A REVISED IMPERIALIST COMPETITION ALGORITHM FOR CELLULAR MANUFACTURING OPTIMIZATION BASED ON PRODUCT LINE DESIGN

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ABSTRACT. Due to the fierce market competition, enterprises try to satisfy customers’ requirements for personalized products in order to maximize profit or market share of their products. This not only needs to determine the product variants through product line design, but also needs to pay attention to resource allocation in the manufacturing process. This paper proposes a cellular manufacturing optimization model that considers the market and production. If the company excessively pursues the satisfaction of customers’ personalized needs, the manufacturing time and cost may increase accordingly. Of course, with the restriction of production capacity in manufacturing cells and the expectation of reducing cost, managers cannot design attributes’ levels of a product line casually, which may result in its unstable marketing share and profit. Therefore, the product demand influenced by customers’ preferences could be a key factor to link market and production. The objective of the propose model is to maximize product profit which consists of revenue and miscellaneous costs (material, processing, transportation, final assembly and fixed costs). A revised imperialist competitive algorithm (RICA) is developed to optimize the discrete problem. Extensive numerical experiments and t-test are carried out to verify the effect of this method. The results demonstrate the proficiency of RICA over another imperialist competitive algorithm based method and genetic algorithm in terms of solution quality.

1. Introduction. With market segmentation in industrial settings, the production mode with small batch and multi-variety characteristics has become a development trend. Cellular manufacturing system (CMS) is suitable to this production mode because of its unique advantages, but it may not automatically achieve benefits from both the market and manufacturing aspects. Customers have demands for more and more personalized products or services, and also hope to obtain the deliveries at the lowest expense. In contrast, the production cost is bound to increase for the products that can better meet the personalized needs of customers, but the

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enterprise expects to achieve the benefit from reducing production cost. In order to solve this dilemma, it is worth to analyse the problems of cellular manufacturing optimization and product line design considering customer preference.

On one hand, from the perspective of production, cellular manufacturing system should consider the trade-off among various costs, such as processing cost, material handling cost, assembly cost and fixed cost in the production process. Let us take the component dispatching as an example. If a type of components of many product variants is all processed within a cell, the intercellular material handling cost can be saved. However, it may give rise to longer makespan of this type of components in the cell, thus resulting in high fixed cost. Consequently, how to organize manufacturing resource and assign tasks is a very key issue in cellular manufacturing system.

On the other hand, from the view of product line design (PLD), a product can be regarded as “a basket of attribute”, and a product line is a combination of product variants. Customer preference for products is manifested through the selection of different levels of different attributes [40]. For an individual customer, the enterprise can easily determine a product line design scheme maximizing customer preference through choosing his/her favorite attribute’s levels. However, for the whole market with a lot of customers, a certain product line design scheme that is welcomed by some customers is often not popular with others. It is difficult to find a suitable design scheme such that all customers are willing to purchase the products with the largest probability.

Obviously, there is a relationship between the product line design and production. If the company excessively pursues a popular design scheme for customers, the processing time of certain component may become longer. Thus, the component is not appropriate to be assigned in the cell with too many this kind of components, and otherwise its production is probably delayed. In addition, for a candidate method of component dispatching, in order to reduce the makespan of all products, managers should consider the processing time which each component occupies in the corresponding cell. This has an impact on the determination of how to select the attributes’ levels of products.

Meta-heuristic algorithms, such as genetic algorithm and particle swarm optimization [12, 11, 10, 38], are of profound importance in solving optimization problems especially when the problems are either too difficult or too complicated to find a solution using traditional methods. Imperialist competitive algorithm (ICA) is a socially-inspired meta-heuristic method based on the competition for colonies among imperialists. Since ICA was proposed by Atashpaz-Gargari and Lucas in 2007, it has been successfully applied to a variety of optimization problems, including mathematics problems, scheduling problems and classification problems. For instance, Abdollahi et al. [1] employed ICA for solving the systems of nonlinear equations. Ardeh et al. [4] proposed an Explorative Imperial Competitive Algorithm (EXPLICA) with explorers and retention policies, which was utilized for optimizing the real-valued functions. Nemati et al. [34] used ICA to solve the Travelling Salesman Problem. Rad et al. [39] applied ICA in the feature selection problem. Classical ICA usually deals with continuous problems, and it can also be applied to discrete problems through some improvements.

