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A decision support model in mass customization

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ABSTRACT

Mass customization (MC) is one of the leading strategies used in production industries in today's market filled with competition. MC is an oxymoron of controlling production costs and satisfying customers' individual requirements. It is well known that economy of scale and economy of scope is a pair of conflicts, and how to get the balance between them is the key issue to promote enterprises' competition. By analyzing and processing information of customer preference, product features and cost, this paper proposes a decision support model in mass customization to obtain the optimized production solution. Genetic algorithm is used for optimization, and the results of an illustrative example show that the model is efficient in production industries.

1. Introduction

With the rapid improvement of human's production level and information processing ability, simply considering the mode of mass production and/or personalized customization cannot meet people's requirements. New production paradigms are driving by changeable markets and diverse evolved social needs (Koren, 2010). Companies began to call for a comprehensive production mode considering both customers' personalized needs and low cost brought by mass production, which can promise sustainable development of companies. With continuous exploration and practice, a new production mode is gradually applied in manufacturing industries, which is known as mass customization. In "Future Shock", Toffler, 1970 creatively proposed an innovative idea which can meet the specified requirements of customers with cost close to that of standardized production. Davis, 1987 named the proposed production mode as mass customization in "Future Shock". Mass customization considers both the economics of scale and economics of scope, in order to achieve personalized customer demand at the cost of mass production. Mass customization (MC) is usually referred as a term as an oxymoron of mass production and customized goods (Kaplan & Haenlein, 2006), and it has become an undisputable reality that MC is one of the leading strategies in satisfying customers and assuring companies survival in today's markets characterized by constantly changing environment, rapid technology progress and fierce market competition (Daaboul, DaCunha, Bernard, & Laroche, 2011).

With the improvement of peoples' living standards, consumers no longer simply focus on product function, but more and more prefer personalized products, which can satisfy their subjective perception

(Trentin, Perin, & Forza, 2014). On the other hand, personalized production will cause reduction of production scale, expansion of product range and cost rising, because it is unable to make multiple products with a single production template. Different modern production systems are used to solve the above mentioned problems, such as lean manufacturing, cellular manufacturing and batch production. Lean manufacturing is a management philosophy derived mostly from the Toyota Production System (TPS). It is a systematic method for waste minimization within a manufacturing system without sacrificing productivity, by reducing everything which is not adding value (Onyeocha, Khoury, & Geraghty, 2015). As a subsection of lean manufacturing and just-in-time (JIT) manufacturing, cellular manufacturing is a process of manufacturing which encompass group technology. It moves as quickly as possible, while making a wide variety of similar products and, at the same time, as little waste as possible (Bootaki, Mahdavi, & Paydar, 2016). Different from mass production, also called as flow production or continuous production, which is a production mode to provide large amounts of standardized products, batch production is a technique used in manufacturing, in which a series of workstations stage by stage is created, and different batches of products are made (Al-Salamah, 2016). Different from those modern production system, mass customization aims at providing diversified products and service to consumers, and ensuring that each consumer can get the specific product he/she needed with a reasonable price (Trentin, Forza, & Perin, 2015). Mass customization will not meet all of consumers' individual needs regardless of cost, because relatively high cost is not economical for both consumers and companies. The features of mass customization are: reducing production cost by economics of scale and better meeting

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clients' requirements by economics of scope. As a result, mass customization will become the main production mode used in manufacturing industries.

2. Mass customization analysis

Mass customization refers to the capability to provide customized product/service for a mass market. The essential value of mass customization is to satisfy customers' individual preference at a low cost brought by mass production (Wang, Zhang, Sun, & Zhu, 2016). High quality and high efficiency are required in mass customization, and customers are usually involved in the production and service process, so as to get the products featured by their own personal attributes.

Mass customization makes high added-value products/services, and enhances profitability by reducing the costs of production and logistics and better satisfying the customer personalized requirements (Grenci & Watts, 2007; Jiao, Ma, & Tseng, 2003). When an enterprise is able to offer personalized or customized products, customer is then involved in the product design process, which may increase the value of the product – customer perceived value (CPV) (Gautam & Singh, 2008). One of the most distinguished features of mass customization is to provide customers with the possibility to co-design products/services according to their personalized preferences and interests (Ogawa & Piller, 2006). Products/services can be considered to be an integration of different modules, and different features of these modules can satisfy customers' needs and provide value, which requires an efficient product family design strategy (Tyagi, Yang, Tyagi, & Verma, 2012). However, excess complexity in product configuration has a negative impact on performance, especially for small companies, as Brunoe and Nielsen (2016) pointed out. Fang, Li, and Lu (2016) pointed out that learning and innovation can also significantly influence process automation so as to enhance performance.

Implementing mass customization in manufacturing industry is quite challenging and a variety of elements such as customer requirement and preference, supply chain management, customer relationship management, manufacturing process, price issues should be considered. Information about all these elements is recognized as a manageable key resource for enterprises to survive and develop (Bernard & Tichkiewitch, 2008), and people are paying more and more attention in knowledge and information processing during production development (Xu, Bernard, Perry, Xu, & Sugimoto, 2014). How to process production information in a quantitative way is very crucial to improve decision support model in a given business context, for example, mass customization. Scale effect is one of the primary means to reduce costs (Easton & Sommers, 2003). A decision support model should be applied to balance the two sides of scale effect and customized requirements. This paper will make a quantitative study to solve the core problem in mass customization: to what extent the benefit brought by customization can compensate the increased cost caused by quantity reduction.

One important issue to be discussed is how to determine the customization degree in mass customization from the point of view of product lifecycle. Manufacturers should take into account clients' requirements and production cost to decide what categories of product should be produced at what quantity, then make production plan of each stage of the whole product lifecycle. Taking clothing industry as example, apart from luxurious product such as customized suit, clothing industry is mainly based on mass production strategy. However, as new brands are emerging on the market, more competitors are dividing the market, so that personalized production directed by distinguished customer groups is a trend. Therefore, it is necessary to consider using mass customization model in clothing industry, and to integrate factors like diverse customers' needs gathered through market research, production cost, time delay, etc. By constructing a quantitative model, producers can decide the best balance point between customers' preference and product cost.

Due to the diversity of market and the limit of enterprise resource, enterprise can hardly meet any needs of all the customers. A relatively rational strategy for enterprise is to make market division so as to fix the target markets and potential consumers, and then clarify market and consumer positioning. On one hand, enterprises should concentrate resources to meet part of customers' needs, and on the other hand, enterprises should consider alternative choice to substitute the other part of customers' need, in order to maximize company's profit by reducing costs and promoting sales.

Due to the fixed costs and technique development, economies of scale would reduce the average cost of products to some extent, so mass production strategy is usually chosen by companies. However, homogenous products can hardly meet consumers' diverse needs. Taking sport clothing industry as example, it is a buyer's market and consumers have many choices as alternatives that are quite available.

