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Clustering and selecting suppliers based on simulated annealing algorithms

Z.H. Che *

Department of Industrial Engineering & Management, National Taipei University of Technology, 1, Sec. 3, Chung-Hsiao E. Rd., Taipei 106, Taiwan, ROC

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ABSTRACT

This study proposes two optimization mathematical models for the clustering and selection of suppliers. Model 1 performs an analysis of supplier clusters, according to customer demand attributes, including production cost, product quality and production time. Model 2 uses the supplier cluster obtained in Model 1 to determine the appropriate supplier combinations. The study additionally proposes a two-phase method to solve the two mathematical models. Phase 1 integrates k-means and a simulated annealing algorithm with the Taguchi method (TKSA) to solve for Model 1. Phase 2 uses an analytic hierarchy process (AHP) for Model 2 to weight every factor and then uses a simulated annealing algorithm with the Taguchi method (ATSA) to solve for Model 2. Finally, a case study is performed, using parts supplier segmentation and an evaluation process, which compares different heuristic methods. The results show that TKSA + ATSA provides a quality solution for this problem.

1. Introduction

Global competition means that companies must integrate with upstream and downstream supply chain partners efficiently to increase market opportunities and competitiveness and to adapt to rapid changes in market trends and customer demands. To satisfy customer demand and to lower internal cost and risk, companies select appropriate suppliers to make more competitive products and distribute these products to customers, according to the varied demands of those customers. Nonetheless, for a supply chain with a large number of suppliers, each supplier has a different product strategy and therefore a different level of competitiveness and customer demands are varied, in accordance with their preferences. If customer demand is not considered, then product types that are incompliant with customer expectations are produced, causing members of the supply chain system to suffer great losses. He et al. [1] mentioned that good supply chain management requires that companies select appropriate suppliers, according to the nature of the product purchased and the upstream market. Sun et al. [2] pointed out that the process of supplier evaluation is a process where both parties seek optimally balanced decisions in accordance with actual supplier manufacturability and serviceability. Appropriate incentives or punishments ensure a win–win situation for both parties.

Wang and Wang [3] suggested that cluster analysis could be used to cluster all suppliers and to establish a supplier evaluation index, to effectively manage suppliers. Bottani and Rizzi [4] pointed out that suppliers with similar characteristics could be clustered by using cluster analysis to reduce supplier combinations. Sung and Ramayya [5] stated that cluster analysis could effectively differentiate supplier types. Therefore, this paper proposes a two-phase model to find the appropriate supplier combinations, which ensure that customer demand is fulfilled. In Model 1, suppliers are divided

* Tel.: +886 2 2771 2171x2346; fax: +886 2 7317168.
E-mail address: zhche@ntut.edu.tw.

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Notations

h	Hierarchy number, $h = 1, 2, 3, \ldots, H$
i	Part number, $i = 1, 2, 3, \ldots, I$
j	Supplier number, $j = 1, 2, 3, \ldots, J$
k	Supplier cluster number, $k = 1, 2, 3, \ldots, K$
m	Module number, $m = 1, 2, 3, \ldots, M$
s	Quantity discount level
H	Lowest hierarchy number
I	Total number of parts
J	Total number of suppliers
K	Total number of supplier clusters
M	Total number of modules
S	Total number of levels of quantity discount
$b_{i,j}^{k}$	Part i provided by supplier j belongs to cluster k
$f(OC_{i,j})$	Cost function of the order of supplier j providing part i
$hc_{i,j}$	Unit holding cost of supplier j providing part i
${}^{h}m$	The mth module in hierarchy h
O_{PC}^{k}	Production cost centroid in the kth cluster
O_{PQ}^{k}	Product quality centroid in the kth cluster
O_{PT}^{k}	Production time centroid in the kth cluster
AD_i	Actual demand for part i
$AT^{h,{}^{h}m}$	Assembly time for module ${}^{h}m$
$AC^{h,{}^{h}m}$	Assembly cost for module ${}^{h}m$
$C_i^{h,{}^{h}m}$	Module ${}^{h}m$ at hierarchy h
D_i	Demand for part i
HC_i	Inventory cost for part i
I_i	Inventory for part i
$MPT^{h,{}^{h}m}$	Maximum production time of part for module ${}^{h}m$
$UC_{i,j}$	Unit cost of part i provided by supplier j
$UQ_{i,j}$	Unit quality of part i provided by supplier j
$UT_{i,j}$	Unit time of part i provided by supplier j
$ND_{i,j}^{s}$	Order quantity level s of part i provided by supplier j
$O_{i,j}$	Order part i provided by supplier j
$OC_{i,j}$	Order cost of part i provided by supplier j
$PT_{i,j}$	Production time of part i provided by supplier j
$PD_{i,j}^{s}$	Unit price discount at level s of part i provided by supplier j
$ST_{i,j}$	Shipping time of part i provided by supplier j
TC	Total production cost
TQ	Total product quality
TT	Total production time

into several clusters, depending on the characteristics of customers' demands. In Model 2, the more efficient supplier combinations are determined with respect to customer demand in the specific cluster determined by Model 1.