In the context of personalized customization, enterprises want to cater for customer preferences greatly, so production cost may be relatively high under the constraints of existing manufacturing condition. Moreover, if the enterprises only
design the product configuration from the point of view of the production cost, they may not be able to produce the favourable products for customers. This motivates us to study cellular manufacturing optimization based on product line design. The main contribution of this paper lies in the following two aspects. Firstly, the proposed model takes full account of the influence of customer preferences on product design and production cost, which can achieve a balance between customer personalized demand and enterprise profit. The objective is to maximize sale revenue and minimize material cost, processing cost, transportation cost, etc. Secondly, this paper proposes a revised imperialist competition algorithm (RICA) to optimize the discrete problem, so that RICA can be effectively applied to the actual industrial scale manufacturing system.

The remainder of this paper is organized as follows. The literature review about cell formation in CMS, product line design and consumer preference are presented in Section 2. The proposed problem and its mathematical model are described in Section 3. Section 4 develops a revised imperialist competitive algorithm and explains its implementation. Section 5 introduces the genetic algorithm (GA) as a comparison benchmark. In Section 6, numerical experiments and t-test are carried out to compare the effect of RICA, another ICA based method, and GA. Finally, Section 7 concludes this paper with some valuable research directions.

2. Literature review.

2.1. Cell formation problem in CMS. Cell formation (CF), as a fundamental issue of CMS, aims to solve the problem that which machines or parts are assigned to which cell. In most of the CF problems, some factors such as intercellular and intracellular movements, cell load variation, and grouping efficacy were often considered. Gupta et al. [14] initially used genetic algorithm (GA) to solve CF problems. They considered three independent objectives of minimizing intercellular and intracellular moves, minimizing cell load variation, as well as minimizing both above objectives simultaneously. Kashan et al. [19] developed a new discrete particle swarm algorithm to solve the cell formation problem with the objective of maximizing grouping efficacy. Liu and Wang [27] studied an integrated problem of cell formation and task scheduling considering multi-functional resource and part movement using hybrid simulated annealing. Wang et al. [45] further investigated worker movement for this kind of problem. Kamalakannan and Pandian [17] identified machine cells and part family to establish production cells for reducing cell load changes. A feasible tabu search (TS) algorithm was proposed to investigate possible solutions. Moreover, a modified grouping efficiency (MGE) was formulated to assess the grouping efficiency of TS. Bagheri and Bashiri [6] designed the cells under indefinite demand values with multi-objectives of minimizing the total cell load variation, the total intercellular and intracellular part trips, etc. They proposed a genetic imperialist competitive algorithm, and tested the proposed model by a real-world case study taken from a glass mold company.

Many researchers investigated conventional CF optimization objectives associated with cost and time. Zohrevand et al. [50] proposed a tabu search-genetic algorithm (TS-GA) to optimize two objectives, one of which is minimizing the total cost related to machine, parts and workers, and the other is maximizing labor utilization. Wang et al. [46] designed an improved bacterial foraging algorithm for cell formation and product scheduling considering learning and forgetting factors in
order to minimize makespan. Jouzdani et al. [16] considered the machine reliability, material processing cost of intercellular and intracellular movement, and setting cost. They proposed a generalized model and designed an improved simulated annealing algorithm for solving the CF problem. Li et al. [24] studied the flowline manufacturing cell scheduling problem (FMCSP) with sequence-dependent family setup times (SDFSTs). A hybrid harmony search (HHS) was developed based on NSGA-II to minimize total tardiness and mean total flowtime. The technique was compared with NSGA-II, memetic algorithm (MA) and other meta-heuristic technique to prove its efficiency. Liu et al. [25] considered a joint decision model of cell formation and task scheduling in cellular manufacturing system, and proposed an efficient discrete bacteria foraging algorithm to minimize the material handling costs as well as the fixed and operating costs of machines and workers. They [28, 29] also analysed backorder cost, holding cost, salary cost, transfer cost of facilities, and material cost in CMS. Zhao [49] proposed the scheduling problem in the rotating seru production system with new job arriving, and designed multiple strategies of memetic algorithm to minimize the total flow time of jobs and total labor hours. The memetic algorithm uses NSGA-II as global search algorithm, and two improved Nawaz-Enscore-Ham (NEH) heuristics as local search algorithms. This method can help to simulate the effort of the majority of general public and a few social elites with professional knowledge in order to promote the progress of social culture. Mehdizadeh et al. [30] considered cell formation and production planning simultaneously. The objectives were to minimize total costs involving machines, parts and workers, as well as minimize the summation of machines’ idle times. They proposed a vibration-damping optimization for finding Pareto-optimal frontier.