If enterprises choose mass production mode without specifying customers' requirements and personal preferences, it will likely lead to the loss of customers, or the decrease of customer's satisfaction and loyalty. In such cases, significant decline in sales will reduce company's profit, or even lead to losses. Potential impacts may include harm to corporate image. So choosing traditional mode of production or marketing is not appropriate. On the other hand, although to provide clients with fully customized product will meet their personal needs and ensure high customer satisfaction and loyalty, product sales quantity will be quite few, especially in luxury industry. Further, fully customized product leads to high costs. Clients have a diversity of requirements, mapping to diverse products, and each type of product has quasi-fixed cost (cost which will happen if this type of product is produced, otherwise no cost is needed), so if production quantity of each type of product is too small, income may not cover cost and overall profit will drop. As for sport clothing industry, apart from special customization for professional athletes, most companies rely on large quantity sales, so pure customization mode is not appropriate either. As insightful results in mass customization application, Yao and Liu (2009) set up a dynamic and multi-objective optimization mathematical model and appropriate solving algorithm to solve optimization and scheduling problems in mass customization. Yang, Dong, and Chang (2012) presented a direct approach to encoding configuration models into the Dynamic Constraint Satisfaction Problems (DCSP), where low-level components join in the solving process only after its high-level component is selected in the configuration. Dou, Zhang, and Nan (2016a) proposed an approach to customer-oriented product collaborative customization for manufacturer to improve the design process, and experimental results demonstrated that the approach could effectively identify customers' preference and obviously improve their customization efficiency. Dou, Zong, and Nan (2016b) proposed a multi-stage interactive genetic algorithm (MS-IGA) to ameliorate user experience and evaluation process, and when it is applied to the conceptual design system, the knowledge of users' personalized requirements is better captured.

From analysis above, we may infer that traditional mass production method and pure customization mode are either appropriate choice for sport clothing companies, so mass customization, which is a balance between them, could be an ideal choice to maximize companies' profit.

In spite of a certain degree of risk caused by the attempt of applying mass customization, it is worth making this choice as customer satisfaction and loyalty can be greatly improved without increasing too much cost, especially in today's society characterized by individualization and differentiation.

The most interesting task of mass customization is how to increase product diversification and customization without too much increase of product costs. Thus, mass customization is applied by more and more enterprises to attract customers and make more profits. A survey based on market investigation shows that customers are willing to pay more to get customized sport clothes (different colors, logos, words, graphics, etc., which can be determined by customers) rather than homogeneous

clothes. Another result got from the investigation is that customers are willing to pay more for personalized requirements but they would like to pay extra fees as less as possible (Xu, 2015). Consequently, an obvious conclusion can be made: enterprises which can apply mass customization to provide customized product and/or service with a lower price will win in the fierce market competition.

The following sections will discuss about the modeling and testing process of the decision support model based on mass customization. In the modeling section, assumptions and variables are given, and in testing section, a case on numerical simulation will be studied and discussed.

3. Mass customization modeling

Sportswear manufacturing will be chosen as the object of case study, and both modeling and testing processing will consider the feature of that industry. The case of sportswear is supposed to be a monopolistically competitive market, as in real world practice, there is no dominant vendor, but individual manufacturers have still control on prices. In case study, different clients have different preference on different T-shirt classes, so the core problem is to help companies determine which production solution be chosen. For the objective function of decision making, it is modeled according to the total sales income and production cost. Detail assumptions about the case is illustrated as follows.

3.1. Assumptions

Assumption 1. The industry of sportswear is a monopolistically competitive market, which is between the monopoly market and competitive market, including both competition and monopoly.

In a perfectly competitive market, all companies are price takers. Price is determined by market supply and demand, and the industry achieves a balance of supply and demand. All manufacturers can sell products at the equilibrium price, so there is no incentive to cut the price. As the products from every manufacturer have exactly the same characteristics, small price increase will cause loss of all the customers. In other words, individual manufacturer has no control on prices.

In a monopoly market, only one or a few dominant vendors, and the products have few alternatives for clients, so customer loyalty is often quite high. In such cases, vendors have great influence on the market price, and the elasticity of demand curve is often quite low. When vendors raise product prices within a certain range, the loss of customer is quite small, and thus the profit increase with increase in price.

In a monopolistically competitive market, products are sets of close substitutes of all vendors for the customers. From the point of view of vendors, every product is unique, but from the point of view of clients, each product is a substitute to some extents. In such cases, vendors have a certain influence on product prices, and when prices increase, vendors will lose some customers, but not all. These losses of clients depends on to what extent the customers consider the similarity of different products, in other words, they depend on the elasticity of the demand curve faced by the vendors.

On one hand, vendors have some autonomy in deciding the price, compared to perfectly competitive market makers where they could only passively accept the market price. On the other hand, vendors must compete in terms of price, quality and range of products provided in order to obtain and retain consumers. Due to the different brand effect and the different style, quality, location, products provided by various manufacturers, customers have different preferences and evaluate the products differently. At the same time, as there are many similar clothing brands on the market, due to some price advantage and large-scale publicity, each may occupy a certain market share. In such situation, the clothing industry is a monopoly (a limited number of competitive firms) and also competing (competitions among companies

exist for prices, product quality, etc.). Therefore, the hypothesis about monopolistic competition market is reasonable.

Assumption 2. The objective function of producers is to maximize profits.

In real world production activities, companies often have to consider a variety of factors when setting target, such as market share, profit, customer satisfaction and loyalty, brand concept, and corporate image and culture. For long-term development, enterprises may even choose loss of business in some cases. However, in order to focus on the main objective of this paper and simplify the model, a single target to maximize profit is set, so the objective function is noted as:

$$\max \pi = \sum P(x_i) * Q(x_i) - C$$

where π means enterprise profit, which is obtained by total revenue minus the cost. Companies tend to produce a variety of products to meet the different individual needs of customers. So, x_i represents the amount of the i th product, and $P(x_i)$ represents the price of the x th product determined by the production yield. As manufacturers cannot guarantee that all the products can be sold out, so the number of actual sales is represented by a function of yield, noted by $Q(x_i)$. Thus $\sum P(x_i) * Q(x_i)$ represents the total revenue, and C represents the total cost, including fixed and variable costs. In order to maximize profits, enterprises should determine the production yield according to balanced marginal cost and marginal revenue. Explicit definition of the total cost part of the objective function, i.e. C , is illustrated in detail in the following section of modeling.

3.2. Modeling

Quantitative models can help searching for the optimal solution to maximize profits. The model parameters mainly include consumer preferences and the demand function for each type of product, which can both be obtained from market investigation.

3.2.1. Consumer preferences

Consumer preferences mainly indicate the degree of preference for each product. A product can have different aspects and features, and thus can be designed differently. The problem is how to combine and integrate those kinds of design to meet consumers' preferences mostly (Pillera & Blazekb, 2014). Suppose there are n factors to consider when designing a product, and each factor can have g_i ($i = 1, 2, 3, \dots, n$) options, thus the manufacturer can provide $\prod_{i=1}^n g_i$ types of T-shirt in all. Take T-shirt design as example, cloth weave can be knitted and non-knitted; fabric can be cotton, yarn, and chemical fiber; collar design can be crew-neck, V-neck, square-neck, and polo-neck, so there are $2 \times 3 \times 4 = 24$ types of shirt designed.

