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A two-phase algorithm for product part change utilizing AHP and PSO

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ABSTRACT

This study presents a two-phase algorithm approach to deal with the issue of product part change, and the issue of supplier selection derived from the former. In the first step, Analytical Hierarchy Process (AHP) was used on expert interview records to select the module in a product that needs to be changed with top priority. In the second step, after changing the module, the supplier selection process, including building a mathematical programming model, was initiated to select the best suppliers using Particle Swarm Optimization (PSO) algorithm. We tried to use this method to maximize the value of product updating so as to extend the product life cycle, under the conditions of limited resource, and keeping the scope of change to a minimum. Finally, we selected a switchboard manufacturer as a case study to test the proposed algorithm.

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1. Introduction

At a time when the average product life cycle of a product is getting increasingly short, the significance of product part change is being recognized in stages. To maintain continuous improvement over the product line, including modifications of product weaknesses, introduction of new technologies, improvements over manufacturing processes, this optimization approach not only extends the product life cycles, but also can satisfy the needs of customers and market demand. In other words, in order to remain its product competitiveness, enterprises need a systematic approach to understand and manage the issue of product part change. Following the product part change, the supplier selection issue is another hot topic. In post-change stage, the selection of appropriate suppliers allows products of an enterprise to maintain and enhance its competitiveness in the market.

Previous studies treated related issues in a different way. Once a product was considered for internal part change, it had to go through the supplier selection process for all parts, whether the parts were changed or not. However, in actual practice, when a change of product components is considered, it is not necessary to change or redesign all components because that would set off the problem of re-selection of all suppliers. Taking a notebook computer product as an example, when a model change is needed, it may be because of improved technologies relating to core components (CPU, hard disk, memory body, etc.), leading to change of certain parts necessary in the product, while the rest of the internal parts still follow the original specifications and are obtained from the original suppliers. Therefore, this study determines to look into the supplier selection issue derived from the product part change. Researchers believe that when dealing with the issue of product part change, two questions must be considered. One of them is to identify which components need to be changed with top priority, and the other one is to find appropriate suppliers following the product part change. In other words, when faced with a need to change the product, but only limited resources available, the only way out is to change product parts. Our tasks are to find out which one part (or which group of parts) needs to be changed with top priority, or, from an alternative viewpoint, which one part (or which group of parts) will create the most additional value after the product part change. Furthermore, we need to find the most suitable suppliers for such product part change. By settling these issues over the product part change, it could help an enterprise save on unnecessary costs and increase the success rate of new product marketing.

To solve these two problems effectively, in this study, we have introduced a two-phase algorithm model to deal with the issue of product part change, and the issue of supplier selection derived from the former. Our problem-solving approach is based on AHP and PSO. Firstly, AHP analysis over expert interview records is conducted to find out which module in a selected product has to be changed with top priority. Secondly, the results of our analysis are optimized with PSO to find the most suitable supplier in line with such change. To verify the problem-solving method proposed in this study, a switchboard manufacturer is chosen for our experiment. The company's existing product line is analyzed to pick out product parts that need to be changed. By the introduction of the two-phase algorithm model, we hope to create additional values for their product after such change of product parts. Then, we try

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to find the best supplier following the change of product parts, in order to make the whole assessment model more systematic.

This study is organized in the following manner: the literature review is presented in Section 2 for understanding the issues related to product part change. Our two-phase algorithm model is introduced in Section 3. An actual case of manufactured product and related experimental results are provided in Section 4. Finally, some of the conclusions of the study are described in Section 5.

2. Literature review

In view of demands for continuous improvement, and needs for customer-oriented manufacturing environment, changes of product specs throughout the life cycle of a product are becoming quite commonplace. This kind of change is inevitable and also necessary in order to extend the product life. Many discussions by scholars and engineers have focused on the product configuration changes, dealing with the issues of management of product part change, engineering changes and design changes. In general the content of engineering change can be divided into two sub-categories, namely, design change and engineering change. The scope of engineering change involves small numbers of relevant units that belong to the same product, such as process change or change of product materials in the manufacturing process, but the changes mainly stem from the need for product quality upgrade. However, the design change relates to the architecture of a product. The content of such product change includes partial re-designing of a product or replacing of certain components for a product.

Barzizza (2001) believes that changes in market competition and consumption patterns often set a trend of increasingly short product life cycle, giving rise to frequent change of product configuration and change of product components. As Li, Chen, Huang, and Zhong (2006) mentioned, product configuration is more complicated than other issues during the manufacturing process, thus it needs a systematic and effective decision-making system to solve the problems in a rapid manner. Rouibah and Caskey (2003) points out that by effective handling of product part change during its product life cycle could allow an enterprise to lower its production costs, shorten development time, and improve its product quality so as to enhance its competitive edge on the market. Jonghoon and Lee (2002) refer to the fact that the model design of a product often has to go through frequent modifications in the production process. Once parts change is made, it could affect subsequent manufacturing processes, as well as related production costs and time. Wright (1997) indicates that the product configuration is a special design activity. The designers have to select components with given component properties, as well as the assembly of components in accordance with the customers' needs.

