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INTEGRATED METHODOLOGY FOR SUPPLIER SELECTION: THE CASE OF A SPHYGMOMANOMETER MANUFACTURER IN TAIWAN

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Abstract. Supplier selection is a critical multi-criterion decision-making activity for successful supply chain management. This study involved developing an integrated supplier selection methodology, which is constructed using analytic network process, data envelopment analysis, and multiple objective particle swarm optimization. The proposed integrated methodology can account for multiple supplier selection criteria and set boundaries on weight value for multiple objective data envelopment analysis inputs and outputs. To solve the data envelopment analysis model, a new algorithm based on multiple objective particle swarm optimization is introduced, which embeds with tabu list and group mechanisms, and then, it is found to be superior to the compared algorithms in solving performance on three test functions and the illustrative case. In addition, the proposed integrated methodology was applied to a supplier selection problem of sphygmomanometer manufacturer in Taiwan to verify its applicability of decision-making process. The results show that the methodology can be implemented as an effective decision aid for supplier selection under multiple criteria with weight restrictions.

Keywords: supplier selection, decision-making, ANP, DEA, PSO, algorithm.

JEL Classification: C61, M11.

Introduction

Selecting appropriate suppliers is a critical challenge for enterprise purchasing managers in contemporary competitive conditions. Proper suppliers allow buyers to provide their customers with quality products and services at appropriate times and prices. Supplier selection plays a vital role in operational production and operation because most production costs stem from raw material purchases (Kokangul, Susuz 2009). Liu and Hai (2005), Hadi-Vencheh (2011), and Hadi-Vencheh and Niazi-Motlagh (2011) indicated that selecting suppliers is a difficult task for purchasing managers and Ustun and Demirtas (2008) said that supplier selection is a multi-criteria problem that may involve conflicting factors such as price and quality. To address such complicated decision-making tasks, a systematic methodology is needed to help decision makers scientifically select an alternative.

Data envelopment analysis (DEA) is a mathematical programming model to evaluate the relative efficiencies by multiple inputs and outputs of decision making units (DMUs) and has been one of the most effective methods to the alternative assessment (Cooper *et al.* 2007). DEA has been widely and successfully applied in various industries (Cooper *et al.* 2007; Fried *et al.* 2008). It estimates the ratio of weighted outputs to weighted inputs to be the relative efficiency of each DMU, and then, comparing the efficiency of all DMUs (Lau 2013). In addition, Li and Reeves (1999) proposed a multiple objective DEA model that can be used to improve the discriminating power of traditional DEA methods. The supplier selection can be treated as an evaluation process with multiple inputs and outputs and a multiple objective DEA-based supplier selection model has been proposed in Che *et al.* (2011). DEA aims at finding the most favorable input and output weights for maximizing the efficiency of each DMU. From the practical decision-making perspective, however, the weight of each criterion in the DEA model should be restricted in the reasonable boundary to yield realistic efficiency scores. Moreover, distinct criteria are often mutually dependent in practical cases and can affect the outcome of the multi-criteria problem evaluation process. Inspire by this, this study continues and extends the work of Che *et al.* (2011) and introduces the analytic network process (ANP) approach in DEA model to determine the weight restriction for each input and output criterion based on decision-maker preferences with pondering interdependence interaction among these criteria to enhance the rationality of the model. Hence, the proposed DEA model can be used to find the appropriate suppliers whose weights of input and output criteria fit into the reasonable boundaries.

In addition, the proposed DEA model comprises multiple objectives that must be simultaneously achieved. In the past decade, numerous meta-heuristic algorithms have been proposed to solve multi-objective optimization problems and simultaneously optimize multiple factors such as the non-dominated sorting genetic algorithm (NDSGA) (Srinivas, Deb 1994), non-dominated sorting genetic algorithm II (NSGA-II; Deb *et al.* 2002), and non-dominated sorting particle swarm optimization (NSPSO) (Li 2003). Researchers have begun to focus on PSO to solve multi-objective problems and certain studies have proposed NSPSO as a method for such problems (Benabid *et al.* 2009; Liu 2009; Sedighizadeh *et al.* 2014); hence, we propose an NSPSO-based algorithm, namely NSPSOtg, which involves integrating tabu list and group mechanisms. The tabu list mechanism is employed to avoid scenarios in which all particles reach identical solutions and fall into the local solutions during evolution. The group mechanism is applied to prevent the located non-dominated solution sets from being over-concentrated, allowing the DEA model to be solved. Accordingly, this study involved developing a systematic supplier selection methodology, namely, *hy*ADMOPSO, which integrates data envelopment analysis (DEA), analytic network processing (ANP), and multiple objective particle swarm optimization (MOPSO) to enhance enterprise competitiveness by facilitating the selection of appropriate suppliers. The characteristics of the methodology are the consideration of the multiple criteria and boundary constraints inherent to the decision making process, and the quality solving performance in the decision making environment with multiple objectives. Hence, the *hy*ADMOPSO can be an effective methodology to be adopted by managers for supplier selection decision making.

