An Optimal Design Search with Conjoint Analysis Using Genetic Algorithm

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Abstract

It is important for the R&D division to develop a product, which satisfies both the designer and the consumer. An integrated design model based on conjoint analysis can find several feasible solutions to combinations of design parameters in product designing. In this study, a relationship matrix is used to keep the characteristics of designer and the attributes of consumer related with one another. Along with the increasing number of the characteristics and attributes, there are more solutions to combination sets of product design with conjoint analysis. It becomes increasingly difficult using obtained conjoint data to evaluate product design that involve many characteristics, attributes and levels based on a discipline of "satisfy the most under the least sacrifice". The applicability of conjoint analysis is improved by using a genetic algorithm (GA) to help search the possible combination sets between levels of characteristics and those of attributes. The experiment results show it is promising for us to use GA in searching the solutions to complex design problem.

Key Words: Conjoint Analysis, Integrated Design Model, Genetic Algorithm, Design Characteristics, Design Attributes

1. Introduction

Product can be defined by attributes and levels. In the past, a product design always focused on the optimization to either the attributes of consumer or the characteristics of designer. For various specialized products such as washes, shoes, luxury automobiles, high-end sailboats, and corporate aircraft, it made sense to design a product based on the combined inputs of the two groups. This study presents a method for creating an optimal product design based on distinct and parallel opinions from the consumer and the designer. Because how a consumer looks at the attributes of product is usually quite different from how a designer does at the characteristics of it [1]. Our integrated approach using conjoint analysis proceeds with the product design without ignoring the relationship between the attributes of consumer and the characteristics of designer. For example, a consumer may think about a dress in terms of attributes such as good looking and endurance, whereas a designer may think of these same concepts in terms of technical characteristics such as thickness (g/m^2), cover factor, …etc.. Therefore, a relationship between the set of consumer attributes and that of designer characteristics, much like the "house of quality" matrix [2], is needed when the attributes and characteristics are first defined. Once the attributes, characteristics, and the relationship between them are defined, conjoint analysis is used to collect data from both the two groups. A design system model of integrating both of the obtained conjoint data is developed to determine an optimal or near-optimal product design in this study.

Conjoint analysis was introduced to marketing research in the early 1970s [3]. Since that time, applications to industry and marketing problems have been extensive and varied world-widely. Conjoint analysis is a survey-based technique for measuring consumers' trade-offs among product and service attributes [4]. Conjoint

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analysis has been used to design a wide variety of product designing from food products to automobiles. A survey by Cattin et al. [5] showed a continued growth and acceptance of conjoint analysis applications in U.S. A study by Wittink et al. [6] showed this same trend in Europe. The first approach to product-design optimization using conjoint data was proposed by Zufryden [7]. He formulated the problem as a 0–1 integer-program that maximized the weighted share-of-choices for the new products. Each individual was assumed to deterministically choose the new product if she/he associated a higher utility with it than with a currently favored brand. Methods have been developed to take conjoint data to approach to optimal or near-optimal product designs. Kohli et al. [8] developed a dynamic-programming heuristic to find solutions to the problem of identifying a multi-attribute product profile associated with the highest share-of-choices in a competitive market. Conjoint analysis was used by Wind et al. [9] to design the Courtyard by Marriott hotel chain, and by Tscheulin and Helmig [10] to design hospital advertising. Balakrishnan and Jacob [11,12] used genetic algorithms, which are based on population genetics, with conjoint data to generate product designs that are close to optimal. Moreover, Srinivasan et al. [13] recommended integrating prototypes with conjoint analysis into the product design and development process, especially when considering nonquantitative attributes such as usability and aesthetics.

In summary, conjoint analysis is a widely accepted and well researched technique that has many applications to product design. Many methods exist to determine optimal or near-optimal product designs from conjoint data, but the methods use data from only one source: consumers. There is no attempt in previous research to analyze distinct conjoint data from multiple sources such as consumers and designers, both of which are concerned in this study.

Along with the increasing number of the characteristics and attributes, there are more solutions of combination sets to product design with conjoint analysis. It becomes more and more difficult to evaluate product design that involves many characteristics, attributes and levels based on the discipline of "satisfy the most under the least sacrifice" with present conjoint analysis techniques. This paper mainly focuses on using GA with an excellent heuristic searching done from a population of points to help find an optimal or near-optimal solution to product design. It is promising of using GA to search the solutions to complex clothing design problem and help search the possible combination sets between levels of characteristics and those of attributes that further ensures the applicability of conjoint analysis.

2. Conjoint Analysis

2.1 Assembly of Design Factors

The conventional procedures using conjoint analysis to evaluate the combinations of design factors before developing an innovative product are illustrated as follows.

