals and study reports, we summarize critical reference criteria that will influence supplier selection and collect rating data of the reference criteria from experts (top management such as the company's chief executive officer (CEO), procurement manager) via questionnaire survey. The rating is given using the 5-point Likert-scale proposed by Likert (1932). After deleting reference criteria with lower rating from experts, we summarize 8 evaluation indicators from 4 major dimensions, as described in Table 2.

Setting up the MODEA model

Regarding input/output setup, we use Smaller-the-Better (STB) as an input and Bigger-the-Better as an output. Data of input and output is provided in Table 3. To avoid deviation due to different units of inputs and outputs, we normalize all inputs and outputs. Data of input and output after normalization is provided in Table 4.

A MODEA model is introduced after data normalization. Taking Supplier 1 for example, the introduction is given below:

$$f_1 : Max \quad Z_1 = 0.75 * u_{11} + 0.8 * u_{21} + 0.6 * u_{31} + 1 * u_{41}$$

$$f_2 : Min \quad M$$

$$f_3 : Min \quad d_1 + d_2 + d_3 + d_4 + d_5 + d_6 + d_7 + d_8$$

Table 3. Data of inputs and outputs.

Supplier No.	Input 1 Purchase cost (dollars)	Input 2 Transportation cost (dollars)	Input 3 Defect rate (%)	Input 4 Repair turnover time (days)
1	15	4	1.5	14
2	12	3	2	7
3	10	2	1	7
4	20	5	2.5	14
5	11	1	1.5	7
6	11	1	1	14
7	20	4	2	14
8	10	1	1	14
Supplier No.	**Output 1 Reliability (%)**	**Output 2 Supply capacity (units)**	**Output 3 Warranty time (months)**	**Output 4 On-time delivery rate (%)**
1	90	1000	12	90
2	85	1000	12	99
3	70	800	6	88
4	95	1000	18	90
5	60	800	6	80
6	65	800	6	90
7	90	900	12	90
8	65	800	6	85

Table 4. Normalized data of inputs and outputs.

Supplier No.	Input 1 Purchase cost (dollars)	Input 2 Transportation cost (dollars)	Input 3 Defect rate (%)	Input 4 Repair turnover time (days)
1	0.75	0.8	0.6	1
2	0.6	0.6	0.8	0.5
3	0.5	0.4	0.4	0.5
4	1	1	1	1
5	0.55	0.2	0.6	0.5
6	0.55	0.2	0.4	1
7	1	0.8	0.8	1
8	0.5	0.2	0.4	1
Supplier No.	**Output 1 Reliability (%)**	**Output 2 Supply capacity (units)**	**Output 3 Warranty time (months)**	**Output 4 On-time delivery rate (%)**
1	0.947	1	0.667	0.909
2	0.895	1	0.667	1
3	0.737	0.8	0.333	0.889
4	1	1	1	0.909
5	0.632	0.8	0.333	0.808
6	0.684	0.8	0.333	0.909
7	0.947	0.9	0.667	0.909
8	0.684	0.8	0.333	0.859

Table 5. Experiment design for factors.

Factor	Level 1	Level 2	Level 3
G	50	100	250
N	50	100	200
Cr	0.9	0.9	0.9
Mr	0.125	0.125	0.125

$s.t.$

$$0.75*u_{11}+0.8*u_{21}+0.6*u_{31}+1*u_{41}-0.947*v_{11}-1*v_{21}-0.667*v_{31}-0.909*v_{41}+d_1=0$$

$$0.6*u_{11}+0.6*u_{21}+0.8*u_{31}+0.5*u_{41}-0.895*v_{11}-1*v_{21}-0.667*v_{31}-1*v_{41}+0.889*v_{41}+d_2=0$$

$$0.5*u_{11}+0.4*u_{21}+0.4*u_{31}+0.5*u_{41}-0.737*v_{11}-0.8*v_{21}-0.333*v_{31}-d_3=0$$

$$1*u_{11}+1*u_{21}+1*u_{31}+1*u_{41}-1*v_{11}-1*v_{21}-1*v_{31}-0.909*v_{41}+d_4=0$$

$$0.55*u_{11}+0.2*u_{21}+0.6*u_{31}+0.5*u_{41}-0.632*v_{11}-0.8*v_{21}-0.333*v_{31}-0.808*v_{41}+d_5=0$$