In recent years, a few researchers discussed corporate responsibility in the process of cell formation, such as part quality, job opportunity and energy consumption. Bootaki et al. [8] proposed a model considering minimization of parts movements and maximization of part quality. They dealt with the problem using a new technique called GA-AUGMEON, which is tested on some randomly generated small and large size examples. Niakan et al. [36] adopted NSGA-II to solve a CF problem which minimizes the cost related to machines and workforce, and maximizes social issues such as job opportunity. They used randomly generated datasets to test their model. Liu et al. [26] configured a virtual cellular manufacturing system which involves resource constraint, time cost and energy consumption level.

2.2. Consumer preference. The purchase behavior of customers is the basis of predicting the market demand, and each customer has his/her own preference and value measurement criteria [48]. Howard and Sheth [15] believed that customer preference could be regarded as an attitude, and this attitude could guide customers’ purchase decisions, resulting in a behavioral tendency to purchase a specific product rather than other products. Norton [37] believed that customer’s preference was a subjective judgment of the product in his/her heart, and its criteria came from the characteristics of product and the customer’s usage feeling. Customers can develop a set of their own value evaluation system with psychological changes. Cao et al. [9] thought that customers’ preferences were related to their emotions and experiences, and had a considerable influence on purchase decisions. Ng and Law [35] developed an approach to summarizing the user-generated content (UGC) from social networking media using fuzzy set and evidential reasoning (ER) without the need to review all the comments. It is a new attempt in investigating consumer preferences for product designs. Scholars have been studying consumer preferences
through different products. Achabou et al. [2] examined consumer preferences for ethical fashion products by focusing on the importance of animal welfare attribute. To explain the attitude-behavior gap, this research explored the costs and sacrifices associated with the adoption of responsible behaviors. Cluster analysis helped to identify different profiles of consumers by taking into account the individuals' characteristics. Agnew and Dargusch [3] examined the role of consumer in the emerging household-level battery market. They used stated preference data and choice modelling to measure household preferences for battery attributes and functionality. Grasso and Asioli [13] provided the first critical scientific investigation of UK consumers' preferences for novel food products made with upcycled ingredients using four attributes: price, flour, protein and Carbon Trust label. Results from a hypothetical ranking experiment suggested that there was heterogeneity in consumers' valuation.

2.3. **Product line design problem.** A product line is a product category, which is composed of several product items with the same functions and different specifications, models and colors to meet the needs of the same kind of customers. There are a few studies on the optimization of product line design. Michalek et al. [32] proposed a unified method for product line optimization, which could coordinate the problems of market positioning and engineering design. Tookanlou and Wong [42] analyzed the problem of optimal product line design involving marketing channels where consumers were heterogeneous in both horizontal and vertical dimensions. They developed a model to evaluate the effect when it was preferable for a firm to extend the product line in a vertical or horizontal direction. Tsafarakis et al. [43] presented a new hybrid particle swarm optimization (PSO) method, which was able to search for the best product line in large design space with discrete and continuous design variables. They [44] also proposed a fuzzy self-tuning differential evolution (FSTDE), which is compared with differential evolution (DE) methods with different mutation strategies, as well as GA and SA, using real and artificial data of consumer preferences. The results showed that FSTDE was an attractive alternative to solve the PLD problem. Kuzmanovic and Martic [22] proposed a new conjoint-based approach to designing competitive new product lines using the Nash equilibrium concept. The optimal production line design problem of each enterprise is formulated as a nonlinear integer program. Tookanlou and Wong [41] researched the product line design decisions of manufacturers when selling customized products in markets where customers had heterogeneous value for product attributes. This model provided insight for the manufacturer to choose two product strategies with two different customization levels or one product strategy with a single customization level. Kuzmanovic et al. [23] proposed a model which designed a competitive profit-maximizing product line for a heterogeneous market. Preferences were modelled by partial utilities associated with the corresponding attribute’s levels through logit model. The proposed model was tested on the previously published conjoint data set to confirm its efficiency and applicability.