By market investigation, the proportion of consumer preferences about various factors of different design options can be obtained. Due to the independence of each factor, we can calculate the ratio of consumer preferences for different products by multiplication. Using p_{ji} to represent the consumer preference ratio of the i th alternative of the j th factor, the proportion of the market demand for each product can be calculated by $\prod_{ji} p_{ji}$. Specific application will be introduced in the case study section.

3.2.2. Cost analysis

The composition of production cost is very diverse, and its accounting is very complex. It may include procurement costs of raw materials, manufacturing costs, human resource costs, transportation costs, depreciation of fixed assets, marketing costs, etc. Some of its content is beyond the limit of our research, so this model mainly considers the following costs:

- Fixed costs. Costs required once the manufacturing process is

activated. The rent or purchased cost of factory and machine is a kind of such cost. Fixed cost does not vary with changes of yield, and thus can be considered as sunk cost. When companies are making production decisions about yield, it is not considered. However, it will affect the average cost of the product, thus change the total profit. It determines whether or not to withdraw the product family from company's supply.

- **Quasi-fixed costs.** Costs required once a specific type of product is planned to be manufactured, and independent on the yield. R & D cost of a specific type of product belongs to this kind of cost. Quasi-fixed costs depend on which types of product the company decides to provide.
- **Variable costs.** It is closely related with the product yield. Such costs include the cost of raw materials for one product unit, packaging costs per product, etc. Some costs that cannot be explicitly designated can be shared equally in variable cost of each product, such as human resource cost, depreciation of fixed assets, and maintenance fee. Variable cost is one of the most critical parameter when companies are making decisions.

3.2.3. Modeling process

Based on analysis above, cost of a chosen solution is represented as follows.

$$C = \sum C_i(x_i) + \sum F_i * n(x_i) + FC$$

$$n(x_i) = \begin{cases} 1, & x_i > 0 \\ 0, & x_i = 0 \end{cases}$$

where C represents the total cost of the chosen solution. $C_i(x_i)$ represents the variable cost of the i th product when its yield is x_i ($x_i > 0$). When $x_i = 0$, there is no production of the i th product. F_i represents the Quasi-fixed cost of the i th product. FC represents fixed cost.

For the income part, corporate earnings can be expressed as follows.

$$R = \sum P(x_i)Q(x_i)$$

where R is revenue of the chosen solution, which is the production result of P, price of each product, and Q, quantity of the related product.

The marginal revenue (MR) when one unit of product is manufactured is:

$$MR = \frac{dR}{dq} = p(q) + q \frac{dp}{dq} = p(q) \times \left(1 + \frac{q}{p(q)} \frac{dp}{dq}\right) = p(q) \times \left(1 - \frac{1}{|\varepsilon|}\right)$$

ε is the price elasticity of demand, which gives the percentage change in quantity demanded in response to one percent change in price. As price elasticity is usually negative, the model uses their absolute values for all ε . As optimal yield is obtained when the marginal cost equals marginal revenue, we have:

$$MR = p(q) \times \left(1 - \frac{1}{|\varepsilon|}\right) = MC$$

and we get:

$$p(q) = MC \times \left(1 + \frac{1}{|\varepsilon| - 1}\right)$$

The price is thus calculated as follow.

$$P(x_i) = C'_i(x_i) * (1 + \eta_i)$$

where $C'_i(x_i)$ is the marginal cost of the i th product, and $\eta_i = \frac{1}{|\varepsilon| - 1}$.

In most cases, quasi-fixed costs exist when a given type of product is manufactured, so if all types of products are produced in full accordance with the individual needs, there will be a relatively small number of products of each type, and that will greatly increase the overall production costs, resulting in lower profits or even negative profit. Therefore, an optimal production strategy is usually to

manufacture some of the product types, not all, so as to reduce quasi-fixed costs. As substitution can usually be made (especially in clothes market) when clients cannot find what exactly meet their requirements, similar product are chosen instead. Often, the more a type of product is produced, a lower price can be provided, and more demands appear.

In order to determine $Q(x_i)$, a third hypothesis is proposed as follow.

Assumption 3. When the yield of a given type of product is less than a threshold, all products of this type can be sold out; when the yield exceeds the threshold, a certain percentage of the excess part cannot be sold out, and the more the yield exceeds, the ratio of product that cannot be sold out is higher.

Thus, the final sales amount can be regarded as an increasing function of yield, with a growth rate slowing down.

Based on the analysis above, the total sales quantity of the i th product is defined as follows.

$$Q(x_i) = \begin{cases} g(x), & x \geq M * w_i \\ x, & x < M * w_i \end{cases}$$

where M represents the manufacturer's production capacity, in other words, how many products in all the manufacturer can produce, and w_i represents the proportion of client requirement. Also, we have $g'(x_i) > 0$ and $g''(x_i) < 0$

In all, the objective function is noted as follow.

$$\pi = \sum P(x_i) * Q(x_i) - C = \sum C'_i(x_i) * (1 + \eta_i) * Q(x_i) - \sum C_i(x_i) - \sum F_i * n(x_i) - FC$$

The aim is to calculate the maximum value of this function and obtain the optimal quantity of each product.

4. Model testing and analysis

In order to make numerical simulation of the model, relevant functions and parameters should be given.

The following function is used to characterize the demand curve.

$$q = P * w_i^{-\sigma}$$

where P is the product price, w_i is its demand ratio, and σ is a constant value.

Thus, we have:

$$|\varepsilon| = \left| \frac{\frac{dq}{q}}{\frac{dp}{p}} \right| = \left| -\sigma \cdot \frac{1}{w_i} - 1 \right| = \sigma \cdot \frac{1}{w_i} + 1$$

The cost function of the i th product is defined as follows, shown in Fig. 1.

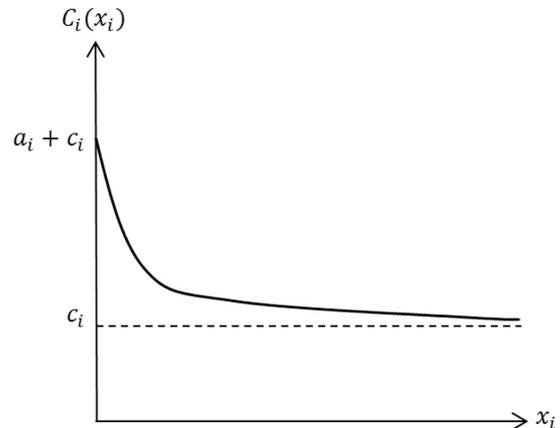


Fig. 1. Function $C_i(x_i)$.

