



A Simulated Annealing Algorithm for the Joint Optimization of Product Family Design and Supplier Selection in SCM

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Abstract- *Product family design involves design of various product variants under a product family which aims to satisfy the needs of various market segments. In the development of product families, it is quite common for companies to adopt sourcing strategy for reducing product cost and development time. One major issue of the sourcing is supplier selection. Previous studies have shown that companies commonly spent 60% of product cost on sourcing. Various studies have been conducted in the areas of product family design and supply chain issues separately. However, only few studies found so far have investigated the optimal product family design together with supplier selection consideration. In this paper, a simulated annealing method for integrating supplier selection with product family design is proposed. The results have shown that optimal product family design with a consideration of supplier selection can be determined, and the specifications of the product variants can be generated. On the other hand, suppliers of components and modules can be selected with the considerations of minimum sourcing cost. The method reported that the simulated annealing algorithm in solving this problem better with percentage 49-50 % than other algorithms used before.*

Keywords- *Supply chain, Product Family, Supplier selection.*

I. INTRODUCTION

Nowadays, the rapid pace of technological change, markets globalization, and growing demand for customizable or configurable products involves an increasing number of product variants and a growing complexity of products while controlling the product costs and the customer lead-time [1]. This task becomes more difficult when the supply chain layout has a significant influence on operating costs [1]. Product family is an enabling technology for mass customization that has many advantages such as increased flexibility, reduced development cost, and improved ability to upgrade products [1]. Numerous studies have contributed to the development of design approaches to product family design and platform-based product development [2]. Product family design needs to consider customer requirements of various market segments and competitive products. Once customer requirements are defined, it is common nowadays for companies to develop their new products with the involvement of suppliers [3]. This can help them to produce their new products with lower cost, better quality and in a shorter time.

Supplier selection is another critical process that affects cost, quality and performance of products; previous studies found that sourcing cost can take up more than 60% of product cost [1],[4]. Therefore, product cost could be reduced through the selection of the right suppliers and, furthermore, customer satisfaction and competitiveness of products would be enhanced [5]. Traditionally, supplier selection is conducted after a product design is completed as product components of a product family are usually defined first by product development teams and, then, the suppliers offering the lowest component prices are selected [6]. Component price is not only a decision-making factor for selecting suppliers. Companies should consider some other factors such as quality, reliability and performance [7]. Given the importance of developing methodologies for integrating the two decisions (joint optimization of product family design and supplier selection), this problem has started to gain attention in literature [14].

Gupta and Krishnan [8] proposed an integer-programming model to integrate component selection and supplier selection for a product family. Their work complemented Goldberg and Zhu's work [9] by considering one-way component substitutability. However, a product variant may have different utilities for heterogeneous consumers and the assumption of one-way component substitutability may not be true in product family design [10].

Balakrishnan and Chakravarty [10] formulated the integration of product variants selection and supplier selection as a profit-driven decision-making problem, established a mathematical model for finding an optimal set of product variants and suppliers from given reference sets. However, their model for product family design is based on a two-step approach [11]. As the problems involve a large number of components, reference-set enumeration in this approach can become formidable [12]. Luo et al. [1] proposed a one-step mixed-inter nonlinear programming optimization model that integrates supplier selection into product family design with the objective of maximizing the total profits. Deterministic choice rule was adopted in their optimization model to simulate consumer choice behavior. Since deterministic choice rule assumes that consumers only choose the products with the highest utility surplus, this rule is too rigid and restrictive; moreover, evidence exists that for many product categories, consumers may purchase several similar products at the same time [13].

Xing Gang Luo [14] research is an extension of Luo et al.'s [1] research. As discussed above, although deterministic choice rule is mathematically simple and easy to be embedded into an optimization model, it overestimates the market share of a product if its utility surplus is the highest and underestimates the market share if its utility surplus is not the highest. As a result, the calculated market income is not accurate and thus the obtained solution may deviate from the optimal one. To overcome this limitation, his research adopts multinomial logit (MNL) consumer choice rule to formulate consume behavior during the modeling. As a kind of widely used discrete choice model, the MNL choice rule is regarded to be more realistic in simulating consumer purchase behavior and more flexible in approximating deterministic choice rule [15]. Based on the MNL consumer choice rule, a one-step product family optimization model integrating supplier selection decision is established.

All the above studies used in solving their models methods as: Taboo search (TS), or Genetic algorithm (GA). This research proposes SA method to solve the problem proposed in [14]. SA is a powerful stochastic technique for solving (hard) combinatorial optimization problems. It differs from other techniques based on iterative improvements of the cost function in that it allows occasional worsening in the cost function thus avoiding to get stuck into local minima [23].