(1) Tabling variables of questionnaire

The number of combination sets of design factors can be minimized with an orthogonal array while using conjoint analysis. For instance, during proceeding with a seasonal promotion project, there are 3 levels for each design factor: style (cutting edge, fashionable, and classic), feature (fit, tight, and loose), color (personally favorite, integrated, and voguish), and purchasing habit (department store, boutique, vending stall). Then, there are 81 ($= 3 \times 3 \times 3 \times 3$) sets of possible assembly for the 4 factors with 3 levels mentioned above. The number of combination sets can be reduced to 9 according to an orthogonal main-effect design [14, 15] shown as Table 1.

(2) Ranking and Scoring

The interviewer is asked to rank the various combinations of levels of factors on their relative importance. Table 1 shows results after interviewers proceed with the scoring from the ranking results of the combination sets from questionnaire composed of 9 sets mentioned above.

2.2 Conjoint Data Collection

(1) Full Profile

Most commonly used procedures [13] for conjoint data collection include tradeoff matrix, full profile, and adaptive procedure. Full profile is used in this paper due to its simplicity and easy applicability. It is not only hard but also time-consuming for interviewers to rank the 81 sets of factors combination mentioned above. Fortunately, it can be simplified using orthogonal array [16], which is a design for experimental planning to balance the contributions among factors under the minimal number of combination sets. Table 1 shows results composed

Table 1. Instance of questionnaire for an orthogonal array

No.	Style	Feature	Color	Purchasing habit	Interviewer's Evaluations	
					Ranking	Scoring
1	cutting edge	tight	personally favorite	department store	8	2
2	cutting edge	fit	integrated	boutique	5	5
3	cutting edge	loose	voguish	vending stall	4	6
4	fashionable	tight	integrated	vending stall	6	4
5	fashionable	fit	voguish	department store	9	1
6	fashionable	loose	personally favorite	boutique	2	8
7	classic	tight	voguish	boutique	3	7
8	classic	fit	personally favorite	vending stall	1	9
9	classic	loose	integrated	department store	7	3

of 9 combination sets, which is obtained from questionnaire of 81 combination sets processed with an orthogonal matrix for conjoint analysis.

(2) Utilities

Most commonly used methods to acquire utilities are LINMAP, MANOVA, and OLS. The ordinary least squares dummy variable regression (OLS)[4] is used in this paper. One of the levels for each factor (Characteristics or Attributes), regarded as dummy variables, is eliminated. Coefficients of the obtained regression equation denote the responded contributions for levels of each factor (Characteristics or Attributes) and called part worths or utilities. The overall summations of utilities for levels of each factor are 0. Table 2 shows the calculated results of utilities from Table 1 processed with OLS. Comparing the utilities among levels of each factor, customers' preference can be obtained as follows. Consumers are mostly in favor of "classic" for style, "loose" for feature, "personally favorite" and "voguish" for color, and "boutique" and "vending stall" for purchasing habit.

3. Integrated Design Model

Figure 1 illustrates the architecture of integrated product design model for creating an optimal product design based on distinct and parallel opinions from the consumer and the designer. Because how a consumer looks at the attributes of product is usually quite different from how a designer does at the characteristics of it. Our integrated approach using conjoint analysis proceeds with the product design under considering both the demands of consumer and the expertise of designer simultaneously.

3.1 Designer Characteristics and Utility Evaluation

A designer, who is trained with expertise, can exactly use characteristics when design. The most concerned ones [17] include texture, material, pattern, color, shape, overall setting, and marketing. The number of levels is set to 2 for each characteristics, i.e., texture (plain, rough), material (soft, hard), pattern (printing graph,

Table 2. Utilities of orthogonal array for questionnaire in Table 1

Attributes	Levels	Utilities
1. Style	1. cutting edge	-1
	2. fashionable	-1
	3. classic	2
2. Feature	1. fit	-0.67
	2. tight	0
	3. loose	0.67
3. Color	1. personally favorite	0.83
	2. integrated	-1.5
	3. voguish	0.67
4. Perchasing habit	1. department store	-3
	2. boutique	1.67
	3. vending stall	1.33

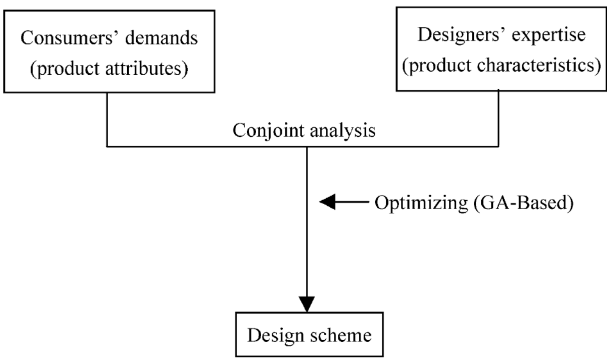


Figure 1. Architecture of integrated design model.

weaving graph), color (wild, graceful), shape (gentle, rude), overall setting (locally, globally), and marketing (grade A, grade B). Table 3 illustrates levels of design characteristics and the utilities of two designers.