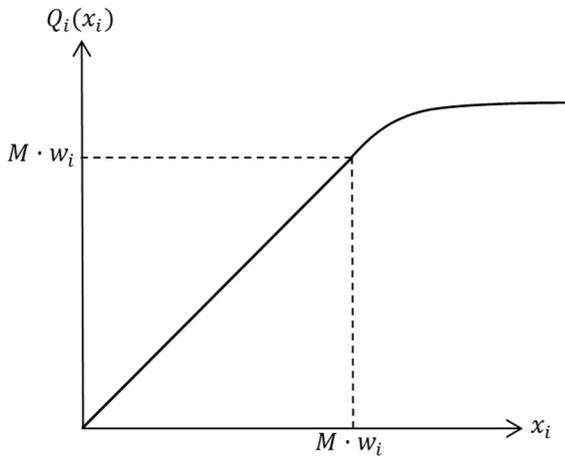


Fig. 2. Function $Q_i(x_i)$.

Table 1
Preference percentage of different design options.

Factors	Options	Preference percentage
Cloth weave	Knitted (A)	0.7
	Non-knitted (a)	0.3
Fabric	Cotton (B)	0.6
	Chemical fiber (b)	0.4
Neck design	Square-neck (C)	0.8
	V-Neck (c)	0.2

Note: the addition of each factor is 1.

Table 2
Preference percentage of different product types.

Product type	Type 1	Type 2	Type 3	Type 4	Type 5	Type 6	Type 7	Type 8
	(ABC)							
Preference percentage	0.336	0.144	0.224	0.084	0.056	0.036	0.096	0.024

$$C_i(x_i) = x_i * \left(c_i + \frac{a_i}{e^{b_i x_i}} \right)$$

where c_i represents material cost of each product, and e^{bx} is used to characterize technical maturity level (with the increment of x , techniques will be more mature, at a speed of exponential function). As the value of b will be assigned differently for different techniques, and it doesn't have impact in the optimization process, thus it could be regarded as a constant and its actual value is beyond the limit of this paper. $\frac{a_i}{e^{b_i x_i}}$ represents the cost equally shared by of each product (such as human resource cost and technical cost). With the expansion of production quantity of a commodity, relevant technologies (including workers experience, etc.) become more mature, so the fixed costs shared by each product become less.

The sales amount of the i th product is given as follows, shown in Fig. 2.

$$Q_i(x_i) = \begin{cases} \log_m(x_i - k_i) + l_i, & x \geq M \cdot w_i \\ x, & x < M \cdot w_i \end{cases}$$

As two functions tangent to the point $(M \cdot w_i, M \cdot w_i)$, we have

$$\begin{cases} M \cdot w_i = \log_m(M \cdot w_i - k_i) + l_i \\ Q'(M \cdot w_i) = \frac{1}{(M \cdot w_i - k_i) \ln m} = 1 \end{cases}$$

So we get

$$\begin{cases} k_i = M \cdot w_i - \frac{1}{\ln m} \\ l_i = M \cdot w_i - \log_m \frac{1}{\ln m} \end{cases}$$

In the equation above, k_i and l_i are two parameters to characterize the translation of the logarithmic function, to make the two parts of the function $Q_i(x_i)$ at the point $(M \cdot w_i, M \cdot w_i)$. For the parameter m , it characterizes the shape of the logarithmic function. As k_i , l_i and m will not affect the optimization process of the objective function of MC model, their values could be assigned randomly.

The model will be tested on a case of T-shirt production, and Table 1 shows preference percentage of different design options.

From Table 1, we may obtain preference percentage of different product types, shown in Table 2.

For mathematical simulation, the parameters are given values as follows.

$$a_i = 50, b_i = 0.01, c_i = 100 \quad (i = 1, 2, 3, 4, 5, 6, 7, 8), \sigma = 0.1, m = 1.06, F = 5000, M = 1000 \quad (\sum x_i = 1000)$$

For fixed costs, as they will not affect production strategy, in order to simplify the calculation process, it is assigned with 0.

In all, the optimization problem of the model is to maximize the

objective function subjected to the constraints, which are characterized as follows.

The objective function:

$$\begin{aligned} \pi = & \sum \left(\frac{50}{e^{0.01x_i}} + 100 - \frac{0.5x_i}{e^{0.01x_i}} \right) \times \left(1 + \frac{w_i}{0.1} \right) \times Q(x_i) \\ & - \sum x_i \times \left(\frac{50}{e^{0.01x_i}} + 100 \right) - 5000 \times \sum n(x_i) \end{aligned}$$

where $n(x_i) = \begin{cases} 1, & x_i > 0 \\ 0, & x_i = 0 \end{cases} \quad (i = 1, 2, 3, 4, 5, 6, 7, 8)$, $w_1 = 0.336, w_2 = 0.144, w_3 = 0.224, w_4 = 0.084, w_5 = 0.056, w_6 = 0.036, w_7 = 0.096, w_8 = 0.024$,

$$Q(x_1) = \begin{cases} \log_{1.06} \left(x_1 - 336 + \frac{1}{\ln 1.06} \right) + 336 - \log_{1.06} \left(\frac{1}{\ln 1.06} \right) x_1 > 336 \\ x_1 x_1 \leq 336 \end{cases}$$

$$Q(x_2) = \begin{cases} \log_{1.06} \left(x_2 - 144 + \frac{1}{\ln 1.06} \right) + 144 - \log_{1.06} \left(\frac{1}{\ln 1.06} \right) x_2 > 144 \\ x_2 x_2 \leq 144 \end{cases}$$

$$Q(x_3) = \begin{cases} \log_{1.06} \left(x_3 - 224 + \frac{1}{\ln 1.06} \right) + 224 - \log_{1.06} \left(\frac{1}{\ln 1.06} \right) x_3 > 224 \\ x_3 x_3 \leq 224 \end{cases}$$

$$Q(x_4) = \begin{cases} \log_{1.06} \left(x_4 - 84 + \frac{1}{\ln 1.06} \right) + 84 - \log_{1.06} \left(\frac{1}{\ln 1.06} \right) x_4 > 84 \\ x_4 x_4 \leq 84 \end{cases}$$

$$Q(x_5) = \begin{cases} \log_{1.06} \left(x_5 - 56 + \frac{1}{\ln 1.06} \right) + 56 - \log_{1.06} \left(\frac{1}{\ln 1.06} \right) x_5 > 56 \\ x_5 x_5 \leq 56 \end{cases}$$

$$Q(x_6) = \begin{cases} \log_{1.06} \left(x_6 - 36 + \frac{1}{\ln 1.06} \right) + 36 - \log_{1.06} \left(\frac{1}{\ln 1.06} \right) x_6 > 36 \\ x_6 x_6 \leq 36 \end{cases}$$