Maria [6] and Kanungo et al. [7] pointed out that, for unsupervised learning, k-means is the fundamental and most widely used clustering algorithm. However, Kanungo et al. [7] stated that selection of the initial cluster centroid for k-means has a great influence on clustering result. If selection of the initial cluster centroid is flawed, the quality of the clustering is compromised. Liu et al. [8] also pointed out that k-means is subject to initial weighting, which yields an unsatisfactory clustering result. A clustering solution that uses k-means is usually confined to a local optimum, during the optimization clustering process. Wang et al. [9] proposed that the probabilistic acceptance of local minima, for SA, could provide strong local search capabilities and avoid confinement to a local optimum. Bandyopadhyay [10] applied SA to clustering and obtained good quality clustering results, as determined through experiments with artificial and real data sets. Wu et al. [11] applied SA to the clustering of incomplete data and the results showed a reduction in clustering errors. Hence, Model 1 uses SA to combine k-means, for supplier clustering.

Supplier evaluation and selection procedures in Model 2 include a quantity discount. Wang et al. [9] stated that when quantity discounts are used in planning, the associated problems are very complex and not easily solved through ordinary commercial software. Tsai [12] pointed out that it is difficult to find a global optimal solution for a nonlinear model with quantity discount variables. As already mentioned, SA provides a strong local search capability, so it is also used to solve for supplier selection for Model 2. The Taguchi method is used to set the proper level for each parameter of SA to yield a quality solution.

The major aims of this study are as follows. (1) Create two optimization mathematical models for the clustering and selection of suppliers. In Model 1, suppliers are clustered with minimal total within cluster variation (TWCV), according to customer demands for the product type. Model 2 uses the results of Model 1 to determine the optimal supplier combination with consideration to quantity discount and customer demands. AHP is used, in this model, to weight each factor. (2) Create a two-phase method to solve Models 1 and 2. Phase 1 develops the TKSA method, which consists of the Taguchi method, *k*-means and simulated annealing to solve for Model 1, and Phase 2 uses an ATSA method, which consists of an analytical hierarchy process, Taguchi method and simulated annealing to solve for Model 2. (3) Compare the quality of the solutions for different heuristic methods in each phase and verify that the proposed method TKSA + ATSA provides the best quality solution to the proposed problem.

2. Literature review

2.1. Supplier evaluation and selection

Supplier selection is one of the most important decisions and is a widely researched area in the field of supply chain management. Che [13] stated that the selection of quality suppliers from a large pool of potential suppliers is a very important factor in supply chain decision-making. A series of previous studies of supplier selection defined evaluation criteria and decision methods. For example, Liao and Rittscher [14] used three evaluation criteria – cost, quality and delivery time – for supplier selection. Xi and Wu [15] proposed a multi-objective mixed-integer programming model for the selection of quality suppliers with respect to price, quality and time. Wadhwa and Ravindran [16] used price, quality and time to develop a multi-objective supplier selection plan. Wang and Che [17] considered cost and quality as the evaluation criteria for the selection of suitable parts suppliers for the problem of changed product parts. Che [13] proposed an optimization mathematical model and a heuristic solving method to evaluate suppliers in a multi-echelon supply chain system, using cost, time, quality and environmental criteria. This paper refers to other related literature for supplier selection with multiple criteria, such as [18–23].

Based on the papers discussed above, this study uses cost, quality and time as the major selection criteria, in order to construct a optimization mathematical model to identify and evaluate quality suppliers.

2.2. Analytic hierarchy process method (AHP)

AHP was developed by Saaty in 1971. It is one of the best methods for solving decision-making problems involving multiple criteria (Saaty, [24]). AHP contains three main elements; a hierarchical structure, a pair-wise comparison matrix and a method to compute weight, to evaluate the alternatives for complex decisions that involve qualitative and quantitative criteria. Many papers have been published, concerning decision-making with AHP. Ngai and Chan [25] used AHP to evaluate strategies for knowledge management. Chin et al. [26] used AHP to screen a project. Ghodsypour and O'Brien [27] proposed an integrated method for the selection of quality suppliers, using tangible and intangible factors, which combined AHP and linear programming. Other related studies concerning the use of AHP for the evaluation of suppliers are [28,29,19,13].