It's usually more than one single designer employed for the design department in an enterprise. The viewpoints on the apparel fashion design among designers aren't always the same because each has one's own on it. The method to integrate them all to the maximum in common is by means of opinion poll, through which the maximal sum of utilities among designers can be obtained. The bigger the sum of utilities, the better design quality of the product is. Equation 1 is used to calculate the sum of utilities of characteristics for the designer.

$$u_i = \sum_{k=1}^{K} d_{ij^*k} \quad (1)$$

where
u_i: total sum of utilities of designer i
d_{ij^*k}: the utility of the selected level j of characteristic k for designer i
i: designer
j*: the selected level
k: characteristic
K: the number of characteristics

3.2 Customer Attributes and Utility Evaluation

Due to the lack of expertise training, the customer cannot exactly use the design characteristics as a designer during design stage. They can only describe roughly about their demands and habits during purchasing. In general, design attributes, with which the consumer most concerns [4,14], include style, feature, color, and purchasing habit. The number of levels is set to 3 for each attribute, i.e., style (cutting edge, fashionable, classic), feature (fit, tight, loose), color (personally favorite, integrated, voguish), and purchasing habit (department store, boutique, vending stall). Table 4 illustrates levels of design attributes and the utilities of four consumers.

The calculation of the total sum of utilities for each consumer is similar to that for each designer mentioned above.

$$v_i = \sum_{k=1}^{K'} c_{ij^*k} \quad (2)$$

Where
v_i: total sum of utilities of consumer i
c_{ij^*k}: the utility of the selected level j of attribute k for consumer i
i: consumer
j*: the selected level
k: attribute
K': the number of attributes

In order to integrate both the demands of the designer (i.e., designer characteristics) and consumer (i.e., consumer attributes) group, a relationship matrix between characteristics and attributes must be defined in advance.

Table 3. Utilities for various designers

Characteristics	Levels	Utilities (Design A)	Utilities (Design B)
1. Texture	1. plain	1	-1
	2. rough	-1	1
2. Material	1. soft	1	2
	2. hard	-1	-2
3. Pattern	1. printing-graph	-3	3
	2. weaving-graph	3	-3
4. Color	1. wild	-4	-4
	2. graceful	4	4
5. Shape	1. gentle	2	1
	2. rude	-2	-1
6. Overall setting	1. locally	-1	-1
	2. globally	1	1
7. Marketing	1. grade A	2	2
	2. grade B	-2	-2

Table 4. Utilities for various consumers

Attributes	Levels	Utilities (Consumer A)	Utilities (Consumer B)	Utilities (Consumer C)	Utilities (Consumer D)
1. Style	1. cutting edge	1	-1	1	-1
	2. fashionable	-1	0	0	1
	3. classic	0	1	-1	0
2. Feature	1. fit	1	2	1	2
	2. tight	-2	-1	1	0
	3. loose	1	-1	-2	-2
3. Color	1. personally favorite	2	1	2	-1
	2. integrated	-1	-2	-1	2
	3. voguish	-1	1	-1	-1
4. Purchasing habit	1. department store	-2	0	2	0
	2. boutique	1	2	0	-2
	3. vending stall	1	-2	-2	2

3.3 Relationship Matrix

Table 5 shows the relationship between designer characteristics and consumer attributes. Our methodology assumes that the relationship matrix can be created, and that it is realistic in terms of its characteristics, attributes, and levels. There is definitely something in common between designer characteristics and consumer attributes. The related degree between them can be evaluated by weights, which can be determined through the expertise of the professional expert. For instance, what the style "fashionable" means to the consumer is nothing much related with that does to the designer characteristics such as texture, material, and pattern. Thus, the relation values between the level of "cutting edge" to those of characteristics such as texture, material, and pattern are all set to zero. On the other hand, what the style "cutting edge" means to the consumer is rather related to that does to the designer characteristics such as color, shape, overall setting, and marketing. For example, the bigger chroma values of colors or those of the contrast colors are used in design, the more obvious "cutting edge" sense is represented. [15] Thus, the relation value between "cutting edge" and "wild" is set to "10", which is higher than between "cutting edge" and "graceful" to set as "5". The other weights between characteristics and attributes in Table 5 are obtained through experts' estimating by the same way as illustrated in the above-mentioned instance.

3.4 Integrating between Designer and Consumer

We can find the best-integrated product design decision strategy under the condition of "minimum sacrifice to afford maximum demand". Suppose 2 designers (i.e., i = 2) for the group, 7 characteristics for the designer (i.e., K = 7), and 2 levels for each characteristic (i.e., j = 2). As for the consumer group, there are 4 consumers (i.e., i' = 4), 4 attributes for the consumer attributes (i.e., K' = 4), and 3 levels for each attribute (i.e., j' = 3). We can expect to obtain the best product design using Equation 3, which is developed under the condition of "minimum sacrifice to afford maximum demand" to acquire the maximum of share of choices (i.e., Z_{SC}) between designers and consumers.