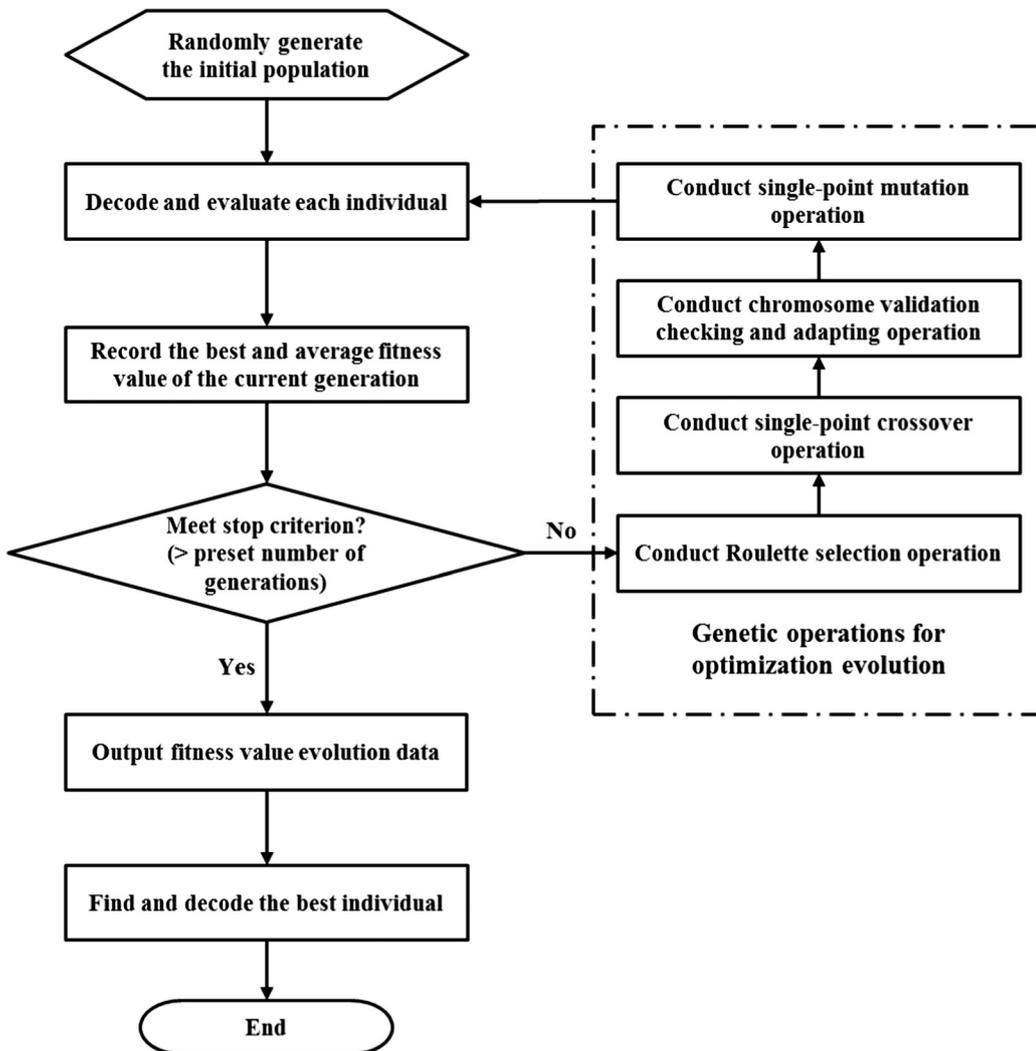
$$Q(x_7) = \begin{cases} \log_{1.06} \left(x_7 - 96 + \frac{1}{\ln 1.06} \right) + 96 - \log_{1.06} \left(\frac{1}{\ln 1.06} \right) x_7 > 96 \\ x_7 x_7 \leq 96 \end{cases}$$

$$Q(x_8) = \begin{cases} \log_{1.06} \left(x_8 - 24 + \frac{1}{\ln 1.06} \right) + 24 - \log_{1.06} \left(\frac{1}{\ln 1.06} \right) x_8 > 24 \\ x_8 x_8 \leq 24 \end{cases}$$

s.t. $\sum x_i \leq 1000, x_i \geq 0, x_i$ is integer.

In order to obtain the maximum value of the objective function introduced above, there is a need to apply an optimization algorithm.

Fig. 3. Flowchart of the developed GA.



The optimization example here is a non-linear and discrete combinatorial optimization problem. The most basic characteristic of the combinatorial optimization problem is that the variables are discrete, which leads to the fact that the objective function and the constraint function in the mathematical model are discrete in their feasible domain. In the real world, many of the practical problems are essentially discrete events rather than continuous events. Most of these problems are usually NP-hard (Gary & Johnson, 1979). These problems are still a computable problem, that is, there is an algorithm to solve. The methods for solving such kinds of combinatorial optimization problems are divided into two types: exact algorithm and approximate algorithm. The exact algorithms can only solve some small-scale problems with an acceptable computation time. Approximation algorithms are widely adopted to solve large scale problems to get a satisfactory solution with acceptable computation cost though they cannot guarantee the global optimal solution of the problem. However, this is a commonly accepted compromise in practice when facing large scale problems. In this example, for simplicity and computation comparison analysis, the variables are limited to $[0, 1000]$. But, it still cost nearly two days of computation time to touch the optimal solution by using enumeration method. For future users of the proposed decision model, the intervals of variables can be redefined, which may lead to large scale problems. Therefore, to be generic, approximate algorithms are preferred. Approximation algorithms usually include mathematical programming algorithms, heuristic algorithms and evolutionary algorithms. Among these algorithms, the evolutionary algorithms have an advantage that they use a common algorithm framework but are not limited to problem

contexts, which is convenient for adaptation with minimum local changes based on the algorithm framework. Hence, a popular tool for solving integer programming problems, evolutionary algorithm (EA), is proposed to deal with this example for demonstration due to their advantages against other algorithms (Dorigo, Caro, & Gambardella, 1999; Gen & Cheng, 2000; Rajeev & Krishnamoorthy, 1992).

In this paper, Genetic Algorithm (GA), a representative of EA, is adopted. A basic genetic algorithm using integer encoding is designed and implemented to solve an example optimization problem for model testing. Fig. 3 shows the main architecture of the developed GA. Details on the design and implementation of the GA as well as the optimization result are introduced in as follows.

To design a GA, the most important step is to design a chromosome that represents a valid solution structure for a targeted optimization problem. Then, fitness function usually derived from objective function should be set for evaluating alternative solutions from the solution space during the evolutionary procedure. To advance the global searching by improving the diversity of alternative solutions and improving local searching, genetic operators including Crossover operator, Mutation operator and Selection operator, should be designed.

- **Encoding:** the designed chromosome is a sequence of integers which contains the complete variables of the objective function. For a chromosome, each variable takes up a fixed gene position to represent a gene type, and each gene's phenotypes are the integer values within the interval of $[0, 1000]$. Regarding the constraint of the optimization problem, a valid chromosome must meet the

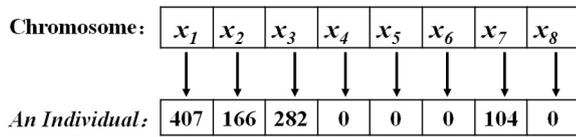


Fig. 4. Chromosome and an example of an individual.

requirement that the sum of variables' values should be less than or equal to 1000. Fig. 4 shows the chromosome structure with integer encoding and an example of an individual or alternative solution.