Because the effect of product part change and the scope of change are very extensive, an efficient method or system is needed to solve these issues. Wang and Che (2007a),Wang and Che (2007b) proposes a method to process product part change of TFT-LCD, using the fuzzy theory, T-score technology, and genetic algorithms, so as to select suitable suppliers for each component after the design change. Zhang, Wang, Wan, and Zhong (2005) propose the application of knowledge management and configuration-oriented modeling to integrate the product information and to manage complex product-related matters. Wang and Liu (2005) classify the restrictions for re-assembly of component into two types: (i) restrictions on pure re-assembly, and (ii) restrictions on complex re-assembly. A heuristic algorithm is used to develop the best combination policy for re-assembly of components. Wang et al. (2008) utilizes value engineering, fuzzy theory, and genetic algorithms to tackle the issue of supplier selection following the product part change.

From the above-mentioned literature, in view of increasingly short product life cycle, we can see that product part change is inevitable. For example, the product life cycle of today's notebook computers and mobile phones may be only about six months. The following task of supplier selection is also a hot issue. Therefore, the question on how to establish a systematic way to deal with the whole change process in an efficient and prompt manner has become a common topic for many research works. However, when dealing with the issue of supplier selection that follows a product part change, most of the previous studies had assumed that all components of the products need to be changed, but this study rejects the previous assumption. The previous studies failed to meet the actual demand in the real world, thus we propose a two-phase algorithm model to deal with product part change and its related selection of component suppliers. The problem-solving method is based on AHP and PSO.

3. Proposed two-phase algorithm

The study can be separated into two parts. The first part is to use AHP to confirm that some components in a product need to be changed, in order to meet the minimum customer requirements for a product. In other words, the product needs to be able to maintain its basic operations and functions. Therefore, expert interviews are used to analyze the product and to find out which module has caused most frequent failures, and also to confirm which module change could create the greatest benefits under limited resources available. The second part follows the product part change, which is to set up the parameters for developing a supplier selection model, and to develop an optimization algorithm based on PSO, hoping to utilize the outstanding performance of PSO to help identify the best supplier package and the allocation amount in quick and accurate manner. This information will be given to policy makers for their reference use in decision making. The structure of this study is shown in Fig. 1.

3.1. Analytic hierarchy process

AHP is a multi-attribute decision-making model (MADM) (Srdjevic, 2005) proposed by Saaty (1980). Since this method has the advantages of structural integrity, simple theory, and easy operation, it is often used in situations with uncertainty and problems involving multiple assessment criteria (Scholl, Manthey, Helm, & Steiner, 2005). for policy makers, the hierarchical structure can put the problem that needs to be solved into proper perspective, but when it is faced with "selection of appropriate policy," the assessment of various alternatives shall be based on certain benchmarks in order to determine the priorities and advantages of alternatives, and then to pick out the most suitable policy. AHP provides a framework for analysis by cutting complex and non-structural circumstances into "hierarchical" moments. Each moment is given subjective value for its importance, and these values are then added to determine the extent of advantage that can be derived from these moments, and it will also be used as moment weights when analyzing the problem.

Saaty (1990) mentioned that AHP is a powerful auxiliary tool for generating set of alternatives, choosing best policy alternatives, and determining requirements for dealing with 12 types of problems. Önüt and Soner (2008) used AHP to generate relative weight, and in the selection of factory site. Lee, Chen, and Chang (2006) used AHP to assess the performance in order to make the performance evaluation of IT manufacturing sector more convincing and standardized. Feng, Chen, and Jiang (2005) used AHP for selection of supplier groups. Chiang (2005) believed that AHP is a dynamic problem-solving method. It can be effectively used to