Maximize

$$Z_{SC} = \rho_1 \times \left[\frac{\sum_{k=1}^{K} \frac{u_{j*k}}{u_{j*k}^{*}}}{K \times I} \right] + \rho_2 \left[\frac{\sum_{k'=1}^{K'} \frac{v_{j'*k'}}{v_{j'*k'}^{*}}}{K' \times I'} \right] \quad (3)$$

Where
i: designer group
i': consumer group
j: level of characteristics
j': level of attributes
k: characteristics
k': attributes
Z_{SC}: share of choices
u_{j*k}: the utility of the selected level j of characteristic k for the designer group
u_{j*k}^{*}: the utmost utility of the selected level j of characteristic k for the designer group
$v_{j'*k'}$: the utility of the selected level j' of attribute k' for the consumer group

Table 5. Relationship matrix between designer group and consumer group

Attributes	Characteristics	Texture: plain	Texture: rough	Material: soft	Material: hard	Pattern: Printing-graphg	Pattern: Weaving-graph	Color: wild	Color: graceful	Shape: gentle	Shape: rude	Overall setting: locally	Overall setting: globally	Marketing: grade A	Marketing: grade B
1.Style	cutting edge	0	0	0	0	0	0	10	5	5	10	10	5	10	5
	fashionable	0	0	0	0	0	0	5	5	5	5	5	5	10	10
	classic	0	0	0	0	0	0	5	10	10	5	5	10	5	10
2.Feature	fit	5	5	5	5	0	0	5	10	0	0	5	10	0	0
	tight	5	10	10	10	0	0	10	5	0	0	10	5	0	0
	loose	10	5	5	5	0	0	5	10	0	0	5	10	0	0
3.Color	personally favorite	0	0	0	0	5	5	5	10	7	3	0	0	5	5
	integrated	0	0	0	0	10	5	10	5	3	7	0	0	10	5
	voguish	0	0	0	0	10	10	5	5	4	4	0	0	5	5
4.Purchasing habit	department store	0	0	0	0	0	0	0	0	0	0	0	0	10	5
	boutique	0	0	0	0	0	0	0	0	0	0	0	0	7	5
	vending stall	0	0	0	0	0	0	0	0	0	0	0	0	3	10

$v_{j'*k'}^{*}$: the utmost utility of the selected level j' of attribute k' for the consumer group

K: the number of characteristics

K': the number of attributes

I: total number of designers for designer group

I': total number of consumer for consumer group

ρ_1: weight value of designer group

ρ_2: weight value of consumer group

Optimization is achieved through finding the level of each characteristic (attribute), which is chosen (preferred) by the largest number of designers (consumers) during designing product. For instance, the design combination of design characteristics for a designer group is set as follows. The "texture" is set to rough, "material" to soft, "pattern" to weaving-graph, "color" to graceful, "shape" to gentle, "overall setting" to globally, and "marketing" to grade A. Firstly, putting all the utilities of above-mentioned characteristics for the designer group into Equation 3, the total agreement in common from designer group (i.e., Z_d) can be calculated as 0.63 (= [(0/2 + 1/2 + 2/2 – 2/2) + (1/2 + 2/2 + 1/2 + 0/2) + (-1/2 + 1/2 + 2/2 + 2/2) + (0/2 + 2/2 – 1/2 + 0/2)]/(4 × 4), where 4 × 4 indicates the denominator K × I in equation 3). Secondly, the chosen level of each characteristic can be referred to a specific level of each attribute based on relationship matrix. The total sum of the referred utilities in the horizontal direction for each attribute of relationship matrix can be obtained and illustrated as Table 6. Thirdly, the utmost value of each attribute (e.g., "classic" level for Style, "fit" for Feature, "personally favorite" for Color, and "department store" for Purchasing habit) is chosen to represent the best in common for the consumer group. Finally, putting all the utilities of the chosen levels of attributes into Equation 3, the total agreement in common from consumer group (i.e., Z_c) can be calculated as 0.31 (= [(-1/1 + 1/2 + 3/3 + 4/4 + 2/2 + 1/1 + 2/2) + (1/1 + 2/2 + (-3)/3 + 4/4 + 1/2 + 1/1 + 2/2)]/(7 × 2), where 7 × 2, indicates the denominator K' × I' in equation 3). The total agreement in common from both designer and consumer group (i.e., share of choices Z_{sc}) for the integrated model can be obtained as 0.47 (= 0.5 × 0.63 + 0.5 × 0.31) based on ρ_1 and ρ_1 set as 0.5.