The remainder of the paper is organized as follows. The research background is explored in Section 1. Section 2 presents the construction of the *hy*ADMOPSO methodology. The problem solving ability of NSPSOtg is evaluated in Section 3. In Section 4, the *hy*ADMOPSO methodology is applied to supplier selection for a sphygmomanometer manufacturer, and the suitability of this methodology is discussed in Section 5. Conclusions are provided in the final section.

1. Research background

An effective supplier selection process is the key factor for organizational success (Wang, Che 2007; Hadi-Vencheh 2011; Ozkok, Tiryaki 2011). Supplier selection is a multi-criteria decision-making problem (Ustun, Demirtas 2008) in which organizations choose suppliers based on numerous concurrent criteria. Weber *et al.* (1991) investigated the citation frequency of each indicator in literature from 1967 to 1990, noting that the three vital criteria were cost, delivery, and quality. Ustun and Demirtas (2008) evaluated tangible and intangible factors before determining the optimal supply quantity. Liao and Rittscher (2007) used cost, quality, and time as the criteria for supplier evaluation. Wang and Che (2008) used cost and quality to address the problem of changed product parts when selecting suitable parts suppliers. Che (2012) clustered and selected suppliers based on production cost, product quality, and production time criteria. Che (2014) designed a methodology for the production and distribution planning, which integrates cost and time criteria.

DEA is an objective method for evaluating the relative efficiency of DMUs with identical multiple inputs and outputs by using production frontier. Various researchers have advanced alternate DEA models and numerous applications thereof. Certain pertinent studies of DEA method applications are considered herein as they relate to supplier selection, such as Ho *et al.* (2010), Chen (2011), and Falagario *et al.* (2012). To improve classical DEA model the criminating power, Li and Reeves (1999) proposed a multi-objective DEA model, minimizing the maximal quantity among all deviation variables and the deviation sum:

$$
\begin{aligned}
&\text{Max } \theta_k = \sum_{r=1}^{R} u_r y_{rk}, \\
&\text{Min } M, \\
&\text{Min} \sum_{j=1}^{J} d_j, \\
&\text{s.t.} \ \sum_{i=1}^{I} v_i x_{ik} = 1, \\
&\sum_{r=1}^{R} u_r y_{rj} - \sum_{i=1}^{I} v_i x_{ij} + d_j = 0, \quad j = 1,\dots,J, \\
&u_r \ge 0, \quad r = 1,\dots,R, \\
&v_i \ge 0, \quad i = 1,\dots,I, \\
&d_j \ge 0 \ \text{ and } \ M - d_j \ge 0, \quad j = 1,\dots,J,
\end{aligned} \tag{1}
$$

where θ_k is the relative efficiency value of the kth DMU; v_i and u_r represent the weight values of input i and output r, respectively; x_{ik} and y_{rk} represent the values of input i and output r, respectively; d_j represents the loss value of the jth DMU; and M represents the maximum loss value for all DMUs.

MOPSO involves using the Pareto front concept to describe the solution set and simultaneously address multiple objective problems. It is critical to select one of the numerous non-dominated solutions as the global optimum. Various scholars have used MOPSO to solve multiple objective optimization problems. These approaches suggest how to select the optimal local guide to facilitate updating the next flight velocity. Coello and Lechuga (2002) introduced a grid-based MOPSO algorithm, which is not necessarily ideal for the selected particle and can cause particle movement in the wrong direction during evolution. Parsopoulos and Vrahatis (2002) introduced the vector evaluated particle swarm optimization algorithm, which simplifies multiple objective functions into a single objective problem by assigning appropriate weight. Li (2003) developed the NSPSO model by adopting non-dominated sorting, crowded-comparison mechanism, and niche method. However, if the first search attains fewer non-dominated solutions compared with the total number of groups in NSPSO, certain solutions fairly distant from the Pareto front are retained in the next generation in addition to the close solutions. This affects the convergence of the algorithm. Therefore, we proposed the NSPSOtg algorithm, adding group and tabu list mechanisms to the basic NSPSO process.

2. *hy*ADMOPSO methodology

The *hy*ADMOPSO methodology is detailed in the following subsections.

2.1. Identify supplier evaluation and selection criteria

After referring to relevant literature, we summarized key reference criteria and distributed a questionnaire to industrial experts to determine the critical supplier selection criteria. The experts comprised professionals (e.g. procurement managers, CTOs) from relevant industries. The questionnaire employed a 5-point Likert scale; the degree of criterion importance was divided into "*completely unimportant*" = 1, "*somewhat unimportant*" = 2, "*neither important nor unimportant*" = 3, "*somewhat important*" = 4, and "*extremely important*" = 5. The criteria that attained high degrees of importance were preserved; those that did not be omitted.

2.2. Determine the weight boundary of each criterion

The questionnaire was released to experts to determine the relative importance between two criteria and calculate the weight boundary of each criterion according by using the ANP supermatrix approach. The ANP procedure is as following steps (Büyüközkan, Çifçi 2011; Che *et al.* 2012):

Step 1: Calculate the pairwise comparison matrix.