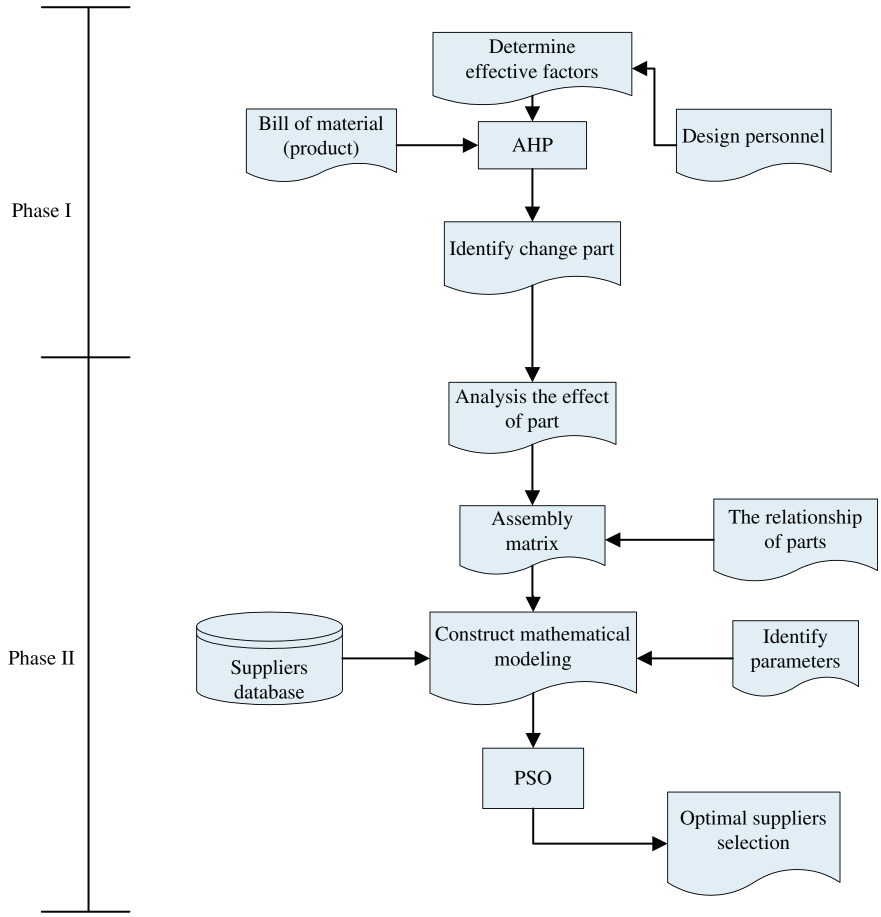

Fig. 1. Product part change process.

solve the problem of supplier changes and its eventual selection of suppliers.

3.2. Particle swarm optimization

PSO was proposed by Kennedy and Eberhart (1995). The fundamental concept stem from the behavior of predatory birds, and it is gradually developed into an intelligence-based optimization algorithm for assessment of biological systems. This is an evolutionary search method.

The main characteristics of PSO algorithm lie in minimal parameter adjustments, easy implementation, and simple instructions. Therefore, it is extensively used by many scholars and has wide applications. Present applications are found in the neural network, engineering optimization and fuzzy system control areas, all yielding very good results (Cura, 2009; Hota, 2009; Lee, Chen, & Wu, 2009; Lin, Chang, & Hsieh, 2008; Yeh, 2009).

From the above-mentioned papers, we can see the analyzing ability of PSO to solve a wide range of applications. No matter where Particle Swarm Optimization (PSO) algorithm is used, its parameter setting, problem solving speed, capacity, and search range have demonstrated better-than-average capabilities. Therefore, this study hopes to make use of PSO advantages to obtain approximate optimal solution in a reasonable time frame, and also be able to meet planned budgets.

However, PSO is not flawless, a number of improved and newer versions of PSO have been introduced by scholars. They hoped that the improved algorithms could produce better results and higher efficiency in problem solving, such as Inertia Weight Particle Swarm Optimization by Shi and Eberhart (1999), Constriction Factor Particle Swarm Optimization by Clerc and Kennedy (2000), Landscape Adaptive Particle Swarm Optimization by Yisu, Knowles, Hongmei, Yizeng, and Kell (2008), and so on. The main difference between the old and newer versions is the significant improvements on the updating capabilities, in which Yisu's method (2008) demonstrated better efficiency in problem-solving than the other two. For that reason, this study has adopted this method to derive the updating formula Eqs. (1)–(3) presented below.

$$A_d = \frac{\max_{i=1}^{n}(x_{id}) - \min_{i=1}^{n}(x_{id})}{abs(\max_{i=1}^{n}(x_{id})) + abs(\min_{i=1}^{n}(x_{id}))} \quad \text{if } r \geq 0.1 \tag{1}$$

$$A_d = \begin{cases} A_{\max}, & \text{if } A_d < A_{\min} \\ A_{\min}, & \text{if } A_d > A_{\max} \\ A_d & \text{otherwise} \end{cases} \quad \text{if } r \geq 0.1 \tag{2}$$

$$v_{id}^{j+1} = \begin{cases} A_d \times \left(v_{id}^{j} + \phi_1 \times rand() \times \left(p_{id} - x_{id}^{j}\right) + \phi_2 \times rand() \times \left(g_{id} - x_{id}^{j}\right)\right) \\ \text{if } r \geq 0.1 \\ v_{id}^{j} + \phi_1 \times rand() \times \left(p_{id} + x_{id}^{j}\right) + \phi_2 \times rand() \times \left(g_{id} + x_{id}^{j}\right) \\ \text{if } r < 0.1 \end{cases} \tag{3}$$

A_d is the distribution vector of particles in d dimension, while r is a random number. The updating is implemented with two different speeds controlled by a random number. Through these experiments the author is convinced that this model can effectively help PSO algorithm not to converge prematurely until the best local condition is attained, so that the accuracy of this algorithm can be improved.