As can be seen, AHP has been widely and successfully used in many studies in various fields. This study uses AHP for the optimization mathematical model that determines the weight of each factor.

2.3. Simulated annealing algorithm (SA)

SA was proposed by Kirkpatrick et al. [30]. It relies on the fact that, when a solid is heated to a certain temperature, the solid molecular structure is broken down into a liquid structure. If the cooling process is then controlled, allowing it to cool down completely, its molecules can be expected to form a solid structure and a stable state. When this state is within an optimal solution interval, the SA method reheats to accept an inferior solution for the probability in a stochastic process. The algorithm can skip the current optimal solution interval, to reach another optimal solution. A temperature probability model enables it to search upward and downward along a gradient, so it is efficient in providing optimization without becoming confined to a local optimal solution.

The SA method relies on a probability concept to generate a perturbed new solution, to avoid becoming confined by a local optimal solution, and to enable a global optimal solution. Dhawan [31] pointed out that SA is an optimized method, which has a superior process for the solution of a global minimized cost function. Suman [32] indicated that, when used in multi-objective programming, SA can efficiently search a wide range of solution sets and attain convergence. Yeh and Fu [33] also mentioned that SA algorithms are efficient heuristic algorithms. Loukil et al. [34] applied SA to solve a multi-objective optimization model in production scheduling and found that SA generated a new approximate solution through continuous perturbation and convergence using the cooling mechanism. When used in a complex multi-objective optimization model, it could determine a global optimal solution.

3. Optimization mathematical models development

In this section, two optimization mathematical models are constructed for clustering and selection of suppliers. In Model 1, based on a customer's required product type, the optimal supplier cluster is created with minimizing TWCV. Using the results of Model 1, Model 2 takes into consideration the supplier cost, quality, and time factors, and weights these factors to create a supplier evaluation decision model for the determination of the best supplier combination.

Model 1:

This model clusters suppliers through the minimization of the TWCV of the objective function according to product type, customer demand, production cost, product quality and production time provided by suppliers with cluster centroid respectively.

$$\begin{aligned} &\text{Minimize} \sum_{k=1}^{K}\sum_{i=1}^{I}\sum_{j=1}^{J}(UCO_{i,j}+UQO_{i,j}+UTO_{i,j})b_{i,j}^{k} \\ &UCO_{i,j}=(UC_{i,j}-O_{PC}^{k})^2 \\ &UQO_{i,j}=(UQ_{i,j}-O_{PQ}^{k})^2 \\ &UTO_{i,j}=(UC_{i,j}-O_{PT}^{k})^2. \end{aligned} \tag{1}$$

Using all characteristic vectors to form the centroid of each cluster,

$$O_{PC}^{k}=\frac{\sum_{i=1}^{I}\sum_{j=1}^{J}(b_{i,j}^{k}\times UC_{i,j})}{\sum_{i=1}^{I}\sum_{j=1}^{J}b_{i,j}^{k}}\quad \forall k \tag{2}$$

$$O_{PQ}^{k}=\frac{\sum_{i=1}^{I}\sum_{j=1}^{J}(b_{i,j}^{k}\times UQ_{i,j})}{\sum_{i=1}^{I}\sum_{j=1}^{J}b_{i,j}^{k}}\quad \forall k \tag{3}$$

$$O_{PT}^{k}=\frac{\sum_{i=1}^{I}\sum_{j=1}^{J}(b_{i,j}^{k}\times UT_{i,j})}{\sum_{i=1}^{I}\sum_{j=1}^{J}b_{i,j}^{k}}\quad \forall k. \tag{4}$$

If $b_{i,j}^{k}=1$, then this supplier belongs to the kth cluster; if $b_{i,j}^{k}=0$, this supplier does not belong to the kth cluster.

$$b_{i,j}^{k}\in\{0,1\}\quad \forall i,j,k. \tag{5}$$

Every supplier belongs to only one cluster.

$$\sum_{k=1}^{K}b_{i,j}^{k}=1\quad \forall i,j. \tag{6}$$

Model 2:

Following the Model 1 process, membership clusters are determined for all suppliers. The optimal supplier combination can be determined for a specific cluster with respect to customer demands, using Model 2.