The rest of the paper is organized as follows: the literature review of the joint for the two decisions; the 'Joint optimization model' section describes the optimization problem and the formulation process of the mathematical model; the 'Design of solving algorithms' section introduces the design of Simulated annealing (SA) for solving the optimization model; in the 'Case study and analysis' section, a case study is provided to illustrate the experiments and the analysis of parameter sensitivity; and the 'Conclusion' section concludes the article.

II. PROBLEM DESCRIPTION AND MODEL FORMULATION

A. Partitioning market segments

Market can be partitioned into a number of segments, such that each segment comprises consumers that have very similar purchasing preferences [24]. To accomplish the segmentation, a market survey first needs to be conducted to understand consumer preferences regarding different product configurations. Based on the survey data, market segments can be identified using proper clustering techniques [25]. The size of each market segment can also be estimated. After the market segmentation, consumers within a segment are considered homogeneous [26, 27].

B. Analysis of customer preference

Conjoint analysis (CA) is a common method used to model customer preference in consumer marketing research [28]. CA applies statistical techniques to approximate the additive conjoint preference structure. A typical procedure in many CA applications is to assess the rank order or overall value for alternatives with different profiles of attribute levels, and then use the holistic judgments information to estimate the discrete levels of single-attribute value functions by regressions, hierarchical Bayes models or linear programming [29]. Following the part-worth utility model widely used in CA, the utility of a product variant can be considered a linear function of the part-worth utilities of configured components for the RCSs:

$$U_{ij} = \sum_{k=1}^K \sum_{l=1}^{L_k} w_{jk} u_{ikl} y_{jkl} \quad (1)$$

where U_{ij} is the utility (measured in dollars) of the j th product variant for the consumers in the i th segment, w_{jk} the utility weights among the RCSs and u_{ikl} the part-worth utility of the l th component of the k th RCS to the i th segment. Numerous methods are available to estimate the regression part-worth utilities, such as full-profile CA, adaptive CA, hybrid CA, experimental choice analysis and choice-based CA [30].

C. Analysis of consumer purchase behavior

The purchase decision of consumer mainly depends on the utility surplus they perceive. By following the most commonly used MNL model [31], the choice probability can be formulated as follows

$$P_{ij} = \frac{e^{\mu(U_{ij} - p_j)}}{\sum_{j=1}^J x_j e^{\mu(U_{ij} - p_j)} + \sum_{j=1}^{N^e} e^{\mu^e_{ij}} + \sum_{j=1}^{N^c} e^{\mu^c_{ij}}} \quad (2)$$

If μ is very large, the model behaviors like deterministic choice rule; if μ is close to 0, the model approximates uniform distribution. The value of μ can be calibrated by the investigational data of practical market share [32]. Because company only earns profits from those consumers who are probable to buy a product variant, the total expected market income of the product family can be indicated as follows

$$R = \sum_{i=1}^I \sum_{j=1}^J (P_{ij} n_i) p_j x_j \quad (3)$$

D. Context

Suppose that a company would like to design a family of new products. In order to satisfy the diversified needs of customers, a set of internal interfaces are specifically designed for the product. For each interface of the set, a number of product components with similar functionalities but different levels of performance or features are completely replaceable. A product variant can be obtained by selecting one component from each interface. It is called a product configuration process. Following the notation of Gupta and Krishnan [8], we define the set of the replaceable components in an interface as replaceable components set (RCS). Suppose that there are K RCSs and L_k components for the k th RCS ($k=1, 2, \dots, K$). Unlike the assumption of Gupta and Krishnan [8] (i.e. components are ranked in order of the level of performance), the components for a RCS can be differentiated in many aspects (e.g. size, colour, style, shape) to meet various customer requirements. According to market survey and customer requirements analysis, we suppose that

the consumers of the product market are clustered into I segments, and each segment contains n_i ($i= 1, 2, \dots, I$) homogeneous consumers. A consumer's preference on a product variant can be represented by a perceived utility measured in dollars, indicating the dollar value the consumer would be willing to pay [26]. The purchase decision of a consumer towards a product variant can be determined by utility surplus, which is the difference between the perceived utility and the price of the product variant [30]. Therefore, price is a decision variable in profit-oriented optimization models [33]. A higher price leads to an increase of the marginal revenue, while the number of consumers who purchase the products decreases due to the decreased utility surplus. Suppose that manufacture of the product components is outsourced to suppliers. There are V qualified suppliers which are capable of providing product components. The v th supplier offers a bidding price, e_{klv} , of the l th component of the k th RCS ($k=1, 2, \dots, K; l=1, 2, \dots, L_k; v=1, 2, \dots, V$). In particular, if the v th supplier does not supply the l th component of the k th RCS, e_{klv} is set as a large positive number. To facilitate the modeling, the following decision variables are used:

p_j : The price of the j -th product variant $x_j = \begin{cases} 1, & \text{if the } j\text{th product variant is included in the product family} \\ 0, & \text{otherwise} \end{cases}$