2.4. **Literature gap.** Table 1 summarizes the above mentioned literature. From this table, we can also observe that cell formation in CMS, consumer preference, and product line design have been important research topics. Many previous studies have discussed cellular manufacturing and product line design as two separate
Table 1. Literature review of research scenario and solution method

| Authors                  | Cell formation | Consumer preference | Product line design | Solution method |
|--------------------------|----------------|---------------------|---------------------|------------------|
| Gupta et al. [14]        | ✓              | -                   | -                   | GAs              |
| Kashan et al. [19]       | ✓              | -                   | -                   | GBPSO            |
| Kamalahkamian and Pandian [17] | ✓          | -                   | -                   | TS, MGE          |
| Bagheri and Bashiri [6]  | ✓              | -                   | -                   | GICA             |
| Zohrevand et al. [50]    | ✓              | -                   | -                   | TS-GA            |
| Jouzdani et al. [16]     | ✓              | -                   | -                   | SA               |
| Li et al. [24]           | ✓              | -                   | -                   | HHS              |
| Liu et al. [23]          | ✓              | -                   | -                   | DBFA             |
| Zhao [49]                | ✓              | -                   | -                   | Memetic Algorithm |
| Mehdizadeh et al. [30]   | ✓              | -                   | -                   | MOVDO            |
| Bizotaki et al. [8]      | ✓              | -                   | -                   | GA-AUGMECON      |
| Niakan et al. [36]       | ✓              | -                   | -                   | NSGA-II          |
| Liu et al. [20]          | ✓              | -                   | -                   | DICAP            |
| Howard and Sheth [15]    | -              | ✓                   | -                   | Buyer Behavior Theory |
| Norton [37]              | ✓              | ✓                   | -                   | Coase Theorem    |
| Cao et al. [9]           | -              | ✓                   | ✓                   | Ontology-based   |
| Ng and Law [35]          | ✓              | ✓                   | ✓                   | Fuzzy-ER         |
| Achabou et al. [2]       | -              | ✓                   | ✓                   | Conjoint Analysis, |
| Agnew and Dargusch [3]   | -              | ✓                   | ✓                   | Cluster Analysis |
| Grasso and Asiori [13]   | -              | ✓                   | ✓                   | BWS, DCE         |
| Michalek et al. [32]     | ✓              | ✓                   | ✓                   | DCMs             |
| Tookanlou and Wong [42]  | ✓              | ✓                   | ✓                   | Conjoint Analysis |
| Tsafarakis et al. [43, 44]| ✓            | ✓                   | ✓                   | Empirical Studies |
| Kuzmanovic et al. [23]   | ✓              | ✓                   | ✓                   | Hybrid PSO, FSTDE |
| This paper               | ✓              | ✓                   | ✓                   | RICA             |

issues, which are in fact related in the customized production environment. Product line design focuses on the market strategy level, and cellular manufacturing pays attention to the production and operation. Of course, product line design has an influence on the organization and utilization of manufacturing cells, while some factors in product fabrication, such as processing time, restrict full satisfaction of consumer preference in the product line design. Few articles have simultaneously taken into account cell formation and product line design in cellular manufacturing enterprises. Both product design managers and shop floor managers hope to determine the attributes’ levels and order demand for product variants in the light of customers’ preferences. Therefore, it is desired to construct a cellular manufacturing optimization model based on product line design, which regards customer preference as a linkage.

3. Problem description and formulation.

3.1. Background of the problem. The problem arises from the design and production of customized products such as vacuum glass. Each product has a bundle of attributes (characteristics) with several specific levels. The detailed description of vacuum glass is shown in Table 2. For example, the attribute ‘thickness’ has levels ‘thin’, ‘thick’ and ‘super thick’. The attribute ‘light transmission’ has levels ‘transparent’, ‘translucent’ and ‘opaque properties’. The attribute ‘thermal insulation’ has levels ‘general’, ‘good’ and ‘excellent’. Customers can select the attribute’s levels according to their requirements. People living in the north prefer excellent thermal insulated glass, while people in the south prefer general thermal insulated glass. Ocean-view rooms usually have good viewing effect when transparent glass wall is installed, some private places require opaque glass, while some office compartments prefer translucent glass.