The objective is to maximize (total quality – total cost – total time) with the given weight of each factor.

$$\text{Maximize } w_1TQ-w_2TT-w_3TC. \tag{7}$$

Total cost is order cost + inventory cost + assembly cost.

$$TC=\sum_{i=1}^{I}\sum_{j=1}^{J}\left[f(OC_{i,j})\times O_{i,j}\right]+\sum_{i=1}^{I}HC_i+\sum_{h=1}^{H-1}\sum_{{}^{h}m=1}^{{}^{h}M}AC^{h,{}^{h}m}. \tag{8}$$

Total quality is sum of all of the qualities of all parts of the product.

$$TQ=\prod_{i=1}^{I}\left[\sum_{j=1}^{J}\left(UQ_{i,j}\times O_{i,j}\right)\right]. \tag{9}$$

Total time is the total of all module times for all hierarchies.

$$TT = \sum_{h=1}^{H} \sum_{^h m=1}^{^h M} MPT^{h,^h m}. \tag{10}$$

The product actual demand is customer-demand–current-inventory.

$$AD_i = D_i - I_i \quad \forall i. \tag{11}$$

Order cost is the product of the minimum quantity of each level and its corresponding unit price discount. If the actual demand is within these levels, then this level of order cost is the actual demand × this level of unit price discount, so calculate the next quantity level, minimal quantity × this level of unit price discount, until the quantity level ends. Take the minimum of all levels of order cost as the order cost for this supplier.

$$f(OC_{i,j}) = \min \left\{ \begin{array}{l} AD_i \times PD_{i,j}^s | ND_{i,j}^s \le AD_i < ND_{i,j}^{s+1} \\ ND_{i,j}^{s+1} \times PD_{i,j}^{s+1} \\ ND_{i,j}^{s+2} \times PD_{i,j}^{s+2} \\ \vdots \\ ND_{i,j}^{s} \times PD_{i,j}^{s} \end{array} \right\} \quad \forall i, j. \tag{12}$$

Order quantity is the quantity ordered from a supplier, according to order cost. If order cost is the actual demand ×, this level of unit price discount, then order quantity will be the actual demand. If order cost is the minimum of the quantity level ×, this level of unit price discount, then the order quantity is the minimum of this quantity level.

$$OQ_{i,j} = \left\{ \begin{array}{l} AD_i \text{ if } f(OC_{i,j}) = AD_i \times PD_{i,j}^s \\ ND_{i,j}^{s+1} \text{ if } f(OC_{i,j}) = ND_{i,j}^{s+1} \times PD_{i,j}^{s+1} \\ ND_{i,j}^{s+2} \text{ if } f(OC_{i,j}) = ND_{i,j}^{s+2} \times PD_{i,j}^{s+2} \\ \vdots \\ ND_{i,j}^{s} \text{ if } f(OC_{i,j}) = ND_{i,j}^{s} \times PD_{i,j}^{s} \end{array} \right\} \quad \forall i, j. \tag{13}$$

In the quantity discount model, quantity beyond the actual demand will be ordered, therefore inventory cost arising from excessive inventory is considered.

$$HC_i = \sum_{j=1}^{J} \left[(OQ_{i,j} - AD_i) \times O_{i,j} \right] \times hc_i. \quad \forall i. \tag{14}$$

The production time function is (manufacturing time + shipping time).

$$PT_{i,j} = UT_{i,j} \times \frac{OD_{i,j}}{UQ_{i,j}} + ST_{i,j}. \quad \forall i, j. \tag{15}$$

The module time of the lowest hierarchy in BOM is the maximum of production time of this module's part.

$$MPT^{h,^h m} = \max \left\{ \left[\sum_{j=1}^{J} (PT_{i,j} \times O_{i,j}) \times C_i^{h,^h m} \right] \middle| \, 1 \le m \le M \right\}, \quad \text{for } h = H. \tag{16}$$

The module time of each assembly hierarchy in BOM is (assembly time of this module + the maximum time of the module sub-hierarchy).

$$MPT^{h,^h m} = \max \left[(MPT^{h+1,^h m} + AT^{h,^h m}) \middle| \, 1 \le m \le M \right], \quad \text{for } h = 1, 2, \ldots, H-1. \tag{17}$$

$O_{i,j} = 1$ indicates that a supplier is chosen. $O_{i,j} = 0$ indicates that a supplier is not chosen.

$$O_{i,j} \in \{0, 1\} \quad \forall i, j. \tag{18}$$

For each type of part, only one supplier is chosen to supply the specific part for assembling the product.

$$\sum_{j=1}^{J} O_{i,j} = 1 \quad \forall i. \tag{19}$$

$C_i^{h,^h m} = 1$ indicates that module $^h m$ contains part i. $C_i^{h,^h m} = 0$ indicates that module $^h m$ does not contain part i.

$$C_i^{h,^h m} \in \{0, 1\} \quad \forall i, h, ^h m. \tag{20}$$

4. Solving method development

This section proposes a two-phase method to solve the two optimization mathematical models mentioned above. In Phase 1, the TKSA is used to search the global solution set for Model 1. In Phase 2, the ATSA is utilized to solve Model 2, using the result for the optimal supplier combination. The details of the solution representation, initial solutions, parameters and procedures of the proposed TKSA and ATSA are described in the following subsections.