$y_{jkl} = \begin{cases} 1, & \text{if the } l\text{th component of the } k\text{th replaceable component sets is assigned to the } j\text{th product variant} \\ 0, & \text{otherwise} \end{cases}$

$z_{klv} = \begin{cases} 1, & \text{if the } l\text{th component of the } k\text{th replaceable component sets is provided by the } v\text{th supplier} \\ 0, & \text{otherwise} \end{cases}$

$\varepsilon_v = \begin{cases} 1, & \text{if the } v\text{-th supplier is selected} \\ 0, & \text{otherwise} \end{cases}$

E. Optimization Model

The problem of joint optimization of product family design and supplier selection can be described as follows. A company plans to design a family of products to satisfy the diversified demands of customers. A product consists of a number of components that may be shared with other products in the family. Manufacture of the components is outsourced to qualified suppliers with different given bidding prices. The situation confronted by the company is to select the appropriate configuration and suppliers for the product family with the objective of maximizing the overall profit. This problem was mathematically formulated by Xing Gang Luo model [14] as follows:

To maximize the overall profit

$$\text{Max } \pi = \sum_{i=1}^I \sum_{j=1}^J (P_{ij} n_i) p_j x_j - \sum_{i=1}^I \sum_{j=1}^J \sum_{k=1}^K \sum_{l=1}^{L_k} (P_{ij} n_i) x_j c_{kl}^{\text{inr}(\text{var})} y_{ijkl} - \sum_{i=1}^I \sum_{j=1}^J \sum_{k=1}^K \sum_{l=1}^{L_k} \sum_{v=1}^V (P_{ij} n_i) x_j y_{ijkl} e_{vkl} z_{klv} - \sum_{v=1}^V g_v \varepsilon_v - c^{\text{inr}(\text{fix})}$$

(4)

Subject to

$$\sum_{l=1}^{L_k} y_{jkl} = 1 \quad j = 1, 2, 3, \dots, J, k = 1, 2, 3, \dots, K(5)$$

$$\sum_{v=1}^V z_{klv} = 1 \quad k = 1, 2, 3, \dots, K, l = 1, 2, 3, \dots, L_k(6)$$

$$\sum_{j=1}^J \sum_{k=1}^K \sum_{l=1}^{L_k} x_j y_{jkl} z_{klv} \leq N \varepsilon_v \quad v = 1, 2, 3, \dots, V(7)$$

$$x_j, y_{jkl}, z_{klv}, \varepsilon_v \in \{0, 1\} \text{ and } p_j \geq 0$$

The overall profit is the difference between the market revenue and the cost of the product family. The first term in equation (4) represents the total expected market income of the product family. Because company only earns profits from the consumers who are probable to buy a product variant, the purchase decision of consumer mainly depends on the utility surplus they perceive. By following the most commonly used MNL model, the choice probability can be formulated as presented in equation (2). If m is very large, the model behaviors like deterministic choice rule; if m is close to 0, the model approximates uniform distribution. The value of m can be calibrated by the investigational data of practical market share [15].

The other three terms in equation (4) represent different parts of cost. Cost is divided into two main parts; (1) the intra-company production cost - the cost incurred in the production processes of products inside the company; and (2) the outsourcing-related cost - the cost related to procure the components of product variants from suppliers. The intra-company production cost is, further, divided into fixed cost and variable cost. The fixed intra-company production cost includes the costs for project setup, infrastructure, and administration, among others. The variable cost includes the costs for producing a product in the company such as assembling, packaging, storage, and delivery. These costs were formulated with reference to the linear-additive cost models [16],[17].

The variable unit production costs are assumed to be estimable by human experts or regression methods based on historical production data if the company has an operating cost-accounting system [18]. Moreover, the outsourcing-related cost can also be divided into the variable outsourcing cost and the fixed outsourcing-related cost. Variable outsourcing cost is the cost paid by a company to its selected component suppliers. The fixed outsourcing-related cost is defined as the cost associated with adopting the suppliers, including the costs used for negotiating, communicating, contract signing, quality assurance, and so on.

The objective function is subject to three sets of constraints: (1) for each RCS of a product variant, only one product component can be selected; (2) each component of a product variant must have only one supplier; and (3) a supplier must be selected if the supplier provides at least one product component for the selected product variant and a supplier does not provide product component for the selected product variant if the supplier is not selected. These constraints are translated into equations 5, 6, and 7 respectively.