4. Experimental research

In many manufacturing industries, the power systems have to rely on switchboards to control the power distribution, hence its stability and reliability are very important to the factory operators. In the event of any short circuit, it will lead to failures of the production lines leaving behind half-finished products, so the losses would be incalculable. A Taiwan manufacturer of switchboard is chosen for our study. The switchboard company specifically installs switchboards for the packaging lines of the traditional industries. A switchboard can be broken down into five modules: filtering system, quantitative system, control system, packaging system, and power supply control. To simplify the awesome task of preparation of a material list, we have decided to use code names instead of conventional descriptors for components, as shown in Fig. 2. In the diagram, M1stands for filtering system, M2 for main control system, M3 for quantitative system, M4 for packaging system, and finally M5 for power control. Each module is further made up by several smaller parts. Through the use of this optimization algorithm, the number of assessment policies could be reduced so as to reduce the workload of experts who are often overwhelmed by massive data. The study assumes that the modules of the product as the basic unit of each assessment policy, rather than the bottom level components.

4.1. Determine effective factors

In this study, professional staff of the switchboard manufacturer were given expert interviews, the experts found that maintenance time, maintenance costs, ease of maintenance, and reliability showed significant impact on the production of switchboards among all factors, therefore this study have chosen these four dimensions as AHP selection criteria.

4.2. Using AHP to determine the worth change module

This study chose B as the set of selection criteria, in which B1 represents maintenance time; B2 as maintenance cost; B3 as maintenance difficulty; and B4 as reliability. These four criteria can be collectively expressed as set B = (B1, B2, B3, B4). The assessment policy set M has five modules (M1, M2, M3, M4, and M5) as members. The second part of this study is to solve the supplier selection problem basing on AHP steps given below:

Step 1. Construct a hierarchy structure, in which the top level represents the goal after the problem is solved, which is to decide which component in the product needs to be changed with top priority; the middle-level is set to be the selection criteria; The bottom level presents the policies to be selected. The relationships between different levels of AHP are shown in Fig. 3.

Step 2. Establish matrices for paired comparison between criteria, and across different policies for a given criterion; finally, the decision-making team is to reach a final consensus after group discussions as to the application of standard

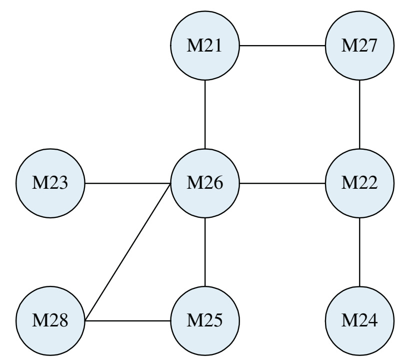

Fig. 3. The relation of parts.

Table 1
Nine-point intensity of importance scale and its description.

Intensity of importance	Definition
1	Equal important
3	Moderate important
5	Strong important
7	Demonstrated important
9	Extreme important
2, 4, 6, 8	Intermediate values