4.1. Solution representation, initial solutions and parameters

In Phase 1, a set of positions is represented by a string of numbers, consisting of the three-dimensional positions of three clusters. A solution is represented as $S_{cd} \in (S_{11}, S_{12}, S_{13}, S_{21}, S_{22}, S_{23}, S_{31}, S_{32}, S_{33})$, where S is the centroid position, c is the cluster index and d is the dimension of each cluster. In Phase 2, a set of quantities of each part is represented by a string of numbers. A solution is represented as $Q_{ij} \in (Q_{11}, Q_{12}, \ldots, Q_{I(J-1)}, Q_{IJ})$, where Q is the quantity, i is the part index and j is the supplier index. To obtain various solutions, the cluster centroid positions and supplier combinations of initial solutions are randomly generated, in the TKSA and ATSA. The random mechanism can generate the initial solutions from a large area of the solution space.

The proposed TKSA and ATSA are based on SA algorithms. Four parameters are used in the TKSA and ATSA; namely IT, the initial temperature, IT_{end}, the final temperature, $IN_{\max}$, the maximum number of iterations and CR, the cooling rate.

4.2. TKSA and ATSA procedures

The TKSA procedures can be algorithmically stated as follows.

Step 1: Set $IT, IT_{end}, IN_{\max}$ and CR and let $T = IT$, $IN = 0$;
Step 2: Create the orthogonal array for parameter combinations;
Step 3: For $PM = 1$ to PM_{num}//PM is the trial index in the orthogonal array; PM_{num} is the total number of trials in the orthogonal array//
{
Step 3.1: Randomly generate an initial solution S;
Step 3.2: For $IN = 0$ to $IN_{\max}$ {
Step 3.2.1: Generate a neighbor solution S' of S, using an exchange operation; //Exchange operation: Randomly select two solutions from the feasible solutions and select and exchange n numbers from the first number in both of the selected solutions. The solution with the best objective function value is denoted as S'.//
Step 3.2.2: $\Delta f = f(S') - f(S)$, $f(S')$ and $f(S)$ are the objective function values of S and S_0;
IF $\Delta f \leq 0$ THEN let $p = 1$;
ELSE $p = \exp(-\Delta f/T)$;
Step 3.2.3: Generate $rn \sim U(0, 1)$;
IF $rn \leq p$ THEN $S = S'$;
}
Step 3.3: $IT = \alpha IT$;
IF $IT > IT_{end}$ {
$IN = 0$;
Go to Step 3.2.1;
}
Step 3.4: $\eta_{PM} = -10\log(\frac{1}{n}\sum_{i=1}^{n} f(S)^2)$; //$\underline{n}$ is the repeated number//
}
Step 4: Compare all η_{PM} ($PM = 1, 2, \ldots, PM_{num}$). If the PMth trial has the largest η_{PM}, the parameters of this trial are the best levels of factors.

The ATSA procedures can be algorithmically stated as follows.

Step 1: Calculate the pair-wise comparison matrix A for the three factors – quality, time, and cost – in the objective function of Model 2;

$$A = \left[a_{ij}\right] = \begin{bmatrix} 1 & a_{12} & a_{13} \\ a_{21} & 1 & a_{23} \\ a_{31} & a_{32} & 1 \end{bmatrix}, \quad i, j = 1, 2, \ldots, 3,$$

where $a_{ij} = 1/a_{ji}$. The assessment coefficients (a_{ij}) are determined from surveys of the major decision makers, using the nine levels of importance ([35]).
Step 2: Calculate the eigenvector and consistency ratio (CR) for the matrix A;
IF $CR < 0.1$ THEN the judgment is acceptable;
ELSE re-evaluate the pair-wise comparison;
$Aw = \lambda_{\max} w$, where $\lambda_{\max}$ is the largest eigenvalue of matrix A and w is its eigenvector.
$CI = \frac{\lambda_{\max}-n}{n-1}$, $CR = \frac{CI}{RCI}$, where RCI is a random consistency index ([35]).
Step 3: Introduce the resulting relative importance weights (eigenvectors) into the objective function of Model 2;
Step 4: Go to Step 1 of the TKSA procedures.