Finally, the model was formulated with a set of assumptions: (1) internal interfaces are already designed for the product family, and for each interface a number of product components with similar functionalities but different levels of performance or features are fully replaceable; (2) the market of the product can be clustered into several segment and the preferences of customers in each market segment are regarded as the same; (3) the product utility of a customer is a random variable and customer purchase probability toward a product follows MNL rule; (4) each product component is only outsourced to one and the only one supplier; and (5) bidding price discount on component quantity is not considered[14].

III. PROPOSED SOLUTION ALGORITHM

A. Simulated Annealing

Simulated Annealing (SA) is "a stochastic relaxation technique based on the analogy to the physical process of annealing a metal"[19]. As a solid is heated the particles take random configurations. Then, the temperature is slowly decreased to let them reach a state of minimal energy. In theory, with SA it is possible to reach the global optimum. SA is commonly said to be the oldest among the meta-heuristics and surely one of the first algorithms that had an explicit strategy to avoid local minima. The origins of the algorithm are in statistical mechanics - Metropolis algorithm [20] - and it was first presented as a search algorithm for CO problems in [18], [21].

The fundamental idea is to allow moves resulting in solutions of worse quality than the current solution (uphill moves) in order to escape from local minima. Simulated Annealing (SA) is a stochastic optimization technique. It constructs a sequence of solution configurations (a walk or path) through the set of permissible solutions called the state space. Based on the current solution and a certain acceptance criterion, a transition mechanism determines which solution to step up to next [22]. The optimal solution steps from the current configuration to another configuration from its neighborhood according to the Metropolis criterion.

The basic structure for SA implementation consists of the following basic elements: (1) a representation of possible solution configurations (search space); (2) a generation mechanism (is a means of selecting a new solution from the neighborhood of the current solution); (3) a means of evaluating the problem objective function (energy); and (4) a cooling (annealing) schedule. SA pseudo code is shown in fig.1.

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Simulated Annealing Procedure


S: = S0; {initial solution}
T: = T0; {initial temperature}
Repeat
Repeat
S' = perturb(S);
Δ= E(S') - E(S);
Θ= random [0, 1);
Prob = e-Δ/T;
If Δ < 0 or Prob ≥ Θ
Then S: = S';
Else retain S;
Until inner loop stopping criterion is met;
T= update (T);
Until outer loop stopping criterion is met;
End;

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T: the control parameter.
Update: Cooling schedule function.
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B. Implementation

1) *Solution Representation*: Given the nature of the problem at hand, mixed binary-integer encoding method is adopted. A solution is composed of J subsections and the j -th subsection contains the relevant information of the j -th product variant. A product variant consists of three sections: product choice section, product configuration section, and product price section. The product choice section in each subsection has one value, and the value of the cell represents that whether the j -th product variant is selected ($j = 1$: selected; $j = 0$: not selected). The product configuration section in a subsection contains K units and the k -th section contains the information related to the k -th RCS. In each unit, the first integer value l represents that the l -th component is selected for the current RCS, and the second integer value v

represents that the v -th supplier is selected for the l -th component in this unit. The price choice section in each subsection has one cell, and the integer value of the cell represents that the j -th discrete price is selected. In summary, a solution can be described by the following integer numbers [move to mathematical model]

$$\bar{x}_j (j = 1, 2, \dots, J); \bar{y}_{jk}, \bar{z}_{jk} \\ (j=1, 2, \dots, J; k=1, 2, \dots, K); \bar{p}_j (j = 1, 2, \dots, J)$$

where $\bar{x}_j, \bar{y}_{jk}, \bar{z}_{jk}, \bar{p}_j$ are integers, and $\bar{x}_j \in 0$ or $1, \bar{y}_{jk} \in [1, L_k], \bar{z}_{jk} \in [1, V], \bar{p}_j \in [1, M]$. There is no cell designed for ϵ_v since it can be calculated according to \bar{z}_{jk} .

Fig. 2 shows an example for solution representation. The example involves two product variants, six RCSs and two product prices. According to the coding of product choice section, the first product variant and the second product variant were chosen in the product family, respectively. According to the coding of product configuration, the first product variant has the following configuration information. The first RCS uses the fourth component sourced from the first supplier; the second RCS uses the second component sourced from the second supplier; and so on. According to the coding of product price section, the price of the 1st product variants is the 15th discrete price. The index numbers of a product variant, a component and a supplier, which are encoded as integers in the cells, are generated randomly with the integer ranges of $[1, J], [1, L_k]$ and $[1, V]$, respectively. Subsection 2 has a similar encoding mechanic