Each criterion is compared pairwise with respect to its effect on other criteria.

Step 2: Calculate the local priority vectors.

The local priority vectors for each matrix are calculated using the eigenvector method: $Aw = \lambda_{max}w$. The λ_{max} is the largest eigenvalue of matrix A and w is the eigenvector.

Step 3: Test the consistency.

The *CR (consistency ratio) = consistency index/random consistency index* is used to evaluate the consistency of the weight assessment. If $CR \geq 0.1$, the decision makers must modify their judgments to generate a consistent comparison matrix.

Step 4: Construct the unweighted supermatrix.

All priority vectors from the matrices in the previous steps are arranged within an unweighted supermatrix.

Step 5: Derive the criteria weight boundaries.

The weighted supermatrix is calculated by multiplying the initial supermatrix by the cluster weight. Subsequently, the global weights are calculated n times by multiplying the weighted supermatrix until the columns are adjusted. Regarding each specific criterion, the upper limit of the weight scope was set based on the maximal expert value and the lower limit was set based on the minimal expert value.

2.3. Normalize data and develop the multiple objective DEA model

For each input x_i and output y_r of each DMU, the normalization is by Formula (2):

$$N(x_i) = x_i \,/\, \mathrm{Max}\{x_i \mid i = 1,\ldots,I\} \text{ and } N(y_r) = y_r \,/\, \mathrm{Max}\{y_r \mid r = 1,\ldots,R\}\,. \tag{2}$$

The ranking of each supplier is determined by the modified multiple objective DEA shown in Formula (3):

$$\begin{aligned}
&f_1\text{: Max } Z_k = \sum_{r=1}^{R} u_{rk} N(y_{rk}),\\
&f_2\text{: Min } M,\\
&f_3\text{: Min} \sum_{j=1}^{J} d_j,\\
&\text{s.t. } \sum_{r=1}^{R} u_{rk} N(y_{rj}) - \sum_{i=1}^{I} v_{ik} N(x_{ij}) + d_j = 0, \quad j = 1,\ldots,J,\\
&\sum_{i=1}^{I} v_{ik} N(x_{ik}) = 1,\\
&U_r \geq u_{rk} \geq L_r, \quad r = 1,\ldots,R,\\
&U_i \geq v_{ik} \geq L_i, \quad i = 1,\ldots,I,\\
&M - d_j \geq 0, \quad j = 1,\ldots,J,\\
&d_j > 0, \quad j = 1,\ldots,J,
\end{aligned} \tag{3}$$

where Z_k is the relative efficiency value of the kth DMU; v_{ik} and u_{rk} represent the weight values of input i and output r, respectively; $N(x_{ik})$ and $N(y_{rk})$ represent the normalized values of input i and output r, respectively; U_i and L_i: represent the upper and lower limits of the weights of input i; U_r and L_r: represent the upper and lower limits of the weights of output r; d_j represents the loss value of the jth DMU; and M represents the maximum loss value for all DMUs.

2.4. Develop the NSPSOtg for solving multiple objective DEA model

2.4.1. Code and create the initial population

Regarding coding, each particle represents the weight values of input and output as shown in Figure 1. Then we randomly established an initial population, comprising I particles and, the input and output weights were randomly generated; the scope of initial weight values were within the weight scope calculated using ANP.

v_1	v_2	v_3	v_4	...	v_I	v_i – input weight value
u_1	u_2	u_3	u_4	...	u_I	u_i – output weight value

Fig. 1. Structure of particle

2.4.2. Sort the non-dominated solution

After calculating the objective values of all particles in the population by Formula (3), NSPSOtg compares the objective values of each solution with others to find a set of individuals that are the non-dominated solutions. The population will be screened and if the particles are not dominated by other particles, they will be moved out from the population and assigned as Level 1. In this way, the repeated screenings have brought the sequentially incremental value of level of whole particles in the population.

2.4.3. Niche method

The crowding distance is employed to be the niche method. When particle i has a larger crowding distance, it yields more diversity among the solutions. Formula (4) shows the crowding distance calculation for particle i (Deb *et al.* 2002), where the crowding distance between the two particles at the boundary is set as infinite:

$$\mathrm{Crod}_i = \sum_k | f_{ki+1} - f_{ki-1} | / (\mathrm{Max}\_f_k - \mathrm{Min}\_f_k), \tag{4}$$

where Max_f_k and Min_f_k are the maximal and minimal values of particle k on the frontline composed of non-dominated solutions set and I is the total number of particles.

2.4.4. Create the new population

The new population creation process is based on the level and crowding distance of each particle. The individual with the lower level and lager crowding distance is preferred to select as a member of the new population. A new population with I particles will be created. Particles will be moved into the new population according to the ascending order of their levels until there are I particles selected. When particles attain identical levels, they are judged based on the crowding distance, where large particles are preferred.

2.4.5. Set a tabu list

Another storage space is set at three times the size of I particles to store the three most recent generations of the optimal values of each particle. This list is continually updated. Once the latest generation of optimal value is generated, the oldest generation the optimal value is removed.