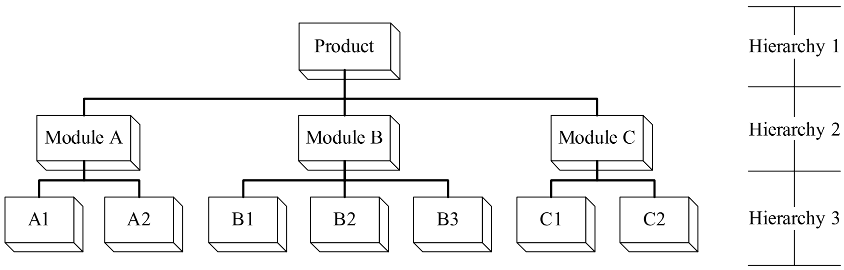

Fig. 1. Product BOM.

Table 1
Parameters of each method in Phase 1 by Taguchi method.

Factor \ method	TKSA			TKGA			TKPSO			Optimal
Initial temperature	100	200	300							100
Markov chain length	30	60	90							90
Cooling rate	0.9	0.95	0.99							0.99
Final temperature	1	5	10							1
Population				100	200	300				200
Generation				100	200	300				300
Crossover rate				0.7	0.8	0.9				0.7
Mutation rate				0.1	0.2	0.3				0.1
Particles							100	200	300	300
Generations							100	200	300	200
V_{max}							2	4	6	2

5. Illustrative example and analysis of results

This study uses the example of a desktop computer mainframe. The product BOM is shown in Fig. 1. Each of the 7 parts in the BOM has 10 suppliers. The system manufacturer must choose one of the 10 suppliers of each part, as a cooperating partner.

A T-transfer technique is usually employed to transfer the original value to the standard T component and to further operate on various types of values. Therefore, this study performs a T component operation on total cost, total quality and total time, before the data is processed, using the proposed model and method. The formula of the T-transfer for the original value X is $Xt = (X - X')/(Sx/10)$, where X' is the mean of X; Sx is the standard deviation of X.

5.1. Experimental design for Phase 1

In Phase 1, a typical genetic algorithm (GA) and particle swarm optimization algorithm (PSO) separately integrate the Taguchi Method and k-means. These are called TKGA and TKPSO and are used for comparison with the proposed TKSA. The Taguchi Method is used to find the optimal parameters for each algorithm. The TKSA control factors are initial temperature, maximum number of iterations, cooling rate and final temperature. The TKGA control factors are population, generation, crossover rate and mutation rate. The TKPSO control factors are particle number, generation number, learning rate and V_{max}. The orthogonal tables are used to determine the optimal parameters for the three methods as Table 1.

To compare the efficiency and quality of algorithms, the algorithms are repeated 30 times, using the respective optimal parameters for TKSA, TKGA and TKPSO and the convergence value and CPU operating time are recorded. To compare the algorithms, this study uses an ANOVA test to determine whether convergence values and CPU times of all of the algorithms displays significant variation. Peumans et al. [36] mentioned that Scheffe's multiple comparison could determine the relationship between populations of samples. Therefore, if an ANOVA test shows significant variation, then Scheffe's multiple comparison test can be used to determine the relationship and to identify the most efficient algorithm. Table 2 shows an ANOVA test of the convergence value for each algorithm; the P-value is 0.112, which is greater than the confidence level α (The mean difference is significant at the $\alpha = 0.05$ level). Therefore it can be inferred that the convergence of these three algorithms displays no significant variation.

Table 2 shows that CPU times exhibit significant variation, so Scheffe's multiple comparison test is used to determine the difference between algorithms. The result is TKSA $<$ TKPSO $<$ TKGA, as shown in Table 3. TKSA is the fastest method for solving this model, therefore TKSA is the optimal operation process at this phase.

5.2. Experimental design for Phase 2

In Phase 2, the typical genetic algorithm (GA) and particle swarm optimization algorithm (PSO) separately integrate the AHP and Taguchi Method, called ATGA and ATPSO. These are used for comparison with the proposed ATSA. AHP is

Table 2
ANOVA for convergence value and CPU time, in Phase 1.

Hypothesis : $H_0 : \mu_{TKSA} = \mu_{TKGA} = \mu_{TKPSO}$ $H_1 : Otherwise$	Convergence value	CPU time
F-value	2.24	5785.33
P-value	0.112	0.000*
Result	Non-reject H_0	Reject H_0

Table 3
Scheffe's multiple comparison test for CPU time in Phase 1.

Method (A)	Method (B)	Mean difference (A–B)	P-value	Result
TKSA	TKGA	−101.844	0.000*	TKSA < TKGA
TKSA	TKPSO	−18.9581	0.000*	TKSA < TKPSO
TKGA	TKPSO	82.8863	0.000*	TKGA > TKPSO

Table 4
An example of the weights of factors in AHP.