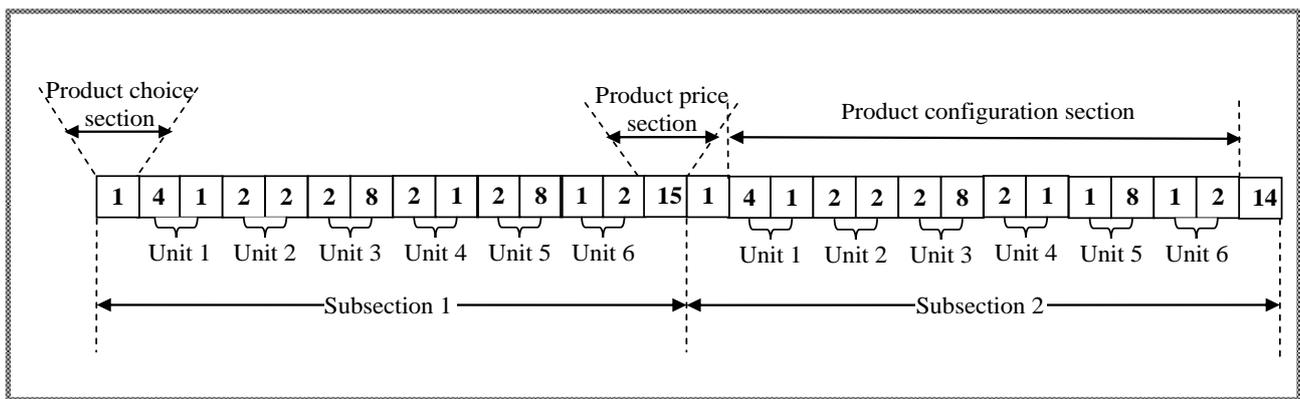


Figure 2 Example for Solution Representation

2) *Generation of the Initial Solution*: SA has proved to be a robust optimization algorithm that is independent of the initial solution configuration [20]. Hence in the present research, an initial solution configuration is generated by selecting randomly any cell and then check whether this solution is efficient or not. This tested process done through the java software for implementing this model. Another alternative that it can be considered is generating an initial solution using any heuristic techniques.

3) *Generation of a Feasible Neighbouring Solution Configuration*: In simulated annealing, a new solution configuration is generated by perturbing the current one. The use of any of method for perturbing mainly depends on the nature of the problem being tackled. The presented research applies a random change to any cell value with another value perturbation strategy. As shown in Fig. 3, this is done in the current solution, selecting any cell value and changes it randomly with another value for the same activity. Some thought need to be given to the generation of a feasible solution when constraints exist. In this case, the algorithm searches only the feasible space by being programmed to reject any proposed solution configuration that results in a constraint violation.

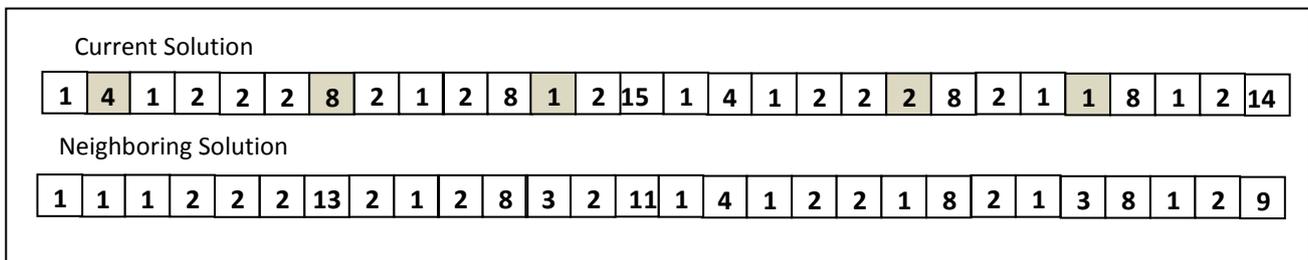


Figure 3 Generating a Neighbouring Solution

4) *Object Function Evaluation*: SA merely requires the value of the objective function for each solution configuration. The algorithm picks up the objective function value of the proposed solution, compare it with the one of the current optimal solution and proceeds to the next step.

5) *Cooling Schedule*: The presented research adopts a geometric cooling schedule, which is the most commonly used cooling schedule in the simulated annealing literature [34]. In this schedule, temperature updating follows Eq. (10) the initial and final temperature values, referred to as T_0 and T_{stop} respectively, and are specified by the user along with the cooling factor, cr

$$T_{K+1} = \alpha T_K, \quad K = 1, 2 \dots (8)$$

6) *Stopping Criterion:* To determine whether the system reaches a meta-stable state, two counters were introduced to keep track of the number of accepted and rejected solutions at each temperature. Iterations at each temperature halt when either counter reaches a pre-defined threshold. The user specified both thresholds. The optimization process, on the other hand, proceeds until it reaches the final temperature, T_{stop} even if no improvements are made during many temperature decrements.