- Fitness function:** in GA, fitness function is used to evaluate alternative solutions. For many optimization problems, the objective function can be directly used as fitness function. However, to facilitate the design of selection operator, the fitness function value is better to fall in the interval of [0, 1]. Hence, in this paper, the objective function is transferred as $fit(j) = \Pi(j) / \sum_{k=1}^n (\Pi(k))$, which enables the fitness value to be within [0, 1]. In the formula, $fit(j)$ is the j th individual's, alternative solution's, fitness value, $j = 1, 2, 3, \dots, n$, and n is the number of a population, one generation's individuals. $\Pi(j)$ is the j th individual's objective value.
- Selection operator:** in the given case, there is only one objective function in optimization. Therefore, the Roulette selection operator, which is widely-used in Single-objective optimization problem, is adopted for selection operation. For more details about this selector, readers are referred to some representative works in literature (Deb, 2000; Goldberg & Deb, 1991).
- Crossover operator:** Crossover operation is used to improve the diversity of the population so as to advance the global searching in the evolutionary optimization. This operation applies different rules to identify a cross point of two selected individuals and exchange their segments of chromosomes. By doing this operation, two parent chromosome can generate a pair of child chromosomes. However, when dealing with classical TSP or other combinatorial optimization problems, one of the main difficulties of applying EA methods is the

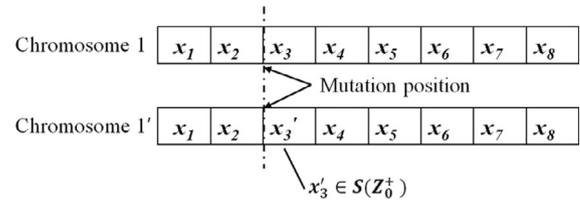


Fig. 6. Single point mutation operation.

design of a suitable crossover operator. Since the child chromosomes directly generated by exchanging a set of genes usually cannot guarantee that they are valid chromosomes representing valid alternative solutions. In this paper, the optimization problem also has this characteristic due to the constraint that the sum of variables' values should be no more than 1000. Hence, an additional operation to check and amend invalid individuals within a population after crossover operation should be designed. In this paper, two methods were tested. The first one is to check all the children chromosomes after crossover operation and then use the original population generation method, which can generate valid chromosomes, to generate a new chromosome to replace any one that is invalid. This method can simplify the GA program by improving code reuse and improve the population diversity. However, it would cause that some children chromosomes miss the potential good 'patterns' from their parent chromosomes. To compensate this, another method is designed. The main idea is to reset only one or several variables' values to ensure that the sum of variables' values does not surpass 1000. When a child chromosome is invalid after crossover operation, then reset its variable with the maximum value. If the reset chromosome is still invalid, then reset two or more variables in order of their values until to meet the constraint. By doing this, good 'patterns' of parent chromosomes have more chance to be passed to their children chromosomes. Fig. 5 shows the single-point crossover operation and the resetting of a variable's value (in red¹ color) for an

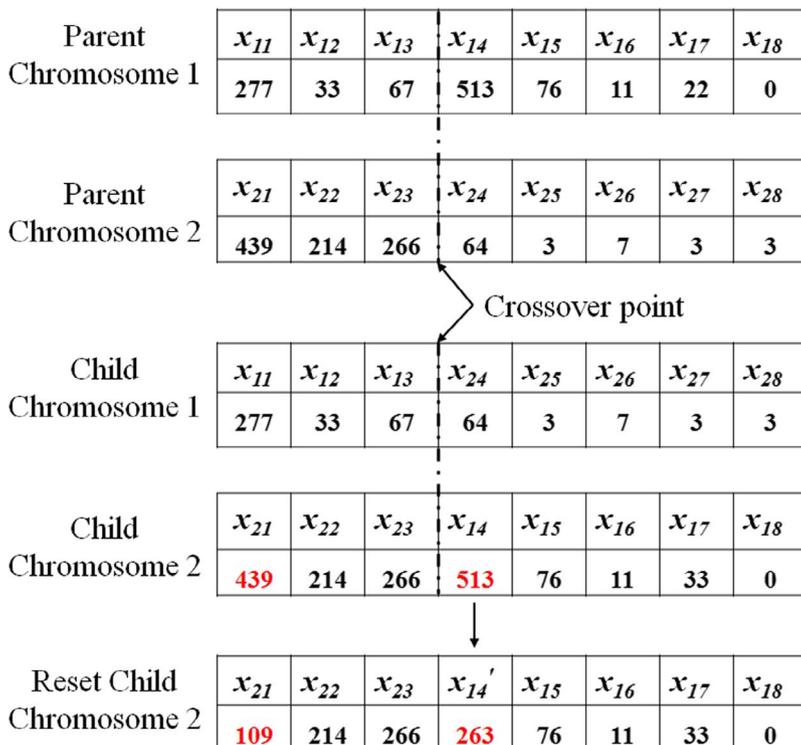


Fig. 5. Single-point crossover operation and example of adjusting invalid child chromosome by resetting two variables' values. Note: x_{ki} is the i th variable of the k th chromosome in a generation.

¹ For interpretation of color in 'Fig. 5', the reader is referred to the web version of this article.

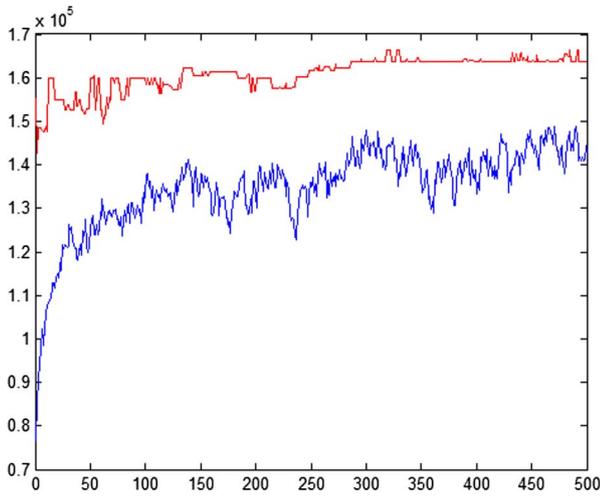


Fig. 7. Optimization result. Note: Red line: best objective function value of each generation. Blue line: average objective function value of each generation. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 3
Experimental results.

x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8
413	152	247	87	0	0	101	0

invalid child chromosome.

To conduct the crossover operation, a crossover point on the chromosome structure is randomly selected, then the two segments of the parent chromosomes after the crossover point exchange with each other to generate two new child chromosomes. As shown in Fig. 4, a child chromosome, *Child Chromosome 2*, is invalid since it cannot meet the constraint. Then two variables' values of that child chromosome are reset, which makes it valid. Actually, in this research, the testing results for applying the two methods dealing with invalid chromosomes are similar. The main reason may be that the complexity scale of the optimization problem in this paper is not high. However, the benchmarking study for the two methods is out of the scope of this paper.