4. Establishment of Search Mechanism

To solve a problem, the GA randomly generates a set of solutions for the first generation. Each solution is called a chromosome that is usually in the form of a binary string. According to a fitness function, a fitness value is assigned to each solution. The fitness values of these initial solutions may be poor, however, they will rise as better solutions survive in the next generation. A new generation is produced through the following three basic

Table 6. Application of relationship matrix

Designer characteristics			1.Texture		2.Material		3.Pattern		4.Color		5.Shape		6.Overall setting		7.Marketing	
Customer attributes	Levels	Levels	1.plain	2.rough	1.soft	2.hard	1.printing-graphg	2.weaving-graph	1.wild	2.graceful	1.gentle	2.rude	1.locally	2.globally	1.grade A	2.grade B
1. Style	1. cutting edge	25	0	0	0	0	0	0	10	5	5	10	10	5	10	5
	2. fashionable	25	0	0	0	0	0	0	5	5	5	5	5	5	10	10
	3. classic	35	0	0	0	0	0	0	5	10	10	5	5	10	5	10
2. Feature	1. fit	30	5	5	5	5	0	0	5	10	0	0	5	10	0	0
	2. tight	30	5	10	10	10	0	0	10	5	0	0	10	5	0	0
	3. loose	30	10	5	5	5	0	0	5	10	0	0	5	10	0	0
3. Color	1. personally favorite	27	0	0	0	0	5	5	5	10	7	3	0	0	5	5
	2. integrated	23	0	0	0	0	10	5	10	5	3	7	0	0	10	5
	3. voguish	24	0	0	0	0	10	10	5	5	4	4	0	0	5	5
4. Perchasing habit	1. department store	10	0	0	0	0	0	0	0	0	0	0	0	0	10	5
	2. boutique	7	0	0	0	0	0	0	0	0	0	0	0	0	7	5
	3. vending stall	3	0	0	0	0	0	0	0	0	0	0	0	0	3	10

operations [18].

(1) Randomly generate an initial solution set (population) of N strings and evaluate each solution by fitness function.

(2) If the termination condition does not meet, do
Repeat {Select parents for crossover.
Generate offspring.
Mutate some of the numbers
Merge mutants and offspring into population.
Cull some members of the population.}

(3) Stop and return the best fitted solution.

4.1 Encoding

In order to apply GAs to our problem, we firstly need to encode the parameters of the factors as a binary string. Seven important factors need determining, i.e., levels of the seven characteristics for designer including texture (plain, rough), material (soft, hard), pattern (printing-graph, weaving-graph), color (wild, graceful), shape (gentle, rude), overall setting (locally, globally), and marketing (grade A, grade B), illustrated in Table 3.

Because two levels for each characteristic need searched during designing, a 1-bit-coding of gene 'level' is used. Table 7, in which "0" and "1" represent "level 1" and "level 2" for each characteristic respectively, shows the encoding of levels for the seven characteristics.

4.2 Decoding

The domain of variable x_i, representing a certain level of attribute i is $[p_i,q_i]$ and the required precision is dependent on the size of encoded-bit. The precision requirement implies that the range of domain of each variable should be divided into at least $(q_i - p_i)/(2^n - 1)$ size ranges. The required bits (denoted with n) for a variable is calculated as follows and the mapping from a binary

Table 7. Encoding of various levels for characteristics

Characteristics	Level	Encoding
1. Texture	1. plain	0
	2. rough	1
2. Material	1. soft	0
	2. hard	1
3. Pattern	1. printing-graph	0
	2. weaving-graph	1
4. Color	1. wild	0
	2. graceful	1
5. Shape	1. gentle	0
	2. rude	1
6. Overall set	1. locally	0
	2. globally	1
7. Marketing	1. grade A	0
	2. grade B	1

string to a real number for variable x_i is straightly forward and completed as follows.

$$x_i = p_i + k_i\,(q_i - p_i)/(2^n - 1) \tag{4}$$

where k_i is an integer between $0\sim 2^n$ and is called a searching index.

After finding an appropriate k_i to put into Equation 4 to have a x_i, which can make fitness function to come out with a fitness value approaching to '1', the desired parameters can thus be obtained.

Combine all of the parameters as a string to be an index vector, i.e., $X = (x_1, x_2, \ldots, x_m)$, and unite all of the encoder of each searching index as a bit string to construct a chromosome shown as below.

$$\begin{aligned} &P = b_{11}\ldots b_{1j},\ b_{21}\ldots b_{2j},\ldots\ldots,b_{i1}\ldots b_{ij} \\ &b_{ij} \in \{0,1\};\ i = 1,2,\ldots,m;\ \ j = 1,2,\ldots,n; \end{aligned} \tag{5}$$

Suppose that each x_i is encoded by n bits and there is m parameters then the length of Equation 5 should be a N-bit ($N = m \times n$) string. During each generation, all the searching index k_is of the generated chromosome can be obtained by Equation 6.

$$k_i = b_{i1}{*}2^{n-1} + b_{i2}{*}2^{n-2} + \ldots + b_{in}{*}2^{n-n} \qquad i = 1,2,\ldots,m; \tag{6}$$

Finally the real number for variable x_i can thus be obtained from Equation 4 and Equation 6. The flow chart for the encoding and decoding of the parameter is illustrated in Figure 2.