From the view of production side, vacuum glass has three components which need to be processed. They are respectively associated with the attribute categories of shape, function and accessory. Each component of each product type is assigned to
Table 2. Attributes and levels of vacuum glass

| Component      | Attribute                  | Level                        |
|----------------|----------------------------|------------------------------|
| Component 1    | Thickness                  | Thin, thick, superthick      |
|                | The shape of the support   | Cylindrical, spherical, oval |
|                | Glass shape                | Square, circular, rhombic    |
| Component 2    | Color                      | Blue, gray, green            |
|                | Light transmission         | Transparent, translucent, opaque |
|                | Thermal insulation         | General, great, excellent    |
|                | Edge banding material      | Metallic, plastic, rubber    |
| Component 3    | Decoration                 | Retro, fashion, chinoiserie  |
|                | Welding of metallic layer  | Metal brazing, gastight welding, laser welding |

a suitable cell for processing on corresponding equipment. For example, the components associated with shape, function, and accessory categories can be processed on available machining, furnace, and welding equipments, respectively.

3.2. Problem hypotheses and notations. The problem is formulated based on the following hypotheses:

- Cells and machines: The number of cells are known in advance. There are all types of machines in each cell, but only one machine of a type is placed in it. Each type of machine can only process one type of component. The number of machine types in each cell is equal to the number of components of each product type. Each component of a product can be processed on the corresponding machine in any cell. The machines are distributed evenly on the production floor and do not need to be moved over the planning horizon.

- Products, attributes and levels: The number of product types is known in advance. Each product type has several key attributes. Each attribute has several candidate levels to be chosen. For designers or decision makers, any combination of attributes’ levels forms a product design scheme.

- Process: Each product type consists of several specific components, each of which is produced on a fixed machine of certain type. The production of components for each product type has no precedence constraint, and the assembly task needs to be completed in a final assembly shop. The setup and unload time of each product between two different machines can be ignored. Moreover, the processing of each component of each product type cannot be interrupted once started.

- Profit: It consists of six parts, one of which is the product revenue, and the others are various costs in the production process. Material cost is determined by unit price of component’s material and product demand. Similarly, the processing cost is determined by unit processing cost of components and product demand. Transportation cost is closely related to the number of times that all components of a product type are transported to the final assembly shop after being processed in one or more cells. It is considered that the transportation capacity from the cell to the assembly shop is large enough, i.e., no matter how many components of a product type are processed in a cell, they can be transported to the final assembly shop together. Therefore, the cost of transportation is determined by the unit material handling cost
and the transportation times. Final assembly cost is determined by the unit assembly cost and product volume. The determining factor of fixed cost is the duration of all products.

The input parameters and decision variables used in the model are listed as follows.