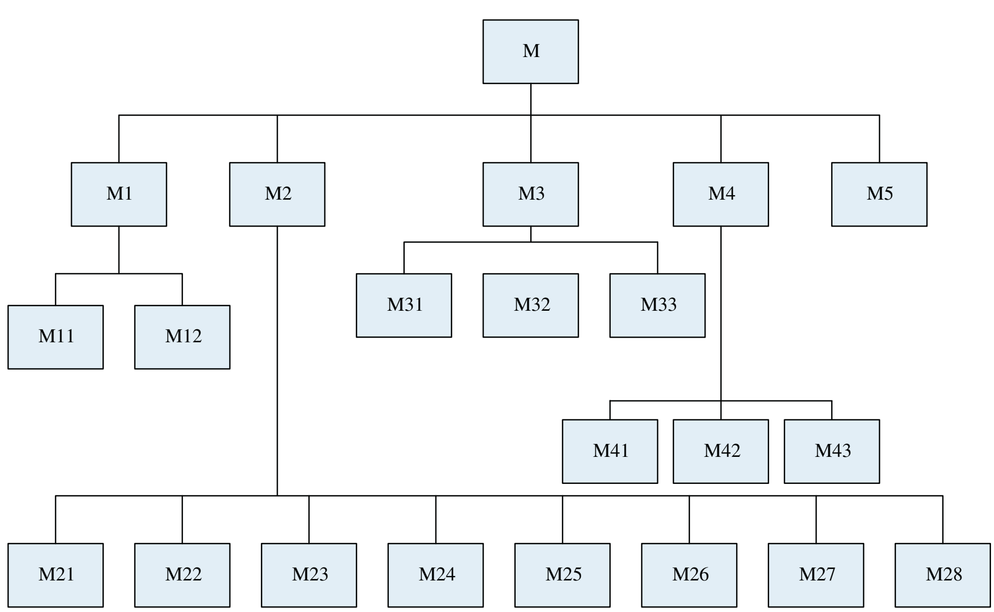

Fig. 2. BOM of switchboard.

values in matching pair comparisons. The values are to be assigned according to the AHP scale proposed by Saaty (1990), as shown in Table 1.

Paired matrix comparisons are to be described below:

B matrix represents relative relationship between selection criteria; RT matrix represents the relative relationship between assessment policies under the factor of repair time; RC matrix represents the relative relationship between assessment policies under the maintenance costs factor; RH matrix represents the relative relationship between assessment policies under the consideration of difficulty levels of maintenance; RE matrix represents the relative relationship between assessment policies under the consideration of reliability.

$$B = \begin{bmatrix} 1 & 1 & 1/5 & 1/3 \\ 1 & 1 & 1/3 & 1 \\ 5 & 3 & 1 & 5 \\ 3 & 1 & 1/5 & 1 \end{bmatrix}, RT = \begin{bmatrix} 1 & 3 & 5 & 5 & 7 \\ 1/3 & 1 & 3 & 5 & 5 \\ 1/5 & 1/3 & 1 & 3 & 5 \\ 1/5 & 1/5 & 1/3 & 1 & 3 \\ 1/7 & 1/5 & 1/5 & 1/3 & 1 \end{bmatrix},$$

$$RC = \begin{bmatrix} 1 & 1/5 & 3 & 5 & 5 \\ 5 & 1 & 3 & 7 & 7 \\ 1/3 & 1/3 & 1 & 3 & 5 \\ 1/5 & 1/7 & 1/3 & 1 & 1 \\ 1/5 & 1/7 & 1/5 & 1 & 1 \end{bmatrix}$$

$$RH = \begin{bmatrix} 1 & 1 & 5 & 3 & 3 \\ 1 & 1 & 3 & 3 & 5 \\ 1/5 & 1/3 & 1 & 1/3 & 1 \\ 1/3 & 1/3 & 3 & 1 & 1 \\ 1/3 & 1/5 & 1 & 1 & 1 \end{bmatrix}, RE = \begin{bmatrix} 1 & 1 & 1 & 3 & 1/3 \\ 1 & 1 & 1 & 5 & 1/3 \\ 1 & 1 & 1 & 3 & 1 \\ 1/3 & 1/5 & 1/3 & 1 & 1/5 \\ 3 & 3 & 1 & 5 & 1 \end{bmatrix}$$

Step 3. Calculate the relative weights between eigenvalues and relative values between policies to establish the eigenvectors of moment matrix basing on moments of paired comparison matrices, and then to obtain the relative weights between criteria through Eqs. (4), (5).

$$PW_{ij} = \frac{a_{ij}}{\sum_{i=1}^{I} a_{ij}}, \quad i,j = 1,2,3,\ldots,n \tag{4}$$

$$IW_i = \frac{\sum_{j=1}^{J} PW_{ij}}{J}, \quad i = 1,2,3,\ldots,n \tag{5}$$

Where PW_{ij} is the weight for individual criteria (= eigenvector/total eigenvalue of individual policy), and IW_i is the relative weight

(= weight/number of individual criteria)

After matrix computation, relative weights of all matrices are obtained as follows:

$$B^w = [0.107\ 0.148\ 0.561\ 0.179]^T$$

$$RT^w = [0.474\ 0.258\ 0.145\ 0.079\ 0.042]^T$$

$$RC^w = [0.243\ 0.494\ 0.161\ 0.052\ 0.049]^T$$

$$RH^w = [0.343\ 0.348\ 0.078\ 0.134\ 0.094]^T$$

$$RE^w = [0.168\ 0.192\ 0.215\ 0.058\ 0.366]^T$$

RT^w, RC^w, RH^w , and RE^w are synthesized to become a new matrix, and then further multiplied by B^w to produce total scores for each assessment policy. M1 = 0.31, M2 = 0.332, M3 = 0.122,M4 = 0.102,M5 = 0.131.