Mutation operator: mutation operation is conducted by applying a

mutation operator. This operator is mainly used to improve the local searching during the evolutionary procedure. It is different from crossover selection which is used to improve the global search by changing large part of genes of chromosomes. While the mutation operation only slightly changes the genes of a chromosome, which can protect good 'patterns' to help convergence and avoid to be trapped by local optimal. In this paper, a single point mutation operator is adopted. At first, a mutation point is randomly selected; then reset the gene's value after the selected point. To ensure that the newly generated chromosome is valid, a value is randomly selected from an integer set with a dynamic up boundary, maximum integer value, for the gene on the mutation position. The integer set is given as follow.

$$S(Z_0^+) = \{0, 1, 2, 3, \dots, N_s\}$$

where N_s is the difference between 1000 and the sum of all the variables' values of a chromosome except the value of the gene on the mutation position. For different chromosomes, the values of N_s are different. Hence, the integer set is dynamic. The mutation operation is described by Fig. 6.

In this research, the designed genetic algorithm is implemented in Matlab environment, where optimization can be conducted. Besides of the design of fitness function and genetic operators, other running parameters (population size, probabilities of crossover operation and mutation operation, etc.) of GA should also be determined. The determination of these parameters is dependent on specific optimization problem and testing of optimization performance. Setting of these running parameters and the optimization result are presented in the following part.

After a couple of computational tests on Matlab platform, the running parameters for the optimization problem are set as follows.

- Chromosome length** = 8, the number of variables;
- Population size** = 800, number of individuals of each generation;
- Pc** = 0.75, probability of crossover operation;
- Pm** = 0.15, probability of mutation operation;
- Generation** = 500, iteration times.

20 times of optimization were conducted by using the designed GA. The average computation time is 4.038 s (computer configuration: Inter Core i3 CPU, 2.53 GHz; RAM, 2.00 GB) and the average optimal value of the objective function is $1.6553e + 05$. One of the optimization results is presented by Fig. 7.

In the optimization shown in Fig. 7, the obtained optimal value is $1.6671e + 05$, and the computation time is 4.065 s. After decoding the

Table 4
Comparison of different production solutions.

Solutions	MC	EQ	PP	S ₁	S ₂	S ₃	S ₄	S ₅	S ₆	S ₇	S ₈
Total profit ($\times 10^5$)	1.67	0.35	1.45	0.69	-0.53	-0.11	-0.77	-0.85	-0.91	-0.73	-0.93

Note:

• Solution MC: To manufacture based on the mass customization model. Its calculation process is shown in the above sections.

• Solution EQ: To manufacture the different products equally. Its calculation process is as follows.

• The quantity of each product type is equal.

• $x_i = 125, i = 1, 2, \dots, 8$.

• Total profit = 0.35×10^5 .

• Solution PP: To manufacture based on the preference percentages in Table 2. Its calculation process is as follows.

According to Table 2, $x_1 = 336, x_2 = 144, x_3 = 224, x_4 = 84, x_5 = 56, x_6 = 36, x_7 = 96, x_8 = 24$, substituting into the total profit function, we get: Total profit = 1.45×10^5 .

• Solution S_i: To only manufacture Product of type *i*. Its calculation process is as follows.

- For Solution S₁, $x_1 = 1000, x_2 = x_3 = x_4 = x_5 = x_6 = x_7 = x_8 = 0$, so Total profit = 0.69×10^5 .
- For Solution S₂, $x_2 = 1000, x_1 = x_3 = x_4 = x_5 = x_6 = x_7 = x_8 = 0$, so Total profit = -0.53×10^5 .
- For Solution S₃, $x_3 = 1000, x_1 = x_2 = x_4 = x_5 = x_6 = x_7 = x_8 = 0$, so Total profit = -0.11×10^5 .
- For Solution S₄, $x_4 = 1000, x_1 = x_2 = x_3 = x_5 = x_6 = x_7 = x_8 = 0$, so Total profit = -0.77×10^5 .
- For Solution S₅, $x_5 = 1000, x_1 = x_2 = x_3 = x_4 = x_6 = x_7 = x_8 = 0$, so Total profit = -0.85×10^5 .
- For Solution S₆, $x_6 = 1000, x_1 = x_2 = x_3 = x_4 = x_5 = x_7 = x_8 = 0$, so Total profit = -0.91×10^5 .
- For Solution S₇, $x_7 = 1000, x_1 = x_2 = x_3 = x_4 = x_5 = x_6 = x_8 = 0$, so Total profit = -0.73×10^5 .
- For Solution S₈, $x_8 = 1000, x_1 = x_2 = x_3 = x_4 = x_5 = x_6 = x_7 = 0$, so Total profit = -0.93×10^5 .