$$0.55*u_{11}+0.2*u_{21}+0.4*u_{31}+1*u_{41}-0.684*v_{11}-0.8*v_{21}-0.333*v_{31}-0.909*v_{41}+d_6=0$$

$$1*u_{11}+0.8*u_{21}+0.8*u_{31}+1*u_{41}-0.947*v_{11}-0.9*v_{21}-0.667*v_{31}-0.909*v_{41}+d_7=0$$

$$0.5*u_{11}+0.2*u_{21}+0.4*u_{31}+1*u_{41}-0.684*v_{11}-0.8*v_{21}-0.333*v_{31}-0.859*v_{41}+d_8=0$$

$$0.947*v_{11}+1*v_{21}+0.667*v_{31}+0.909*v_{41}=1$$

$$u_{11}\ge\varepsilon>0;\ u_{21}\ge\varepsilon>0;\ u_{31}\ge\varepsilon>0;\ u_{41}\ge\varepsilon>0;\ v_{11}\ge\varepsilon>0;\ v_{21}\ge\varepsilon>0;$$

$$v_{31}\ge\varepsilon>0;\ v_{41}\ge\varepsilon>0;\ M-d_1\ge0;\ M-d_2\ge0;\ M-d_3\ge0;\ M-d_4\ge0;$$

$$M-d_5\ge0;\ M-d_6\ge0;\ M-d_7\ge0;\ M-d_8\ge0;\ d_1>0;\ d_2>0;\ d_3>0;$$

$$d_4>0;\ d_5>0;\ d_6>0;\ d_7>0;\ d_8>0$$

Parameter setup

To solve multi-objective optimization problems for supplier selection, this study uses NSGA-II, which includes parameters such as the number of populations N, number of generations G, crossover rate Cr and mutation rate Mr. To acquire the optimal performance for the decision making system, we proceed with experimental design of various parameters first to obtain the best parameters combination. This study uses error ratio (ER) to measure the performance of the multi-objective algorithm. From the ER value, we may understand the extent to which the Pareto front is converged (Rahimi-Vahed et al., 2007), as defined in Formula (5). The more the ER value approaches 0, the more the non-dominated solutions on the Pareto front will be and the more precision the algorithm will have. Rahimi-Vahed et al. (2007) set N and G in the multi-objective genetic algorithm to 50 and 50 to solve small-range assembly line sequencing problems. Tripathi et al. (2007), in a comparison experiment, set N and G in NSGA-II and NSPSO to 100 and 250. Li (2003) sets N and G to 200 and 100. Besides, Deb et al. (2002) and Tripathi et al. (2007) set Cr to 0.9 and Mr to $1/n$, in which n refers to the number of decision-making variables coded in real number. Integrating experience of the scholars given above, we set factors and standards of the experiment design, as shown in Table 5.

$$ER=\frac{\sum_{i=1}^{n}e_i}{n} \tag{5}$$

In which n refers to the number of non-dominated solutions identified by the algorithm; e_i is a binary variable; if non-dominated solution i is a Pareto solution, $e_i=0$; otherwise, $e_i=1$.

The study's algorithm is written by Visual Basic 2005, and the database is created in Access 2003 and executed in an environment of Intel Core 2 Duo CPU E7400 2.8 GHz, 2GB RAM. After analysis of comparison between ER averages obtained from ten times of parameter combinations, the results of experimental design are listed in Table 6. According to the results, when the NSGA-II parameter combination (G, N, Cr, Mr) is (250, 200,0.9,0.125), the set of non-dominated solutions obtained ultimately will show better precision. Therefore, this study sets parameters based on the results.

RESULTS AND DISCUSSION

In accordance with the best parameter combination

Table 6. Results of experiment design for parameters of NSGA-II.

Cr	Mr	G								
		50			100			250		
		N								
		50	100	200	50	100	200	50	100	200
0.9	0.125	0.822	0.799	0.853	0.817	0.797	0.815	0.803	0.806	0.788

Table 7. Results of supplier ranking.

Supplier No.	f_1	f_2	f_3	Level of non-dominated solution	Rank
1	0.999	0.177	0.328	2	2
2	0.999	0.205	0.512	3	4
3	0.999	0.353	0.767	5	7
4	0.999	0.128	0.259	1	1
5	0.829	0.323	0.667	5	7
6	0.999	0.342	0.734	4	5
7	0.847	0.154	0.293	2	2
8	0.992	0.292	0.572	4	5

Table 8. Weight of each supplier.