Step 3. Consistency rate calculation. Basing on the results obtained from Step 2 it still needs a consistency ratio (CR) to determine whether the relationships between any paired matrices are consistent. Consistency rate is derived from consistency index (CI) and random index (RI), such as Eqs. (6), (7) and Table 2. When $CR \leqslant 0.1$, the consistency rate of paired matrices achieve the satisfactory level.

$$CI = \frac{\lambda_{max} - n}{n - 1} \tag{6}$$

$$CR = \frac{CI}{RI} \tag{7}$$

Where λ_{max} is the largest eigenvalue; n is a number of assessment criteria; RI is a random index of assessment matrix, as shown in Table 2.

After matrix computation, the results are shown in Table 3. It can be seen that CR values of paired comparison matrices constructed in this study are all less than 0.1, representing that all passed the consistency test.

Step 3. Through the above AHP process, because M2 = 0.332 it means that the importance of M2 is greater than the other policies. Therefore, it can be concluded that M2 policy needs to be changed with top priority, thus the product part change is confirmed.

4.3. Confirming scope of change and relative relationship of parts

As indicated by Ho (1994) the design changes will affect components of all levels in the materials list, since every product has different property and different design structure. Therefore, the materials list and relevant design staff are used as basis for analysis of components that may be affected. According to components liaison graph proposed by De Fazio and Whitney (1987), nodes are used to denote components, and arcs to represent the relationships between components, thus a component assembly matrix is constructed by linking all its component relationships. Using the component liaison graph to derive the component assembly matrix can facilitate the computation of optimal supplier selection. From the standpoint of this study, picking M2 as product part change policy is because M2 is derived from M21–M38, thus these matrices are indirectly affected by the product part change. Fig. 4 shows its connectivity.

4.4. Mathematic modeling

Liao and Rittscher (2007) suggest that price, quality, and delivery date are the assessment factors commonly used for selecting suppliers. For that reason, this study uses purchase costs, transportation costs, assembly costs, and quality parameters to construct an integer planning model. For the objective function part, since the scales of parameters are all different (including costs and quality). To facilitate the mathematical operation, we have used T-score technology in this study (Che & Wang, 2008; Wang & Che, 2007a, 2007b) to achieve data standardization, so that the criteria of different units and scales can be mixed in the computation. In this study, the symbols are explained as follows:

Table 2
RI index.

Rank	3	4	5	6	7	8	9	10	11	12	13	14	15
RI	0.58	0.89	1.12	1.25	1.35	1.41	1.45	1.49	1.51	1.53	1.56	1.57	1.58

Table 3
The result of consistency test.

	$\lambda_{\max}$	CI	CR	<0.1
B	4.195	0.064	0.072	*
RT	5.352	0.088	0.079	*
RC	5.350	0.087	0.078	*
RH	5.166	0.041	0.037	*
RE	5.194	0.048	0.043	*

4.4.1. Indices

i,s: Index of component, i=1,. . ., I, s=1,. . .,S
j,r: Index of types, j=1,. . ., J, r=1,. . .,R
k,t: Index of suppliers, k=1,. . ., K, t=1,. . .,T

4.4.2. Parameters

P_{ijk}: The manufacturing cost of component i, type j with supplier k.
O_{ijk}: The shipping cost of component i, type j with supplier k.
A^{srt}_{ijk}: The assembly cost of component i, type j with supplier k and component s, type r with supplier t.
Q_{ijk}: The quality level of component i, type j with supplier k.
P_{MAX}: Threshold of purchase cost
O_{MAX}: Threshold of shipping cost
A_{MAX}: Threshold of assembly cost
Q_{MIN}: Threshold of quality level
R^s_i: The assembly relationship of component i and component s.
$R^s_i = 1$: component i and component s have assembly relation, otherwise $R^s_i = 0$

4.4.3. Decision variables

X_{ijk}, X_{srt}: X_{ijk} and X_{srt} ∈(0,1), X_{ijk} = 1:Choices component i,s with type j,r with supplier k,t,otherwise X_{ijk} = 0.