2.4.6. Update the velocities and positions

Formula (5) shows the velocity calculation method and position update (Clerc 1999). The solutions must be distinct from those on the tabu list after each particle update or the particle velocity and position updates must be repeated:

$$v_{id}^{j+1} = k\left(v_{id}^{j} + \phi_1 \times \text{rand}() \times \left(p_{id} - x_{id}^{j}\right) + \phi_2 \times \text{rand}() \times \left(g_d - x_{id}^{j}\right)\right),$$
$$k = 2 / \left(\left|2 - \phi - \sqrt{\phi^2 - 4\phi}\right|\right),\ \phi = \phi_1 + \phi_2,\ \phi > 4,$$
$$x_{id}^{j+1} = x_{id}^{j} + v_{id}^{j+1}, \tag{5}$$

where, v_{id}^{j} and x_{id}^{j} represent the velocity and position of the jth generation of particle i at dimension d; p_{id} represents the position of the optimal value of particle i; g_d represents the position of the optimal value of the entire population; k represents the constriction factor; ϕ_1 and ϕ_2 represent acceleration constants; and *rand*() represents the independent random variable distributed uniformly within $[0,1]$.

2.4.7. Group mechanism

The group mechanism generates a new population by combining a population derived after the position update with the original population. Non-dominated sorting is conducted in this new population and non-dominated Level 1 solutions are temporarily stored in an external storage space. We identified non-dominated solutions among these temporarily stored solutions and those originally stored in the external space, retaining the non-dominated solutions and removing the dominated solutions. The scope of group with radius r was assigned to each particle. One of the solutions is selected as the center of the groups and any other solution falling within this scope of the group is removed. The selection of the group center and the search for the scope of group is conducted for all remaining solutions until all solutions are identified. Only solutions labeled as the group centers are preserved to ensure the diversity of the determined non-dominated solutions. Formula (6) shows the group radius r:

$$r = \text{Min}\left\{\left(\text{Max}\_f_k - \text{Min}\_f_k\right) \middle| k \in 1,\ldots,K\right\} / 2N, \tag{6}$$

where Max_f_k and Min_f_k represent the maximal and minimal values of each particle at objective k on the frontline composed of the non-dominated solutions set and N represents the number of particles.

2.4.8. Derive the population of final solutions

When the number of evolutions doesn't reach the preset number of generations, the evolution continues; otherwise, the non-dominated solution set retained in the external storage space is the set of optimal solutions.

3. Evaluation of problem-solving performance of NSPSOtg

In this section, the problem-solving performance levels of the proposed NSPSOtg algorithm was verified using three standard test functions and compared using two common algorithms: NSGA-II and NSPSO.

3.1. Test function and performance indicator

Table 1. Test functions

Problem	Range of variable x	Objective function (minimize)	Reference
SCH	$[-10^3, 10^3]$	$f_1(x) = x^2$ $f_2(x) = (x-2)^2$	(Tsai *et al.* 2010; Gong *et al.* 2010; Rodríguez *et al.* 2009)
KUR	[–5.5]	$f_1(x) = \sum_{i=1}^{n-1}\left(-10\exp\left(-0.2\sqrt{x_i^2 + x_{i+1}^2}\right)\right)$ $f_2(x) = \sum_{i=1}^{n}\left(\lvert x_i\rvert^{0.8} + 5\sin x_i^3\right)$	(Gong *et al.* 2010; Wang *et al.* 2009; Salazar-Lechuga, Rowe 2005)
ZDT2	[0.1]	$f_1(x) = x_1$ $f_2(x) = g(x)\left[1-\left(x_1 / g(x)\right)^2\right]$ $g(x) = 1 + 9\left(\sum_{i=2}^{n} x_i\right) / (n-1)$	(Tsai *et al.* 2010; Gong *et al.* 2010; Tripathi *et al.* 2007)

Table 1 lists descriptions of three test functions: SCH (Schaffer 1985), KUR (Kursawe 1991), and ZDT2 (Zitzler *et al.* 2000). Zitzler *et al.* (2000) introduced three major evaluation targets as performance level indicators for algorithms:

(a) Accuracy: The final non-dominated solution set should comprise numerous solutions converged to the Pareto front, that includes *Number of non-dominated solutions* (*NNS*) (Rahimi-Vahed *et al.* 2007), *Number of Pareto solutions* (*NPS*) (Schaffer 1985), and *Error ratio* (*ER*) (Rahimi-Vahed *et al.* 2007) indicators. Formula (7) shows the *ER*:

$$ER = \sum_{i=1}^{n} e_i / n, \tag{7}$$

where n is the number of non-dominated solutions; e_i is a binary variable, if non-dominated solution i is a Pareto solution, and $e_i = 0$; otherwise, $e_i = 1$. An *ER* closes to 1 indicates that few non-dominated solutions converged to the Pareto front.