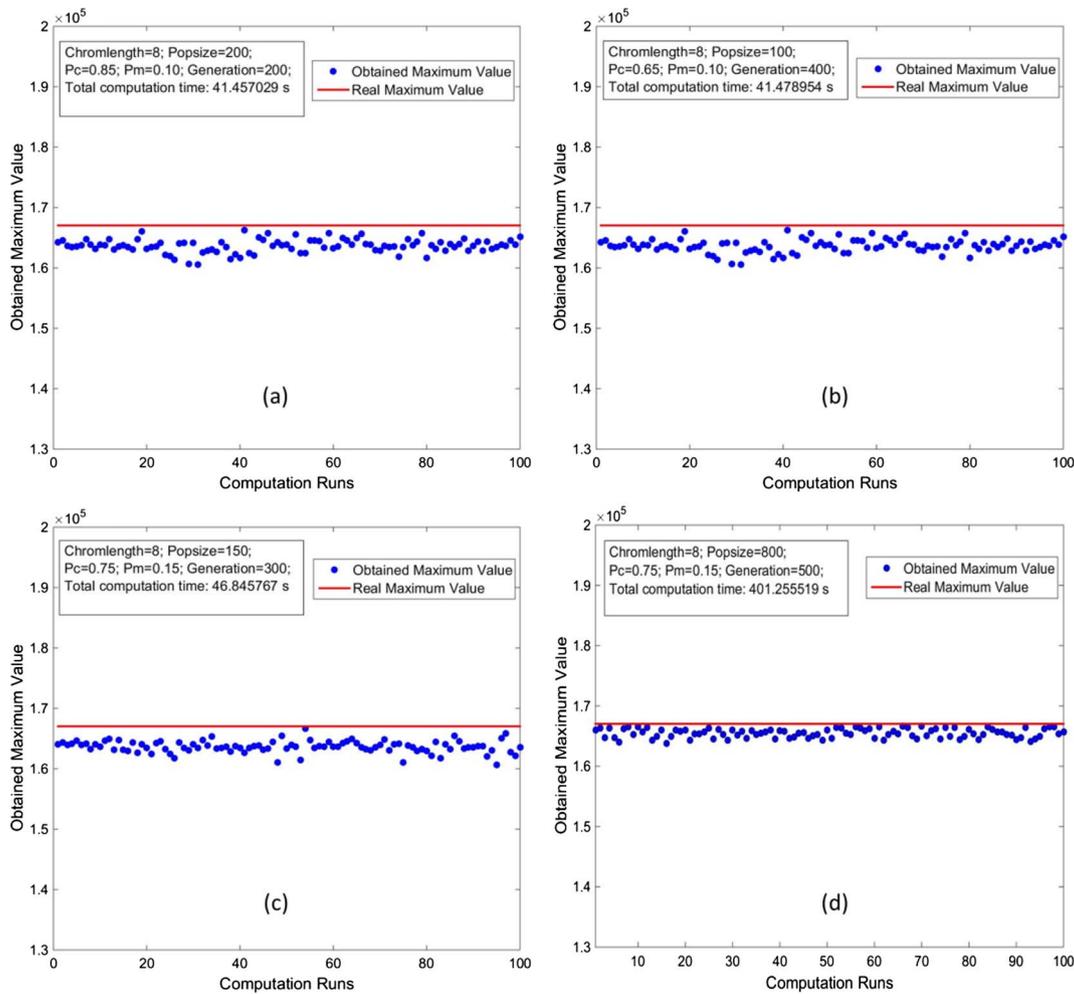


Fig. 8. GA performance testing.

identified genetic chromosome with the best fitness function value, the best chromosome, optimal solution, for the optimization problem is shown in Table 3.

From this solution, the profit gained can be evaluated. A comparison of profits offered by different production solutions are shown in Table 4.

To measure the performance of the designed GA, a set of testing computations are conducted in different parameter setups and the results are compared with the real optimal solution, $1.6703e + 05$, which is obtained by using an enumeration method with a computation time of nearly 2 days (using the same computer configuration). Fig. 8 presents the computation results comparing with the real optimal solution. Four sets of GA running parameters are tested in 100 computation runs respectively. It is easy to observe from the testing computation results that the GA optimization cannot always touch the real optimal solution. But, it can provide solutions which are very close to the real optimal value and the computation teach for each run is less than 5 s. By increasing the size of population without changing GA operators, the obtained optimal solutions are improved in average as shown in Fig. 8(d), where the solutions are closer to the real optimal value. However, this may also increase the computation cost. To widen the comparison analysis, the optimization example is also sent to traditional popular optimization tools, e.g. LINGO, CPLEX, MATLAB Optimization Tool Box, in operation and logistics domains. However, the ordinary versions of these tools have difficulty to solve this non-linear-discrete problem. As claimed by a commercial optimization software company (http://www.lindo.com/doc/online_help/lingo15.0/solver_status_window.htm), ‘in general, this class of model (MINLP, Integer

Nonlinear Program) will be very difficult to solve for all but the smallest cases.’ Hence, the future users of the proposed MC model are advised to adopt EA methods to search for acceptable solutions for their application contexts.

The computation testing results and comparison analysis show that the GA’s performance is sufficient for the current example since the

Table 5
Preference percentage of different design options.

Factors	Options	Preference percentage
Cloth weave	Knitted (A)	0.63
	Non-knitted (a)	0.37
Fabric	Cotton (B)	0.54
	Chemical fiber (b)	0.46
Neck design	Square-neck (C)	0.72
	V-Neck (c)	0.28

Table 6
Preference percentage of different product types.

Product type	Type 1	Type 2	Type 3	Type 4	Type 5	Type 6	Type 7	Type 8
	(ABC)							
Preference percentage	0.245	0.144	0.209	0.095	0.081	0.056	0.122	0.048

Table 7
Comparison of different production solutions.

Solutions	MC	EQ	PP	S ₁	S ₂	S ₃	S ₄	S ₅	S ₆	S ₇	S ₈
Total profit ($\times 10^5$)	1.11	0.43	0.98	0.02	-0.53	-0.20	-0.73	-0.78	-0.85	-0.62	-0.88

solution space and numbers of variables are not very large. For large scale computation problems with multi-objective functions, the proposed basic GA can be improved by adding advanced heuristic searching schemes or more advanced GA operators to improve the searching efficiency. However, this is out of the scope of this paper where the main contribution is the proposed decision model for MC. In future real industrial case studies, an improved GA will be developed.

5. Discussions

The results obtained (Table 4) show that the Mass Customization model offers the best profit overall production solutions tested. A gain of 15% is observed in relation to the solution PP (Preference Percentages) which represents the second best solution and which is usually implemented as production strategy. The MC model may provide substantial additional profits to this current solution.

Table 1 shows the preference percentage of different design options and those data sets can be obtained by market survey or statistical analysis based on the previous sales. The data used in this paper is based on a very small-scale survey, and in case of the possible inaccuracy, a. There is a risk of inaccuracy of the preference percentages evaluated. This can also be the case in larger-scale problems. In order to assess the sensitivity of the MC model to the variation of the preference percentages, a comparable test is also implemented. In Table 5, the preference percentage of the first option of each factor is modified by 10% less than in relation to the data in Table 1.

From Table 5, we may obtain preference percentages of different product types, shown in Table 6.

Table 7 shows the results in terms of profit obtained with the modified data.

The results show that the MC model gives the best profit. A gain of 13% can be observed in relation to the solution PP. The variation of the preference percentages may modify the gain in terms of profit, but the MC model permits to optimize the production strategy. The MC model proposed by this paper can lead to a production decision which has higher profit.

In real world practice, it is not suitable for companies to provide all possible product/service that may have potential buyers in the market. On the other hand side, clients would mostly not pay a relatively extremely high price for what he/she want. In most cases, clients would give up a part of requirements for lower product/service price. In other words, companies should decide what to produce and the quantity of each product by taking into account the willingness to pay of clients. Experimental results shows the proposed MC model can help companies to make production decision and have a better profit compared to other possible solutions.

6. Conclusions

One of the key issues of the proposed mass customization model is to determine what types of product and how many should be provided to clients. Customization does not mean to satisfy all customer requirements without any constraint. Not only the production cost or manufacturing activities should be controlled, but the customer requirements should also be controlled. In other words, customization in our model does not refer to original creativity of customer, and the range of customization is controlled by the company, so as to make the production platform realizable and efficient.

In order to increase the impacts of customers' preference and

control customers' requirements in a reasonable range, customers are required to give weights to their different options during the customer information gathering model. On one hand, companies may have a deeper understanding of customers' preference which can help companies to adjust their commercial activities; on the other hand, customers' preferences are better respected.

This paper proposes a decision support model based on mass customization. Mass customization aims at solving contradictions between mass production and customized requirements, which lead to reduce cost and increase price respectively. Most existed researches in the literature on mass customization are lack of quantitative modeling and calculation for solution optimization in the production process, which is the main contribution of this paper. Based on processing information about products and customers, the quantitative MC model can be applied to maximize total profit and make optimized production decision. Further research opportunities could include taking more consideration on supply chain management as material stock, which will greatly affect product cost and issues of dynamic orders. Client co-design problem is also a challenge to the mass customization issues.

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