	Cost	Quality	Time
Cost	1	3	4
Quality	1/3	1	2
Time	1/4	1/2	1

Table 5
Steps of discount for supplier A1S1.

Material	Supplier	Lower bound	Upper bound	Discount
A1	A1S1	0	99	0.98
		100	199	0.89
		200	299	0.83
		300		0.80

Table 6
Parameters for each method in phase 2 by Taguchi method.

Factor \ method	ATSA			ATGA			ATPSO			Optimal
Initial temperature	100	200	300							100
Markov chain length	30	60	90							90
Cooling rate	0.9	0.95	0.99							0.99
Final temperature	1	5	10							1
Population				100	200	300				200
Generation				100	200	300				200
Crossover rate				0.7	0.8	0.9				0.8
Mutation rate				0.1	0.2	0.3				0.3
Particles							100	200	300	300
Generations							100	200	300	300
$V_{\max}$							2	4	6	2

incorporated to provide weighting for objective factors, so that the optimal solution better mirrors the actual result. An example of an AHP pair-wise matrix operation on factors is shown in Table 4. To facilitate subsequent comparative analysis, this study assumes the weight of each objective factor to be equal.

In the case of the supplier evaluation model with quantity discount, suppliers have different discounts for different order quantities. For example, the supplier of part A1, A1S1, has a quantity discount level as shown in Table 5.

If it is supposed that the supplier order quantity is 100 units, the Taguchi method can be used to create experimental designs for ATSA, ATGA and ATPSO, to find the optimal parameters for each algorithm. Table 6 shows the optimal parameters for the three methods used in Phase 2.

Table 7 shows the ANOVA test of convergence values and CPU times for all algorithms. For the convergence value, the P-value is 0.692, which is greater than the confidence level α, so it can be inferred that the convergence values of these three algorithms exhibit no significant variation.

For the CPU time, the P-value is 0.000, which is less than the confidence level α, so the CPU times for these three algorithms exhibit significant variation. Therefore, Scheffe's multiple comparison test is used to determine the relationships between the algorithms.

Table 7
ANOVA for convergence value and CPU time, in phase 2.

Hypothesis : $H_0 : \mu_{ATSA} = \mu_{ATGA} = \mu_{ATPSO}$; $H_1 : Otherwise$	Convergence value	CPU time
F-value	0.37	13341.68
P-value	0.692	0.000*
Result	Non-reject H_0	Reject H_0

Table 8
Scheffe's multiple comparison test for CPU time in Phase 2.

Method (A)	Method (B)	Mean difference (A–B)	P-value	Result
ATSA	ATGA	−131.087	0.000*	ATSA < ATGA
ATSA	ATPSO	−12.5205	0.000*	ATSA < ATPSO
ATGA	ATPSO	118.566	0.000*	ATGA > ATPSO

Table 9
Average fo each factor, in different clusters.

Factor	Character	Cluster 1	Cluster 2	Cluster 3
Cost	Smaller-the-better	**0.2640**	0.8557	0.5012
Quality	Larger-the-better	0.4343	**0.8391**	0.4292
Time	Smaller-the-better	0.7858	0.6266	**0.1229**

Table 10
ANOVA for factors in different clusters.

Hypothesis : $H_0 : \mu_{cluster1} = \mu_{cluster2} = \mu_{cluster3}$; $H_1 : Otherwise$	Cost	Quality	Time
F-value	24.93	12.8	81.06
P-value	0.000*	0.000*	0.000*
Result	Reject H_0	Reject H_0	Reject H_0

Table 11
Scheffe's multiple comparison test factor in different clusters.

Cluster (A)	Cluster (B)	Mean difference (A–B)	P-value	Result
2	3	0.3545	0.000*	Cluster 2 > Cluster 3
2	1	0.5917	0.000*	Cluster 2 > Cluster 1
3	1	0.2372	0.006*	Cluster 3 > Cluster 1

Table 12
Scheffe's multiple comparison test for quality factor in different clusters.

Cluster (A)	Cluster (B)	Mean difference (A–B)	P-value	Result
2	3	0.4099	0.000*	Cluster 2 > Cluster 3
2	1	0.4048	0.000*	Cluster 2 > Cluster 1
3	1	−0.0051	0.954	Cluster 3 = Cluster 1

Table 8 shows the results of Scheffe's multiple comparison test. It can be seen that ATSA < ATPSO < ATGA, so SA is the optimal operation process in this phase.

5.3. Customized optimal supplier combination

Using the result of Section 5.1, the average of each factor for each cluster is obtained via the TKSA in the Phase 1 supplier cluster and shown in Table 9. Each factor is tested by ANOVA to identify any significant variation between clusters, and Scheffe's multiple comparison test is used to verify the relationship between clusters and to identify the optimal supplier cluster, for the factor and name. Tables 10–13 are ANOVA and Scheffe's multiple comparison tests of cost, quality and time factors.