For instance, by setting the search domain of variable x_i, a level of attribute i to [1,2] (i.e., including level 1 and level 2) and encoding the search index with 1 bit (i.e., n = 1), searched results from equation 1 can be illustrated as follows.

$$\begin{aligned}
k_1 &= 1 & x_1 &= 1 + 1{*}(2 - 1)/(2^1 - 1) = 2;\\
k_2 &= 0 & x_2 &= 1 + 0{*}(2 - 1)/(2^1 - 1) = 1;\\
k_3 &= 0 & x_3 &= 1 + 0{*}(2 - 1)/(2^1 - 1) = 1;\\
k_4 &= 1 & x_4 &= 1 + 1{*}(2 - 1)/(2^1 - 1) = 2;\\
k_5 &= 0 & x_5 &= 1 + 0{*}(2 - 1)/(2^1 - 1) = 1;\\
k_6 &= 1 & x_6 &= 1 + 1{*}(2 - 1)/(2^1 - 1) = 2;\\
k_7 &= 1 & x_7 &= 1 + 1{*}(2 - 1)/(2^1 - 1) = 2.
\end{aligned}$$

The calculated value "1" and "2" for x_i, where i = 1~7, denote level 1 and level 2 of each characteristic respectively.

4.3 Chromosome

The size of chromosome is various with the number of design characteristics. In the case of 7 characteristics × 2 levels for the product design in this paper, the chromosome can be formed and illustrated as Table 8.

4.4 Fitness Function

Through searching based on GA for optimal combination set consisting of various characteristics or attributes under the condition of "sacrifice the minimum to afford the most," an approach to optimal product design can be achieved. The fitness function of GA used in

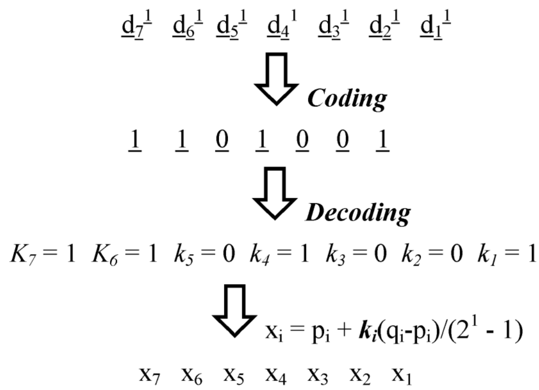
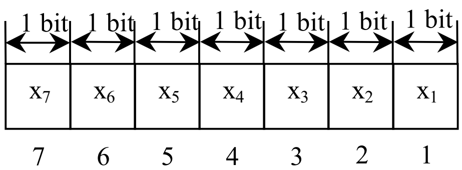


Figure 2. Flow chart for the encoding and decoding with 1-bit precision.

Table 8. Structure and gene size of chromosome

Parameters	Gene (bits)	Order	Chromosome
Texture (x_1)	1	1	
Material (x_2)	1	2	
Pattern (x_3)	1	3	
Color (x_4)	1	4	
Shape (x_5)	1	5	
Overall setting (x_6)	1	6	
Marketing (x_7)	1	7	



search mechanism can be defined as Equation 3 to acquire the maximum of share of choices (i.e., Z_{sc}). It represents that expertise of designers and demands of consumers are integrated perfectly while the value of Z_{sc} is maximized. After generations' evolution, we expect an optimal product design with a fitness value (i.e., the share of choices Z_{SC}) approaching to "1". The flow chart of evolution is shown as Figure 3.

5. Implementation

Apparel fashion design can be different from each other based on view of the designer and consumer. It is important for the R&D division to develop a product of a fashion styling, which can satisfy both the designer and the consumer. Table 3 and 4 illustrate levels of design characteristics and those of consumer attributes respectively There are 7 characteristics with 2 levels each for the designer group and 4 attributes with 3 levels each for the consumer group to concern with during designing.

In this study an integrated design model based on conjoint analysis is applied to obtain the best combination of design parameters (i.e., the characteristics and the attributes) of the designer and the consumer for fashion styling design. The implementation of this instance is described as follows.

5.1 Preprocessing of Utilities

In this paper, utilities are coefficients of a regression equation acquired by using OLS to regard each characteristic (or attribute) as a dummy variable, of which one random level is eliminated. The values of utilities, i.e., coefficients of regression equation, represent the degree of their contribution. The sum of utilities, including the one of the randomly eliminated level, is equal to 0. Therefore, it is possible for the value to be either positive or negative. A positive utility means the level of factor is of positive effectiveness. On the contrary, a negative one