IV. COMPUTATIONAL ANALYSIS

A. Case Description

The SA in the experiments is coded in JAVA and the related data are processed with Excel sheets. Since SA uses randomly generated seeds in computation, the results of an experiment are obtained by running the program n times and then averaging the results.

The case of printing calculator product provided by [14] was used for the experiments. The product has already been designed into a modular structure such that the design and manufacture of the product components are outsourced to third-party companies. The company plans to develop a family of multiple printing calculator products. The modular structure of product can be separated into six RCSs. For each RCS, a set of components with the same assembly interface is available for satisfying the various requirements of consumers. Customers are clustered into three market segments and the product demand of the three market segments are estimated at 210,000, 300,000, and 70,000, respectively. There are two competitive products and a company's existing product in the market and their utility surpluses are listed in Table 1. The part-worth utilities and variable unit production cost of components after CA are listed in Table 2. The bidding prices of product components from the qualified suppliers are shown in Table 3 and the cost of adopting a supplier is 15,000 US\$. By analyzing the highest utility and bidding cost, the range of possible product price can be confined as (25.5, 48.1), and the product price can be discredited as a set of integer prices ranged from 26 to 48.

TABLE 1 THE UTILITY SURPLUS (US\$) OF THE COMPETITIVE PRODUCTS

Data of the three segments	Segment 1	Segment 2	Segment 3
Estimated number of consumers	210,000	300,000	70,000
Utility surplus of competitive product 1	9.1	8.9	10.1
Utility surplus of competitive product 2	11.6	10.4	11.6
Utility surplus of competitive product 1	7.8	9.7	8.8

TABLE 2 PART-WORTH UTILITIES (US\$) AND VARIABLE UNIT PRODUCTION COST (US\$) OF COMPONENTS

RCS	Component	Part-worth utility in segment 1	Part-worth utility in segment 2	Part-worth utility in segment 3	Variable unit cost
RCS1	C11	6.1	4.7	4.5	0.3
	C12	6.3	4.9	4.5	0.3
	C13	6.5	5.3	5.3	0.5
	C14	6.5	6	4.2	0.5
RCS2	C21	16.5	16.9	16.2	0.2
	C22	16.6	18.2	16.2	0.3
	C23	16.6	16.8	16.6	0.3
	C24	16.6	16.8	18	0.4
RCS3	C31	2.6	4.3	3.2	0.2
	C32	2.7	4.5	3.6	0.2
	C33	2.6	4.1	4.3	0.3
RCS4	C41	0.6	0.6	0.4	0.1
	C42	0.6	0.8	0.4	0.1
	C43	0.8	0.8	0.8	0.3
RCS5	C51	12.2	11.7	8.8	0.2
	C52	12.3	12.1	10.2	0.3
	C53	12.4	11.8	10.7	0.3

RCS6	C61	8.5	6.5	6.5	0.1
	C62	8.6	6.5	6.5	0.1
	C63	8.6	6.5	6.6	0.1

RCS: replaceable component sets.

TABLE 3 BIDDING PRICES OF COMPONENTS FROM SUPPLIERS

Supplier	Components (price US\$)
S1	C11(3.2), C12(3.2), C13(3.2), C14(3.2), C31(1.7), C32(1.7), C33(1.7), C41(0.2), C42(0.3), C43(0.3)
S2	C21(6.5), C22(6.8), C23(7.1), C24(7.5), C61(4.6), C62(4.7), C63(4.7)
S3	C11(3.3), C12(3.3), C13(3.3), C14(3.3), C31(1.5), C32(1.6), C33(1.6), C51(6.5), C52(6.8), C53(6.8)
S4	C21(6.6), C22(6.9), C23(7.2), C24(7.5), C41(0.3), C42(0.3), C43(0.4), C61(4.8), C62(4.9), C63(4.9)
S5	C11(3.4), C12(3.4), C13(3.4), C14(3.4), C31(1.7), C32(1.8), C33(1.9), C51(6.6), C52(6.7), C53(6.8)
S6	C21(6.8), C22(6.9), C23(7.1), C24(7.3), C51(6.4), C52(6.5), C53(6.7)
S7	C21(7.3), C22(7.3), C23(7.5), C24(7.5), C31(1.7), C32(1.7), C33(1.8)
S8	C11(3.5), C12(3.5), C13(3.5), C14(3.5), C31(1.6), C32(1.6), C33(1.6), C51(5.9), C52(6.2), C53(6.5), C61(4.9), C62(4.9), C63(4.9)
S9	C41(0.4), C42(0.5), C43(0.6), C51(6.7), C52(6.7), C53(6.8)
S10	C11(3.4), C12(3.4), C13(3.4), C14(3.4), C31(1.8), C32(1.8), C33(1.9), C61(5.0), C62(5.1), C63(5.1)
S11	C21(6.7), C22(6.9), C23(6.9), C24(7.5), C41(0.5), C42(0.5), C43(0.5), C51(6.5), C52(6.6), C53(6.6)
S12	C11(3.5), C12(3.5), C13(3.5), C14(3.5), C21(6.5), C22(6.8), C23(7.3), C24(7.3), C31(1.8), C32(1.8), C33(1.8), C41(0.3), C42(0.3), C43(0.3), C51(6.7), C52(6.8), C53(6.9)
S13	C21(7.0), C22(7.1), C23(7.2), C24(7.3), C51(6.8), C52(6.8), C53(6.8), C61(4.9), C62(5.0), C63(5.0)