The integer planning model is constructed as described below:

$$\min \sum_i^I \sum_j^J \sum_k^K {}^T P_{ijk} X_{ijk} + \sum_i^I \sum_j^J \sum_k^K {}^T O_{ijk} X_{ijk} + \sum_i^I \sum_j^J \sum_k^K \sum_s^S \sum_r^R \sum_t^T {}^T A^{srt}_{ijk} R^s_i X_{ijk} X_{srt} - \sum_i^I \sum_j^J \sum_k^K {}^T Q_{ijk} X_{ijk} \tag{8}$$

s.t.

$$O_{ijk} \le O_{MAX}, \quad \text{for all } i,j,k \tag{9}$$

$$P_{ijk} \le P_{MAX}, \quad \text{for all } i,j,k \tag{10}$$

$$A^{srt}_{ijk} \le A_{MAX}, \quad \text{for all } i,j,k,s,r,t \tag{11}$$

$$Q_{ijk} \ge Q_{MIN}, \quad \text{for all } i,j,k \tag{12}$$

$$\sum_j^J \sum_k^K X_{ijk} = 1, \quad \text{for all } j,k \tag{13}$$

$$R^s_i \in \{0,1\}, \quad \text{for all } i,s \tag{14}$$

$$X_{ijk} \text{ and } X_{srt} \in \{0,1\}, \quad \text{for all } i,j,k,s,r,t \tag{15}$$

$$T = \frac{X - \overline{X}}{\sigma_X/10} + 50 \tag{16}$$

Eq. (8) is to find the minimized objective function, where the formula for T-score conversion is given Eq. (16). Eq. (9) denotes transportation costs that shall be less than the threshold value. Eq. (10) represents purchasing costs that shall be less than the threshold value. Eq. (11) means that assembly costs shall be less than the threshold value. Eq. (12) means that quality must be greater than the threshold level. Eq. (13) means that one supplier shall be selected for each component. Eq. (14) denotes the existence of relationship between two components when the components are assembled. Eq. (15) represents the limits for decision-making variables.

4.5. Solving problem using LAPSO

In the present study, PSO is used to minimize the objective function values. All experiments and programs in this study have been executed with computer having Intel Core 2 Dual CPU 2.8 GHz and 2 GB RAM and the software is programming language Visual Basic 2005. Access 2003 is used for the database system. We have the set number of repetitions to be needed for each experiment, for which the benchmark is 30.

4.5.1. Parameters setting

In general, PSO parameters can be divided into the following types. For this study we either accept the recommendations from previous literature or use own design to give needed parameters for the experiments.

(i) Number of particles: Generally a size of 30 is used for each group. studies of Carlisle and Dozier (2001), Zhang and Yu (2005) also indicated a size of 30 particles is appropriate to produce high performance algorithm with maximized results, without having to incur too much extra costs, thus this set of parameters is used for our study.
(ii) Cognitive parameter φ_1 and social parameter φ_2: He, Wang, and Liu (2007), Kathiravan and Ganguli (2007) suggested that setting the value to 2 can help maintain the convergence rate in the algorithm.
(iii) Maximum speed ($V_{\max}$): Eberhart and Shi (2000), Shi and Eberhart (1998), Zahiri and Seyedin (2007) suggested that setting $V_{\max}$ to maximum value of $X_{\max}$ for any one-dimensional search shall be the same as setting the upper limit for decision-making variables.
(iv) Weighting: no need to set own weights in LAPSO, as these values are calculated according to Eqs. (1), (2).
(v) Largest algebraic number: setting of the maximum algebraic number depends on the types of problems that are encountered. In our study, we conducted experiments for algebraic numbers, and the results are given in Table 4.

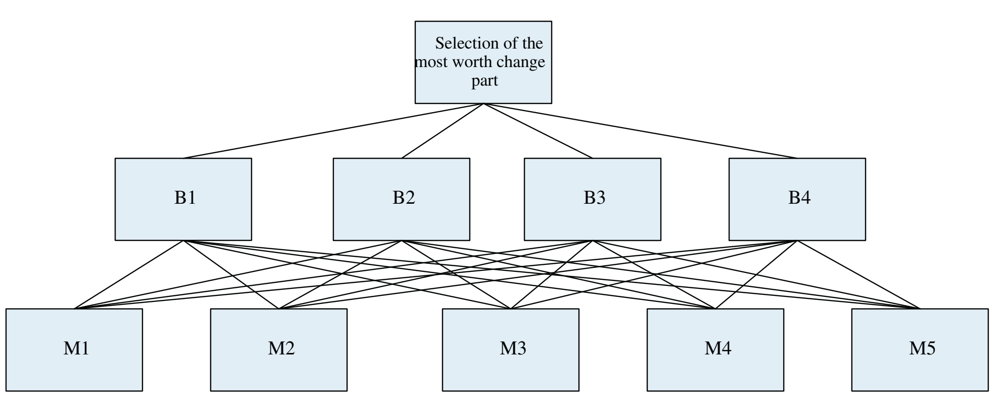

Fig. 4. The decision hierarchy of switchboard.

Table 4
Generation number experiment.

Generation number	100	500	1000	1500
Average run time	0.562	2.016	5.512	10.812
Average optimum	862.809	853.522	851.177	850.848

Table 5
Setting parameters of LAPSO.