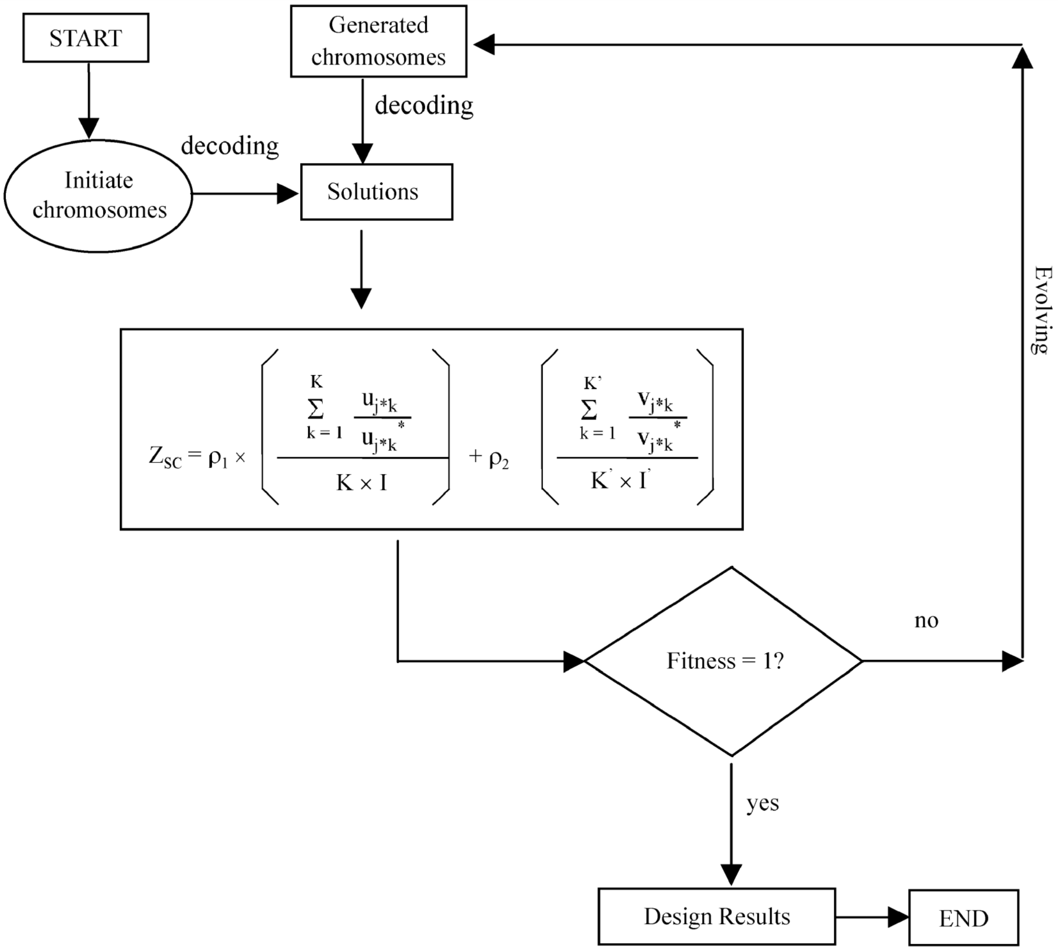


Figure 3. Flow chart for levels searching.

means the level negative. The bigger the value, the more obvious degree of the effectiveness is. In order to be good to acquire the value of Z_{SC}, a preprocessing of utilities by using Equation 7 is needed to transform negative values into positive ones for utilities.

$$X' = X + S \tag{7}$$

where
X: original utility
X': transformed utility
S (= $|0-X_{min}|$): shift
X_{min}: the minimum of values of characteristics (or attributes)

Taking utilities of the 1st designer in Table 3 for instance, firstly we find the minimum (i.e., X_{min}) among utilities is of a value of –4. Secondly, a shift (i.e., S) can be obtained as 4 (=|0 – (-4)|). Finally, by using Equation 7 all original utilities of 1st designer (i.e., 1, -1, 1, -1-3, 3, -4, 4, 2, -2, -1, 1, 2, -2) can be transformed into 5, 3, 5, 3, 1, 7, 0, 8, 6, 2, 3, 5, 6, 2 respectively.

5.2 Weighting Value

It is available for the design division of an enterprise to adapt the weight value ρ_1 and ρ_2 according to design strategies so as to develop a far more flexible design model. For instance, weight ρ_1 is set bigger than ρ_2 (e.g., $\rho_1 = 0.7$, $\rho_2 = 0.3$) while the expertise of the design is worthy to take more seriously during design. On the contrary, the demand of consumers needs taking more seriously, then ρ_2 is set bigger than ρ_1 ($\rho_1 = 0.3$, $\rho_2 = 0.7$). In order to afford the market trend for a product demand of small amount-large varieties, it gets more and more important for an enterprise to enhance the competency in product designing. With the assistance of the design model, developing products can be easier than ever through selecting the best from various combinations of design factors, which are related to expertise of professional designers and demands of consumers.