B. Algorithm Performance

The first step is to compare the performance of proposed algorithm with that published in [14] in which Genetic Algorithm (GA) was used. Table 4 shows the best configuration reached by both algorithms and the associated profit. As shown, the proposed algorithm has 88.6 % improvement over that of the GA. A number of experiments were taken to achieve the optimum and/or near optimum results. For achieving optimum/near optimum test cases we set the starting temperature and cooling rate to 10000 units and 0.00001 units respectively. We executed tested algorithm 15 times for every initial temperature where temperature reduced to 50 units. Acceptance or rejection of test depends on the SCT covering status are from the mainly parameter that control the system status. Figure 4[a, b] shows the SA experimented data graph for different values of the objective function with the parameters of the model; information about initial temperature, feasible temperature, and associate temperature can be explored clearly. In the simulation we found that, some cases, high temperature and steady profit function value causes acceptance probability very high and cause the number of test cases high. The cooling rate is a crucial part to find optimum solution in different input event sequence testing. For each event testing our expectation is to find a unique cooling schedule to get the optimum solution. In this simulation we found that most of the time the fast cooling schedule cannot cover all the t-way tuple. On the other hand, a very slow cooling schedule has near optimum solution and requires a lot of computation. This testing strategy can be expanded for higher strength t-way test generation. As we can see, SA leads to a higher values when the system got slow (decrease cooling rate value), and grow numbers of accept and reject at temperature 100, this initial temperature (100) be the best value after different runs (trail and errors) from experiments.

TABLE 4 COMPARISON BETWEEN SA OPTIMIZATION MODEL AND THE RESULT OF XING GANG LUO MODEL USING GA

	Proposed Algorithm Simulated Annealing	Xing Gang Luo – Genetic Algorithm
Configuration	1,2,5,4,2,1,7,1,1,2,11,1,4,48 1,4,1,1,6,1,8,1,9,1,11,1,13,44	1,4,1,2,2,2,8,2,1,2,8,1,2,15 1,4,1,2,2,2,8,2,1,1,8,1,2,14
Best Profit (US\$)	5,748,112	3,048,250