(b) Distribution: The *Diversity metric* (*DM*) is used to evaluate the diversity among non-dominated solutions and as follows (Deb *et al.* 2002):

$$DM = \left(d_f + d_l + \sum_{i=1}^{n-1}\left|d_i - \bar{d}\right|\right) / \left(d_f + d_l + (n-1)\bar{d}\right), \tag{8}$$

where n is the number of non-dominated solutions determined using the algorithm; d_f and d_l are the distances between the solutions at both ends of the Pareto front and their neighboring non-dominated solutions; d_i is the distance between a non-dominated solution and its neighboring solution; and $\bar{d}$ is the average value of d_i.

(c) Spread: The *Maximum Spread* (*MS*) is used to measure the spread of the non-dominated solution set and as follows (Zitzler *et al.* 2000; Rahimi-Vahed *et al.* 2007):

$$MS = \sqrt{\sum_{m=1}^{M}\left(\max_{i=1}^{n} f_m^i - \min_{i=1}^{n} f_m^i\right)^2}, \tag{9}$$

where n is the number of non-dominated solutions and M is the number of objective functions. The larger the *MS* is, the more optimal the spread of the determined non-dominated solution is.

3.2. Setting the parameters

We developed the NSPSOtg model by using parameters such as N (number of particles), G (number of generations), ϕ_1 and ϕ_2 (acceleration constants), and V_{max} (maximal velocity). Li (2003) set the N and G of an NSPSO model as 200 and 100, respectively, to compare it with the NSGA-II. Rahimi-Vahed *et al.* (2007) set N and G of the multiple objective genetic algorithm as 50 and 50 to solve the problem of the sequence of a small-scale assembly line. Tripathi *et al.* (2007) set the N and G of NSPSO and NSGA-II as 100 and 250, respectively. Clerc (1999) and Clerc and Kennedy (2002) suggested that the sum of ϕ_1 and ϕ_2 should be larger than four to ensure the optimization of the particle swarm acceleration function by adding a constriction factor. However, none of these studies specified optimal parameter combination; the only suggestion was that the two parameters be set as $\phi_1 = \phi_2 = 2.05$. Zhang *et al.* (2005) proposed that when $\phi_1 = 2.8$ and $\phi_2 = 1.3$, the convergence of the population can be accelerated. Clerc and Kennedy (2002) suggested that strong good convergence ability can be attained without restricting the V_{max}. However, Eberhart and Shi (2000) argued that the execution would improve if velocity limitation was considered for particle swarm optimization and combined with the constriction factor. We integrated the aforementioned scholar experiences and Table 2 shows the factors and levels used in the experimental design. Each parameter combination was repeated 10 times to obtain the mean *ER* value for comparative analysis. Table 3 lists the results of the experimental design and shows that when the NSPSOtg parameter combination G, N, ϕ_1, ϕ_2, and V_{max} is set at 250, 200, 2.05, 2.05, and ±1, respectively, it eventually yields an accurate non-dominated solution set. Therefore, these parameter settings were employed to comparatively analyze the performance levels of various algorithms.

Table 2. Experimental design for factors

Factor	Level 1	Level 2	Level 3
G	50	100	250
N	50	100	200
ϕ_1, ϕ_2	(2.05, 2.05)	(2.8, 1.3)	–
$V_{\max}$	no limit	±1	–

Table 3. Experimental design for NSPSOtg's parameters

		G 50			100			250		
(ϕ_1, ϕ_2)	V_{max}	*N* 50	100	200	50	100	200	50	100	200
(2.05,2.05)	no limit	0.307	0.348	0.335	0.397	0.347	0.301	0.347	0.319	0.282
	±1	0.416	0.381	0.283	0.381	0.413	0.297	0.388	0.317	0.231
(2.8,1.3)	no limit	0.298	0.311	0.343	0.459	0.357	0.355	0.329	0.339	0.301
	±1	0.385	0.372	0.364	0.429	0.346	0.349	0.440	0.347	0.309

3.3. Analyzing the results

Table 4. Comparisons of solving performances among different algorithms on test functions

Indicator		NSPSOtg	NSPSO	NSGA-II	F-value	p-value	Ranking
SCH	NNS	197.867	197.467	82.333	2170.810	4.07E-43	NSPSOtg = NSPSO > NSGA-II
	NPS	197.733	197.467	81.533	2110.579	7.31E-43	NSPSOtg = NSPSO > NSGA-II
	ER	0.001	0.000	0.009	11.335	1.16E-04	NSPSO = NSPSOtg < NSGA-II
	DM	0.948	1.071	0.978	29.493	9.97E-09	NSPSOtg < NSGA-II < NSPSO
	MS	5.465	1.031	5.628	582.145	2.39E-31	NSGA-II > NSPSOtg > NSPSO
KUR	NNS	80.000	27.733	42.333	30.408	6.84E-09	NSPSOtg > NSGA-II > NSPSO
	NPS	61.800	19.667	36.933	21.189	4.34E-07	NSPSOtg > NSGA-II > NSPSO
	ER	0.237	0.333	0.136	3.929	0.027	NSGA-II < NSPSOtg = NSPSO
	DM	0.911	0.972	0.918	16.479	5.21E-06	NSPSOtg = NSGA-II < NSPSO
	MS	12.783	4.071	8.922	99.533	1.16E-16	NSPSOtg >NSGA-II > NSPSO
ZDT2	NNS	159.267	49.267	29.200	54.952	1.88E-12	NSPSOtg > NSPSO > NSGA-II
	NPS	151.267	21.267	1.333	72.603	2.34E-14	NSPSOtg > NSPSO > NSGA-II
	ER	0.065	0.582	0.954	53.409	6.78E-12	NSPSOtg < NSPSO < NSGA-II
	DM	0.816	0.918	0.949	34.121	1.58E-09	NSPSOtg < NSPSO < NSGA-II
	MS	1.329	0.898	1.321	28.278	1.66E-08	NSPSOtg = NSGA-II > NSPSO