Generation number	Generations	φ_1 and φ_2	V_{max}
30	500	2	1

From Table 5, we can see that when the algebraic number approaches the largest number 500, good results are produced, for further increase of the algebraic number, such as to 1000, the problem-solving performance merely increased by 2.7%, but the processing time increased by 173.4%. For the overall efficiency, we have chosen 500 as the largest algebraic number for parameter in consideration of fast speed in decision-making process.

Experimental parameters used in this study are either taken from recommendations of the above literature or from our own design for needed parameters of the experiment, as presented in Table 5.

4.5.2. LAPSO algorithm solving procedure

Step 1: Generate N number of particles as initial cluster, and each particle randomly generates its velocities and positions, complying with Eqs. (9)–(15) requirements.

Step 2: Calculate the value of fitness function for each particle, basing on the objective function Eq. (8).

Step 3: Set the fitness function of each particle to be own Pbest when the particle is ancestor; Compare the fitness function value of each particle with own Pbest when the particle is descendent, and if the fitness value is better than Pbest, replace it as the new Pbest;

Step 4: Compare Pbest and Gbest; if Pbest is better than Gbest, then Gbest is replaced by Pbest;

Step 5: Update the particle travel speed according to the updating rule Eqs. (1)–(3).

Step 6: Substitute with updated particle travel speed value into Eq. (17) to get updated location, where i denotes ith particle; j denotes jth algebraic number.

$$x_{id}^{j+1} = x_{id}^{j} + v_{id}^{j+1} \tag{17}$$

Step 7: Repeat steps 1–6 until the preset number of evolution is satisfied.

4.5.3. Experimental result

Through LAPSO optimization, a set of optimal supplier package is produced, while the convergence diagram is shown in Fig. 5, and the best combination of component suppliers is shown in Table 6.

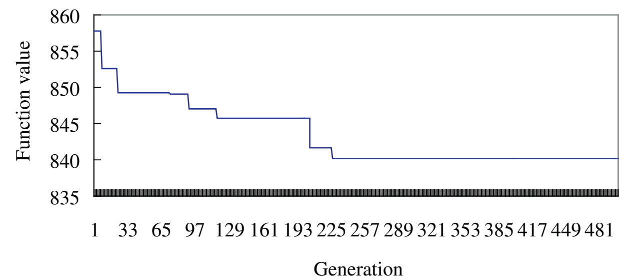

Fig. 5. Objective function convergence.

Taking component M21 as an example, Type 2 shall be selected; the best supplier is SA; and the best fitting function value is 840.2363, while the restored initial cost is 58,834.

5. Conclusions

This study aims to solve the problem over the handling of product part change, and the supplier selection problem derived from the product part change. In contrast to the previous studies, this study proposes a two-phase algorithm model to deal with the problems. The first phase is to use AHP for analyzing which component of a product needs to be changed with top priority, in which each module is viewed as a separate policy to avoid the difficulty of excessive data. This algorithm approach allows us to focus on the part of a product that needs to be improved with top priority. It could avoid huge costs from re-evaluation of all component suppliers. Under the circumstances of limited resources, this algorithm allows us to make more efficient use of resources. The second phase is to settle the supplier selection issue following the product part change, including building of mathematical model to analyze various costs, and developing of PSO algorithm-based method, through which we hope to provide a set of decision-making model, including suggestions for product part change and supplier package, following the occurrence of product part change. In this study, a switchboard manufacturer is chosen for our experiment. Through the use of two-phase algorithm model, reasonable results and the best supplier package available can indeed be generated for fast decision making.

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Table 6
The result of case.

Part NO.			M21	M22	M23	M24	M25	M26	M27	M27	Manufacturing cost	Shipping cost	Quality level
Part type			Type2	Type2	Type1	Type1	Type3	Type1	Type1	Type2			
Suppliers			SA	CH	VO	TM	FG	GP	UO	TE			
M21	Type2	SA	–	–	–	–	–	3.37	1.51	–	1580	59.9	8
M22	Type2	CH	–	–	–	48.6	–	0.69	0.829	–	5300	87.1	9
M23	Type1	VO	–	–	–	–	–	0.77	–	–	750	4.7	9
M24	Type1	TM	–	–	–	–	–	–	–	–	20,500	357.1	7
M25	Type3	FG	–	–	–	–	–	1.03	–	6.98	13,200	222.5	9
M26	Type1	GP	–	–	–	–	–	–	–	27.8	64	1.7	8
M27	Type1	UO	–	–	–	–	–	–	–	–	1350	74.1	10
M27	Type2	TE	–	–	–	–	–	–	–	–	15,800	391.3	10

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