**Input parameters:**
- \( J \): Number of company’s product types, \( j \) denotes the index of product types \( (j = 1, 2, \ldots, J) \).
- \( J' \): Number of competitive product types in the market for each company’s product type, \( j' \) denotes the index of competitive product types \( (j' = 1, 2, \ldots, J') \).
- \( M \): Number of components of each product type (or number of machines in each cell), \( m \) denotes the index of components or machines \( (m = 1, 2, \ldots, M) \).
- \( C \): Number of cells, \( c \) denotes the index of cells \( (c = 1, 2, \ldots, C) \).
- \( A \): Number of attributes, \( a \) denotes the index of attributes \( (a = 1, 2, \ldots, A) \).
- \( L \): Number of levels, \( l \) denotes the index of levels \( (l = 1, 2, \ldots, L) \).
- \( s \): Candidate design scheme for product type \( j \), i.e., the total level configurations for all attributes of product type \( j \) form a design scheme \( s \) \( (s = 1, 2, \ldots, L^A) \).
- \( P_{js} \): Price of product type \( j \) based on scheme \( s \). It is equal to the sum of the prices of each attribute under the given scheme \( s \), i.e., \( P_{js} = \sum_{a=1}^{A} p_{jsa} \), where \( p_{jsa} \) is the price of attribute \( a \) of product type \( j \) based on scheme \( s \).
- \( \Phi_m \): Attribute set of component \( m \).
- \( H_{jms} \): Unit material cost of component \( m \) of product type \( j \) based on scheme \( s \). It is the sum of the material costs of each attribute under the given scheme \( s \), i.e., \( H_{jms} = \sum_{a \in \Phi_m} h_{jsa} \), where \( h_{jsa} \) is the material cost of attribute \( a \) of product type \( j \) based on scheme \( s \).
- \( K_{jms} \): Unit processing cost of component \( m \) of product type \( j \) based on scheme \( s \). It is the sum of the processing costs of each attribute under the given scheme \( s \), i.e., \( K_{jms} = \sum_{a \in \Phi_m} k_{jsa} \), where \( k_{jsa} \) is the processing cost of attribute \( a \) of product type \( j \) based on scheme \( s \).
- \( \theta_j \): Material handling cost of transporting the components of product type \( j \) to the assembly shop each time.
- \( \Omega_j \): Unit assembly cost of product type \( j \).
- \( \phi \): Fixed cost per unit time.
- \( t_{jms} \): Unit processing time of component \( m \) of product type \( j \) based on scheme \( s \). It is the sum of the processing time of each attribute under the given scheme \( s \), i.e., \( t_{jms} = \sum_{a \in \Phi_m} \tau_{jsa} \), where \( \tau_{jsa} \) is the processing time of attribute \( a \) of product type \( j \) based on scheme \( s \).
- \( \varphi \): Preference score of a consumer for an attribute’s level.
- \( v_{ij} \): Utility value measuring consumer \( i \)'s taste or preference for product type \( j \).
- \( PROB_{ij} \): Probability that consumer \( i \) chooses product type \( j \).
- \( I \): Number of sample consumers in the market, \( i \) denotes the index of sample consumers \( (i = 1, 2, \ldots, I) \).
- \( S \): Size of represented population in the market.
- \( D_j \): Number of demand for product type \( j \).

**Decision variables:**
- \( x_{jmc} \): 1 if component \( m \) of product type \( j \) is processed in cell \( c \), and 0 otherwise.
- \( y_{jal} \): 1 if attribute \( a \) of product type \( j \) is designed as level \( l \), and 0 otherwise. For product type \( j \), the total level configurations for all attributes at \( y_{jal} = 1(\forall a, l) \) form a definite design scheme \( \delta \).
3.3. **Mathematical model.** The problem can be formulated as a non-linear integer programming model as follows:

\[
\text{Max} \quad \sum_{j=1}^{J} P_j \delta_j \cdot D_j \\
- \sum_{j=1}^{J} \sum_{m=1}^{M} H_{jm} \delta_j \cdot D_j \\
- \sum_{j=1}^{J} \sum_{m=1}^{M} K_{jm} \delta_j \cdot D_j \\
- \sum_{j=1}^{J} \theta_j \cdot \sum_{c=1}^{C} \min \left\{ \sum_{m=1}^{M} x_{jmc}, 1 \right\} \\
- \sum_{j=1}^{J} \Omega_j \cdot D_j \\
- \phi \cdot \max_{c \in \{1, \ldots, C\}} \left\{ \sum_{j=1}^{J} x_{jmc} \cdot t_{jm} \delta_j \cdot D_j \right\} \tag{1}
\]

s.t. \[
\sum_{l=1}^{L} y_{jal} = 1, \quad \forall j, a \tag{2}
\]
\[
\sum_{c=1}^{C} x_{jmc} = 1, \quad \forall j, m \tag{3}
\]
\[
PROB_{ij} = \frac{\exp(v_{ij})}{\sum_{j'=1}^{J} \exp(v_{i j'}) + \exp(v_{ij})}, \quad \forall i, j \tag{4}
\]
\[
D_j = \frac{S}{I} \sum_{i=1}^{I} PROB_{ij}, \quad \forall j \tag{5}
\]
\[
x_{jmc} \in \{0, 1\}, \quad \forall j, m, c \tag{6}
\]
\[
y_{jal} \in \{0, 1\}, \quad \forall j, a, l \tag{7}
\]

The objective function (1) expresses product profit which consists of revenue and five cost items as follows:

1) Revenue: The total income is determined by the price of each product type and its demand. The former is related with its design scheme.

2) Material cost: The total cost of material is required for all components of all products. \(H_{jm} \delta_j \cdot D_j\) represents the material cost of component \(m\) of \(D_j\) products with scheme \(\delta\).