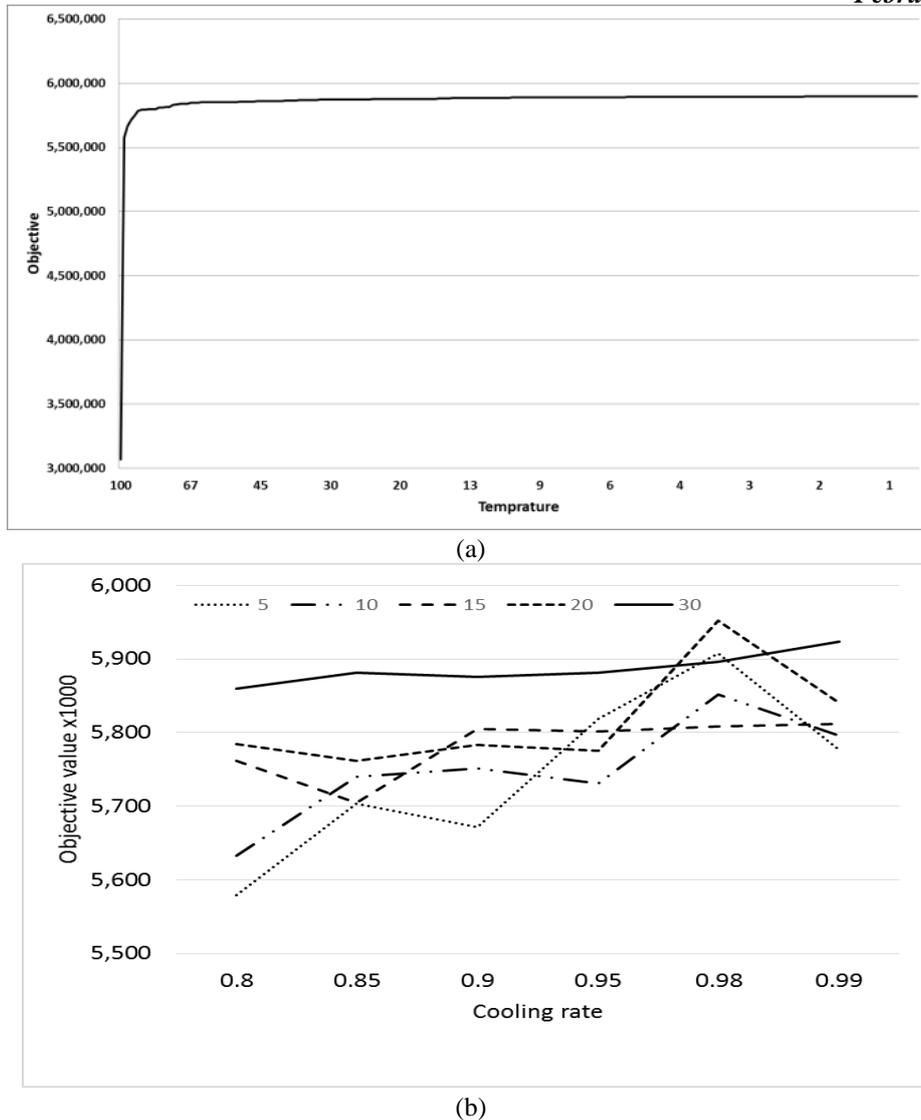


Figure 4 The relationship between objective function value and the problem parameters

V. DISCUSSIONS AND CONCLUSIONS

In this paper, the proposed SA algorithm for integrating product family with supplier's selection is described. The proposed method is able to make up the deficiencies of the previously related studies, which include the results have shown that optimal product family design with a consideration of supplier selection can be determined, and the specifications of the product variants can be generated. On the other hand, suppliers of components and modules can be selected with the considerations of minimum sourcing cost. Price and position of the product variants can also be estimated. Therefore, the proposed optimization model is more general and is more possible to be applied in complex practical scenarios. The SA is specially designed to solve the established combinatorial NP- hard optimization problems. Companies can consider various factors such as a trade-off among profit, revenue, and product cost. The solutions were set as randomly initialized therefore; the optimal solutions obtained are different for different generations. So it's necessary to run a JAVA program many times in order to average the searching results.

APPENDIX 1

NOTATION

C: cost of a product family

c_{inr}, c_{src} : intra-company production cost and outsourcing-related cost, respectively

$c_{inr}^{(fix)}, c_{inr}^{(var)}$: fixed cost and variable cost of the intra-company production cost, respectively

$c_{src}^{(fix)}, c_{src}^{(var)}$: fixed outsourcing-related cost and variable outsourcing cost, respectively

$c_j^{inr (var)}$: variable intra-company production cost of the j-th product variant

$c_{kl}^{inr (var)}$: variable unit production cost for the l-th component of the k-th replaceable component sets

e_{klv} : bidding price of the l-th component of the k-th RCS by the v-th supplier

g_v : cost related to adopting the v-th supplier

I : number of market segments

J : upper bound of the number of product variants

K :number of replaceable componentsets

L_k :the k -th replaceable component sets

N_c, N_e :number of products of competitivecompanies and the number of products that have been launched in themarket by this company, respectively

n_i :number of homogeneous consumersin each segment

P_{ij} :choice probability of the j -th productchosen in the i -th market segment

p_j :decision variable: the price of the j -thproduct variant

R :total market income of the productfamily

r_{ij}^e, r_{ij}^c :utility surplus of the existing and competitiveproduct variant, respectively

U_{ij} :utility (measured in dollars) of the j -thproduct variant for the consumers inthe i -th segment

V :number of qualified suppliers

x_j :binary decision variable such that $x_j=1$ if the j -th product variant isincluded in the product family, and $x_j=0$ otherwise

y_{jkl} :binary decision variable such that $y_{jkl}=1$ if the l -th component of the k -threplaceable component sets isassigned to the j -th product variant,and $y_{jkl}=0$ otherwise

z_{klv} :binary decision variable such that $z_{klv}=1$ if the l -th component of the k -threplaceable component sets is providedby the v -th supplier, and $z_{klv}=0$ otherwise

μ :scaling parameter in multinomial logit

π :total profit of the product family

ϵ_v :binary decision variable such that $\epsilon_v=1$ if the v -th supplier is selected,and $\epsilon_v=0$ otherwise

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