Table 13
Scheffe's multiple comparison test for time factor in different clusters.

Cluster (*A*)	Cluster (*B*)	Mean difference (*A*–*B*)	*P*-value	Result
2	3	0.5037	0.000*	Cluster 2 > Cluster 3
2	1	−0.1592	0.027*	Cluster 2 < Cluster 1
3	1	−0.6629	0.000*	Cluster 3 < Cluster 1

Table 14
Comparisons between the results of phase 1 + phase 2 and the results of phase 2.

		Cost consideration cluster Cost	Quality consideration cluster Quality	Time consideration cluster Time
Phase 1 + phase 2	TKSA + ATSA	9.595	27.048	6.967
	TKSA + ATGA	9.595	27.048	6.967
	TKSA + ATPSO	9.595	27.048	6.967
	TKGA + ATSA	11.426	26.306	8.313
	TKGA + ATGA	11.426	26.306	8.313
	TKGA + ATPSO	11.426	26.306	8.313
	TKPSO + ATSA	10.951	25.982	8.794
	TKPSO + ATGA	10.951	25.982	8.794
	TKPSO + ATPSO	10.951	25.982	8.794
		Non-cluster		
	Factor	Cost	Quality	Time
Phase 2	ATSA	11.079	26.478	10.447
	ATGA	11.079	26.478	10.447
	ATPSO	11.079	26.478	10.447

Cluster 1: According to Tables 9–11, the cost factor belongs to the smaller-the-better type and cluster 1 is obviously lower than other clusters. Thus, cluster 1 is named the "cost consideration cluster".

Cluster 2: According to Tables 9, 10 and 12, the quality factor belongs to the larger-the-better type and cluster 2 is obviously higher than other clusters. Thus, cluster 2 is named the "quality consideration cluster".

Cluster 3: According to Tables 9, 10 and 13, the time factor belongs to the smaller-the-better type and cluster 3 is obviously lower than other clusters. Thus, cluster 3 is named the "time consideration cluster".

To validate the influence of the clustering process on supplier evaluation, the proposed two-phase method compares with a selection method that evaluates the suppliers in the Phase 2 supplier evaluation process without the Phase 1 clustering process, as shown in Table 14.

According to Table 14, after the Phase 1 clustering process, a cost consideration cluster of suppliers is obtained. The cost obtained is 9.595, which is better than the cost of the supplier without the Phase 1 clustering process, which is 11.079. The quality value of the quality consideration cluster of suppliers is 27.048, which is better than the quality value of the supplier without the Phase 1 clustering process, which is 26.478. The time value of the time consideration cluster supplier is 6.967, which is better than the time value of the supplier without the Phase 1 clustering process, which is 10.447. Therefore it is proven that the two-phase supplier evaluation model proposed in this study efficiently provides the customer with a customized choice of supplier, according to the customer demands for a product type. Moreover, as discussed in Section 5.1, TKSA has a better ability to reach a solution in Phase 1 than other algorithms. As mentioned in Section 5.2, ATSA has a better ability to reach a solution in Phase 2 than the other algorithms. Therefore, TKSA + ATSA is the optimal two-phase operation process.

6. Conclusions

This study presents a systematic methodology for the clustering and selection of suppliers. The methodology consists of two optimization mathematical models, which help decision makers to select the quality suppliers from the potential suppliers pool, and a two-phase method to solve the mathematical models effectively. The main results and contributions of this study are as follows. (1) The development of two optimization mathematical models for clustering and selection of suppliers: Model 1 is based on the customer demands to cluster suppliers with TWCV. Using the results from Model 1, Model 2 is primarily to evaluate the candidate suppliers with consideration to quantity discount and customer demands in the specific supplier cluster. (2) The development of the two-phase method for solving the mathematical models: the first phase uses the TKSA method, which consists of the Taguchi method, *k*-means and a simulated annealing algorithm to solve Model 1 for the clustering of potential suppliers. The second phase uses the ATSA method, which consists of an analytic hierarchy process, the Taguchi method, and a simulated annealing algorithm to solve Model 2 and identify the combinations of quality suppliers. (3) A case study of notebooks in supplier clustering and selection, to compare the quality of the solution provided by different heuristic methods. With regard to the performance of the solutions, the results show that TKSA is better than TKGA and TKPSO in Phase 1, that ATSA is better than ATGA and ATPSO in Phase 2. In addition, the supplier selection result using Phase 1 and Phase 2 is better than that without Phase 1.

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