5.3 Simulation Results

Because of two levels (options) for each of the 7 characteristics for each characteristic needed searching during designing, a 1-bit-coding of gene 'level' is used. Initially several chromosomes consisting of 7 bit-string are randomly generated. The level options x_is (i = 1, 2,..., 7) for each characteristics can be acquired from Equation 1 via the obtained search index k_is (i = 1, 2,… ,7) decoded from genes in chromosome. The integrated index of designer Z_d can be obtained. After using the relationship matrix to find the levels of attributes that most related to those of characteristics, the integrated index of consumer Z_c can be obtained as well. According to the design strategy to determine the weighted value of ρ_1 and ρ_2 as mentioned above, the total share of choices (i.e., Z_{SC}) is calculated using Equation 3.

Figure 3 shows the flow chart of evolution. In order to equally focus on both the expertise of designers and demands of consumers, weights for $\rho_1$and ρ_2 in the fitness function are set to the same as 0.5 respectively in this paper. Fitness function simulation runs with the crossover, mutation, and reproduction operations under conditions of crossover probability, mutation probability, random seed, and initial population being set as 0.3, 0.033, 0.8 and 30 respectively. After several generations, we expect a maximum of share of choices (i.e., Z_{SC}) to be obtained. Figure 4 shows the simulation results of the best fitness, and average one for a 30-generation evolution based on the setting mentioned above. The best result comes out with a biggest share of cho-

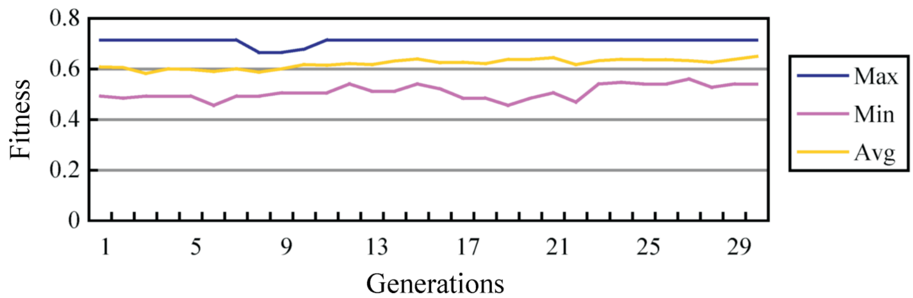


Figure 4. Simulation results.

ices of 0.7140 (i.e., $Z_{SC} = 0.7140$) from generation 1 to 30. Thus, the set of chromosome with a share of choices of 0.7140 can be deemed as the best solution. Table 9 illustrates the best-fitted chromosome (i.e., solution), which is the best solution to be obtained under both the expertise of designers and demands of consumers being equally emphasized. It suggests that the best combination of levels of designer characteristics be: (1) Texture-plain (2) Material-soft (3) Pattern-weaving-graph (4) Color-graceful (5) Shape-gentle (6) Overall setting-globally (7) Marketing-grade A, and that of consumer attributes be: (1) Style-classic (2) Feature-loose (3) Color- personally favorite (4) Purchasing habit-department store.

With the assistance of this developed system, the best-fitted solution, consisting of level assemblies of different characteristics and various attributes, is obtained efficiently for the designer to make decision far easier than ever in product designing. Through selecting the solutions with large fitness values from the evolved chromosome, a designer can obtain several feasible solutions to refer. The approach to optimal product design by integrating both expertise of designers and demands of consumers can thus be achieved.

6. Conclusion

This paper successfully presents an integrated product design model to be applied in clothing product design. The methodology focuses not only on either expertise of designers or demands of consumer but on both of them. A relationship matrix is used to combine both the conjoint analysis data from the two individual groups (i.e., designer and consumer) to design product. Nevertheless, as the number of attributes (or characteristics) with levels associated with a product design increases, the possible combinations for a product design increase in the mean time. It makes the product design problem using conjoint data more difficult. We develop a GA based approach to an optimal design solution for the multi-source product design problem. The experiment results show it is promising for us to use GA in searching the solutions to complex design problem. Thus, an approach to perfect product design can be achieved under integrated conditions. The developed product not only benefits from the innovative inspiration of designers but also afford demands of consumers to increase market share of it. The competence of product design for an enterprise can thus be achieved.

Table 9. The best-fitted solution of the 30th generation

Chromosome

0101100

Characteristics of designer

Texture		Material		Pattern		Color		Shape		Overall setting		Marketing	
plain	rough	soft	hard	printing-graph	weaving-graph	wild	graceful	gentle	rude	locally	globally	grade A	grade B
✓		✓			✓		✓	✓			✓	✓	
1		1		2		2		1		2		1	

Attributes of consumer

Style			Feature			Color			Purchasing habit		
cutting edge	fashionable	classic	fit	tight	loose	personally favorite	integrated	voguish	department store	boutique	vending stall
		✓			✓	✓			✓		
3			3			1			1		

Z_d	Z_c	fitness (= $0.5(Z_d + Z_c)$)
0.8864	0.5417	0.7140

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