Table 4 shows the comparison of problem-solving performance levels among NSPSOtg and NSGA-II, and NSPSO (number of experiments $n = 30$ and $\alpha = 0.05$). First, regarding the SCH problem, the *NNS* and *NPS* indicators show that the *NNS* obtained using NSPSOtg and NSPSO was significantly superior compared with that of NSGA-II. The *ER* indicators of the algorithms were all close to 0, suggesting that the non-dominated SCH problem solutions obtained by these algorithms accurately converge to the Pareto front. In terms of distribution, the *DM* showed that the NSPSOtg was slightly superior compared with NSGA-II and NSPSO demonstrated poor diversity (*DM* > 1). The *MS* indicator showed that NSPSOtg and NSGA-II demonstrated the strongest spread. Analogously, on average, the performanc indicators showed that NSPSOtg is superior to NSPSO and NSGA-II in terms of accuracy, distribution, and spread on the KUR and ZDT2 problems.

4. Implementation of *hy*ADMOPSO methodology in supplier selection

To further verify the suitability of the proposed *hy*ADMOPSO methodology, we empirically investigated a case, where, Company A is a sphygmomanometer manufacturer that uses 16 part suppliers.

4.1. Determination of the supplier selection criteria and weight of each criterion

The key reference criteria are summarized by referring to relevant literature, that affect supplier evaluation and selection. Six experts are selected through the group discussion of managers of the case company. The members of selected experts include three internal managers of case company and three external experts from relevant industries. They scored the criteria by questionnaires and four major dimensions and eight assessment criteria are determined. If the applicability of the data from the expert is doubtful, he/she will be asked to provide an explanation and/or fix the judgment. The relative weights and weighted boundaries of the selected indicators, then, is determined via the ANP model (Table 5).

Table 5. Supplier selection criteria and weight scope of each criterion

Criterion	Sub-criterion	Input/Output	Average	Max	Min
Cost	Purchasing cost (Pc)	Input 1	0.108	0.314	0.032
	Transportation cost (Tc)	Input 2	0.068	0.245	0.010
Quality	Defective rate (Qdr)	Input 3	0.145	0.256	0.047
Service	Maintenance turnaround time (Mtt)	Input 4	0.062	0.128	0.008
Time	On-time delivery rate (Odr)	Output 1	0.241	0.369	0.096
Quality	Reliability (Re)	Output 2	0.235	0.257	0.037
Service	Supply capacity (Sc)	Output 3	0.077	0.235	0.017
	Warranty time (Wt)	Output 4	0.064	0.132	0.008

4.2. Data normalization and results of supplier selection by NSPSOtg

Table 6 lists the input and output data that was normalized and introduced in the multiple objective DEA models. Through problem solving with NSPSOtg, the results are shown in Table 7. For Suppliers 3, 9 and 16 come up with non-dominated solutions of Level 1, these three suppliers are the most preferred choices. Supplier 7 has the worst ranking because of its Level 5 non-dominated solutions.

Table 6. Data of input and output items for suppliers

Supplier	Pc (dollars)	Tc (dollars)	Qdr (%)	Mtt (days)	Re (%)	Sc (units)	Wt (months)	Odr (%)
1	20	4	2	7	75	900	6	80
2	10	1	1	7	60	800	6	80
3	15	2	1.5	7	70	1000	18	90
4	20	4	2	14	90	900	12	90
5	15	2	2.5	7	70	800	6	80
6	11	1	1	14	65	800	6	90
7	11	1	1.5	7	60	800	6	80
8	12	2	1.5	14	65	800	6	85
9	15	4	1.5	14	90	1000	12	90
10	10	1	1.5	7	60	900	12	85
11	10	2	1	7	70	800	6	88
12	15	2	1.5	14	70	800	6	85
13	12	3	2	7	85	1000	12	99
14	20	4	2.5	14	80	1000	12	90
15	10	1	1	14	65	800	6	85
16	20	5	2.5	14	95	1000	18	90