Supplier No.	v1	v2	v3	v4	u1	u2	u3	u4
1	0.0002	0.4724	0.8165	0.1321	0.0296	0.1369	1.2486	0.0039
2	0.0672	0.3095	0.8338	0.2139	0.1481	0.1512	1.0381	0.0251
3	0.5839	0.4637	1.1279	0.1428	0.4356	0.1268	1.1873	0.2056
4	0.0334	0.3246	0.5716	0.0704	0.0331	0.0242	0.9059	0.0404
5	0.2552	0.4292	1.1385	0.1814	0.0641	0.2741	1.4475	0.1082
6	0.2654	0.5707	1.3671	0.1931	0.0634	0.0251	1.7887	0.3749
7	0.0325	0.3636	0.7038	0.1135	0.0725	0.0289	1.0182	0.0812
8	0.0005	0.7885	1.4154	0.2759	0.4382	0.0671	1.9053	0.0049

obtained from the experimental design, the MODEA model is carried out to solve problems. We summarize sets of non-dominated solutions identified using NSGA-II in the MODEA model and rank the non-dominated solutions to find the real DMU on the efficiency front. Ranking results are listed in Table 7 and weights of suppliers are listed in Table 8. In Table 7, f_1, f_2 and f_3 are obtained for problem-solving, representing three objective function values. In Table 8, v_1, v_2, v_3, v_4, u_1, u_2, u_3 and u_4 are also obtained for problem solving, representing four input weights and four output weights respectively. In this case, there are 8 suppliers and thus the problem-solving model should be repeated for 8 times. The result shows the non-dominated solutions of Supplier 4 are ranked level 1, so the supplier is selected as top priority. Suppliers 3 and 5 have the lowest ranked non-dominated solutions (level 5) and are ranked last.

According to a further analysis, for Supplier 4, f_1, f_2 and f_3 are not dominated by other solutions, suggesting Supplier 4 shows performance value superior to other suppliers under three objectives, therefore its non-dominated solutions are ranked level 1, namely Supplier 4 is selected as the best supplier. There are two suppliers whose non-dominated solutions are ranked Level 2, Suppliers 1 and 7. f_1 of Supplier 1 shows better performance than f_1 of Supplier 7; however, f_2 and

f_3 of Supplier 7 are better than those of Supplier 1. In the MODEA model, f_1 , f_2 and f_3 are deemed objectives of equal importance, and therefore we cannot tell which is better. In consequence, Suppliers 1 and 7 are ranked the same level. From observation, Supplier 2 has level-3 non-dominated solutions; its f_1 is superior to f_1 of Supplier 7; however, its f_2 and f_3 are inferior to those of Supplier 7. If f_1 , f_2 and f_3 are deemed equally important objectives, we ought to have ranked Supplier 2 and Supplier 7 in the same level of non-dominated solutions; but the comparison between Supplier 2 and Supplier 1 shows that the two suppliers have same performance for f_1 , but for f_2 and f_3 , Supplier 1 is better than Supplier 2, thus solutions of Supplier 2 are dominated by those of Supplier 1, and non-dominated solutions of Supplier 2 are ranked inferior to those of Supplier 1. According to the comparison, regarding the ranking of non-dominated solutions, Supplier 1 is equal to Supplier 7 and superior to Supplier 2. According to the results, it is clear that the solutions obtained from the multi-objective supplier selection model in MODEA using NSGA-II can distinguish between suppliers in a multi-objective scenario.

CONCLUSION

Examination of supplier selection performance in various industries has received wide attention recently. Because successful supplier selection may effectively help firms reduce costs and create profits as well, supplier selection has become one of the key factors for firms to sharpen their competitive edge. Combining MODEA and MOGA, this study develops a systematic supplier selection methodology – MODP. Basically we use MODEA to establish a multi-criteria multi-objective optimization decision making model and then use NSGA-II in MOGA for solving the optimization model to find out an efficient supplier set. This study also takes hemadynamometer – a health care related product – as a case for empirical analysis of supplier selection. The result shows the MODP is applicable to supplier selection problems, from which we may yield favorable outcomes.

During the course of the study, it was also found that there are a number of critical issues worthy of further researches and they are drawn below: 1) Give preferences of importance to each criterion respectively before supplier selection. 2) Give different weights to objectives in the MODEA model and analyze the effect of changes in weights on problem solving. 3) Apply different heuristic methods to supplier selection problems to improve the operating efficiency of the algorithm and quality of the Pareto set obtained.

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