Table 7. Results of sorting suppliers by multiple objective DEA

Supplier	f_1	f_2	f_3	Level	Ranking	Supplier	f_1	f_2	f_3	Level	Ranking
1	0.603	0.572	4.151	3	8	9	0.855	0.618	3.944	1	1
2	0.995	0.999	6.539	4	13	10	0.995	0.783	5.366	2	4
3	0.999	0.652	4.452	1	1	11	0.995	0.914	5.843	3	8
4	0.639	0.513	3.372	2	4	12	0.689	0.724	4.663	3	8
5	0.716	0.721	4.794	4	13	13	0.982	0.690	4.662	2	4
6	0.952	0.932	5.781	3	8	14	0.568	0.432	3.003	2	4
7	0.886	1.067	6.881	5	16	15	0.982	0.954	5.912	4	13
8	0.743	0.719	4.778	3	8	16	0.665	0.426	2.931	1	1

5. Discussion

Table 8. Comparisons of problem-solving performances among different algorithms on the case

Performance indicator	NSPSOtg	NSPSO	NSGA-II	ANOVA		Ranking
				F-value	p-value	
NNS	26.758	5.200	11.092	1354.592	0.000	NSPSOtg > NSGA-II > NSPSO
NPS	26.058	0.000	1.767	4596.573	6.52E-50	NSPSOtg > NSGA-II > NSPSO
ER	0.115	1.000	0.885	3572.505	1.26E-47	NSPSOtg < NSGA-II < NSPSO
DM	0.857	0.909	0.872	49.309	9.53E-12	NSPSOtg < NSGA-II < NSPSO
MS	1.105	0.735	0.585	105.531	4.17E-17	NSPSOtg > NSPSO > NSGA-II

Table 8 lists the comparisons among NSPSOtg, NSGA-II, and NSPSO. In terms of accuracy, NSPSOtg yields more non-dominated solutions and superior *NNS*, *NPS* and *ER* values compared with the other algorithms. In terms of distribution, NSPSOtg was slightly superior to others in *DM*. The *MS* indicator showed that NSPSOtg had the strongest spread. These performance indicators suggest that NSPSOtg is superior to NSPSO and NSGA-II in terms of accuracy, distribution, and spread in the proposed problem; therefore we summarized the non-dominated solution set of suppliers found using NSPSOtg in a multiple objective DEA model and performed non-dominated solution sorting to determine which DMUs are efficient.

Table 9. Results of sorting suppliers by classical DEA

Supplier	f_1	f_2	f_3	Ranking	Supplier	f_1	f_2	f_3	Ranking
1	0.899	1.199	9.899	11	9	0.976	1.001	5.151	9
2	1.000	1.238	7.482	1	10	1.000	1.249	8.467	1
3	1.000	1.001	6.739	1	11	1.000	1.088	6.539	1
4	0.732	0.474	2.471	14	12	0.718	0.616	3.668	15
5	0.965	0.897	6.321	10	13	1.000	0.975	7.887	1
6	1.000	1.517	8.369	1	14	0.633	0.599	4.949	16
7	0.995	3.167	18.263	8	15	1.000	1.413	7.601	1
8	0.814	0.919	5.589	13	16	0.825	0.442	2.306	12

Table 10. Weights of suppliers by multiple objective DEA and classical DEA

Multiple objective DEA								
Supplier	v1	v2	v3	v4	u1	u2	u3	u4
1	0.1515	0.0100	0.1399	0.1236	0.0370	0.0926	0.0321	0.0960
2	0.2943	0.1368	0.2469	0.1199	0.1898	0.1252	0.0924	0.0999
3	0.2254	0.0155	0.2096	0.0644	0.0546	0.0512	0.1320	0.1203
4	0.1293	0.0100	0.2158	0.0233	0.0428	0.0170	0.1046	0.0960
5	0.2082	0.1659	0.0470	0.1275	0.1900	0.0184	0.0088	0.1003
6	0.2733	0.1787	0.2505	0.0469	0.2540	0.0170	0.1279	0.0960
7	0.2916	0.2420	0.1126	0.1138	0.1623	0.0472	0.0203	0.1839
8	0.2875	0.0447	0.2024	0.0214	0.0370	0.1516	0.0565	0.0960
9	0.2379	0.0138	0.2006	0.0234	0.1021	0.0170	0.1259	0.0960
10	0.3139	0.0100	0.2134	0.0925	0.0906	0.1073	0.1266	0.1089
11	0.3023	0.1282	0.2253	0.0814	0.2362	0.0205	0.1320	0.1098
12	0.2206	0.1554	0.1277	0.0290	0.1770	0.0170	0.0108	0.0960
13	0.3136	0.0611	0.068	0.1074	0.1937	0.0170	0.0616	0.0960
14	0.1592	0.0100	0.1115	0.0545	0.0370	0.0174	0.0800	0.0960
15	0.3109	0.1589	0.2560	0.0436	0.2315	0.0289	0.1320	0.1187
16	0.1592	0.0100	0.1115	0.0525	0.0370	0.0174	0.0800	0.0960

End of Table 10

Classical DEA								
1	0.0000	0.0000	0.0000	1.9999	0.0000	0.9999	0.0000	0.0000
2	1.4249	0.4999	0.3125	0.1249	0.0000	0.0000	0.0000	1.2374
3	1.3333	0.0000	0.0000	0.0000	0.0000	0.0000	0.9999	0.0000
4	0.7141	0.0000	0.3572	0.0000	0.5089	0.0000	0.3749	0.0000
5	0.0000	0.8618	0.0000	1.3104	1.3103	0.0000	0.0000	0.0000
6	0.0000	0.0000	2.4147	0.0340	0.0000	0.0000	0.6988	0.8437
7	0.0000	1.0413	0.0000	1.5834	1.5832	0.0000	0.0000	0.0000
8	1.5708	0.1436	0.0000	0.0000	0.0000	0.0000	0.0000	0.9482
9	0.0000	0.0000	1.6666	0.0000	0.6785	0.0000	0.4999	0.0000
10	0.0000	1.2499	1.2499	0.0000	0.0000	0.7142	0.5357	0.0000
11	1.9999	0.0000	0.0000	0.0000	0.0000	0.0000	0.0989	1.0878
12	0.0000	0.5125	1.1541	0.1025	0.9743	0.0000	0.0000	0.0000
13	0.2500	0.1874	0.0000	1.4749	0.0000	0.9999	0.0000	0.0000
14	0.6665	0.0000	0.3334	0.0000	0.4749	0.0000	0.3499	0.0000
15	0.0000	0.2939	2.3529	0.0000	1.1176	0.0000	0.7058	0.0000
16	0.6665	0.0000	0.3334	0.0000	0.4749	0.0000	0.3499	0.0000

In addition, we compared the results (Table 7) with those attained using the traditional DEA (Table 9). The multiple objective DEA model maximizes its DMU efficiency and accounts for other DMUs during weight calculation such that the total variance and maximal variance are minimized. Thus, the results show that the efficient DMU obtained using the traditional DEA is not necessarily the ideal DMU for use in the multiple objective DEA model. For example, Supplier 13 is ranked first in the traditional

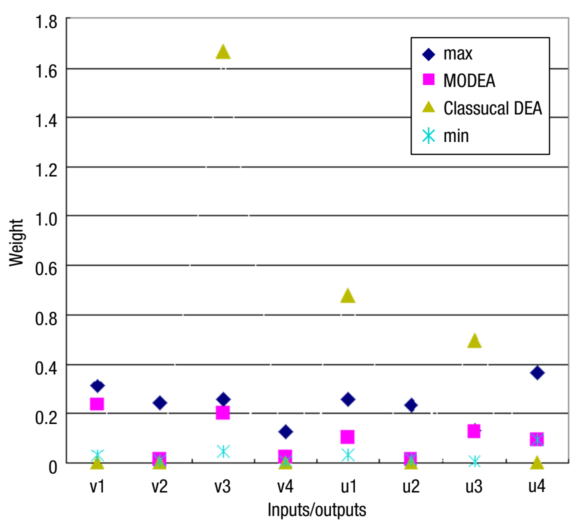

Fig. 2. Weight boundaries of inputs and outputs for Supplier 9

DEA model but fourth in the multiple objective DEA model. Moreover, comparing f_2 and f_3 for all DMUs showed that the weights calculated using multiple objective DEA models typically yield a decreased total variance and maximal variance. The input and output weights were obtained by multiple objective DEA models relatively benefit all DMUs, such that the disadvantages of the traditional DEA are focused only on favorable evaluation conditions. Table 10 lists the weights results for all suppliers, and Figure 2 shows the weight boundaries of the inputs and outputs for Supplier 9. Because the multiple objective DEA model was developed based on the scope of weight suggested by industrial experts with ANP approach, reasonable input and output weights can be generated that address the question scenario.

Conclusions

Supplier evaluation and selection is a critical process for integrating the expertise and experiences of business managers and their supply chain partners, allowing enterprises to reduce costs and generate profits. Thus, supplier evaluation and selection is vital to business competition. We developed a supplier evaluation and selection methodology that integrated ANP, multiple objective DEA, and MOPSO, namely, *hy*ADMOPSO. By integrating ANP and multiple objective DEA, all influential factors were considered and the scope of weight was concluded based on the relative weights suggested in the expert comments. In addition to maximizing the efficiency of its own DMU, multiple objective DEA accounts for other DMUs to ensure that the total and maximal variances are minimized. Furthermore, to effectively solve multiple objective DEA problems, an NSPSO-based MOPSO algorithm, namely, NSPSOtg was introduced. By using three test functions, we verified that NSPSOtg demonstrates satisfactory problem-solving performance levels. Finally, the *hy*ADMOPSO methodology was applied to select suppliers for a sphygmomanometer manufacturer; the results show that the methodology is applicable to select appropriate suppliers when multiple criteria are presented.

Throughout the proposed methodology, although it used for the supplier selection decision in this paper, it can be applied for making the quality decision in other fields such as location selection, project evaluation, and evaluation of energy system. However, in its current form, it may not be introduced into to solving the more complex supplier selection problems. For instance, the *hy*ADMOPSO can not gain the quality solution in the supplier selection problems when decision makers face with uncertain data, capacity restriction, and quality discount situations. In the future studies, the proposed methodology will be extended to these complex situations.

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