3) Processing cost: There is processing cost for product components. \(K_{jm} \delta_j \cdot D_j\) represents the processing cost of component \(m\) of \(D_j\) products with scheme \(\delta\).

4) Transportation cost: It is incurred when the components of product type \(j\) processed in cell \(c\) are transported together to the assembly shop. \(\min \left\{ \sum_{m=1}^{M} x_{jmc}, 1 \right\}\) checks whether there exist some components of product type \(j\) to be processed in cell \(c\). \(\sum_{c=1}^{C} \min \left\{ \sum_{m=1}^{M} x_{jmc}, 1 \right\}\) decides how many cells product type \(j\) is assigned.
in, which implies how many times the components of product type \( j \) are transported to the assembly shop.

5) Final assembly cost: After all components of a product type are transported to the assembly shop, the assembly operation will be performed with corresponding assembly cost in it. \( \Omega_j \cdot D_j \) means the assembly cost of \( D_j \) products.

6) Fixed cost: It is determined by the unit fixed cost and the duration of all production tasks. \( \sum_{j=1}^{J} x_{jmc} \cdot t_{jm} \cdot D_j \) calculates the accumulated processing time of all components processed on machine \( m \) in cell \( c \). \( \max_{c \in \{1, \ldots, C\}} \left\{ \sum_{j=1}^{J} x_{jmc} \cdot t_{jm} \cdot D_j \right\} \) decides which machine in which cell has the longest processing time (i.e., duration).

Constraint (2) ensures that only one level is selected for each attribute of each product type. Constraint (3) indicates that each component of each product type is only assigned to one cell for processing. Constraint (4) is a formula calculating the probability that customer \( i \) chooses product type \( j \). \( v_{ij} \) is a deterministic term utility that is an expression of consumer \( i \)'s taste or preference for product type \( j \). Constraint (5) shows how to determine product demand. \( D_j \) for product type \( j \) can be calculated through multiplying the average \( PROB_{ij} \) across a number of sample individuals (\( i = 1, 2, \ldots, I \)) by the size of represented population [31]. Constraints (6) and (7) ensure that all decision variables are binary.

For example, product type 1 consists of the third levels of attributes 1 and 2 as well as the first level of attribute 3 (as shown in the grey squares of Table 3). The preference scores of customer 1 for the three levels are 5, 3, and 2, respectively (each score is measured in the integer interval [1,5]). Then the three scores are normalized as 0.50, 0.38 and 0.18 (as shown in the parentheses of Table 3), respectively. The utility value that customer 1 perceives product type 1 is equal to 1.06 via the summation of three normalized values (as shown in the grey square of Table 4). Similarly, the utility values that customers 2 and 3 perceive product type 1 are 0.69 and 1.23, respectively. In addition, the utility values that different customers perceive the competitive products of type 1 can also be calculated (as shown in the green squares of Table 4). Thus, the probability that customers 1, 2 and 3 select product type 1 is 0.24, 0.19 and 0.30, respectively according to constraint (4). Finally, the demand for product type 1 is 73 according to constraint (5).

It is widely recognized that the classical CMS problem belongs to the class of NP-hard problems [7, 21]. The proposed model is NP-hard reasonably since it integrates the CMS problem and product line design along with customer preference. Exact algorithms, such as branch-and-bound technique, backtracking or dynamic programming, would be too time consuming even for a moderate problem. Though some meta-heuristic algorithms such as genetic algorithm are able to solve this model, the imperialist competitive algorithm has the competence of deeper exploration and faster convergence speed.

4. Revised imperialist competitive approach. The imperialist competitive algorithm (ICA) is a sociopolitical meta-heuristic, inspired by historical colonization process and competition among imperialists, to capture more colonies. Each country in the population represents a point in the search space or a potential solution of the optimization problem [26]. In fact, those countries are divided into two main groups called imperialists and colonies. Each imperialist rules over a different number of colonies according to its power, and they form an empire. When the competition starts, the colonies begin to move towards their imperialists, and the imperialists tend to acquire more colonies. Gradually, the powerful empires become stronger
Table 3. Preference scores of each attribute

|       | Attribute 1 (A1) | Attribute 2 (A2) | Attribute 3 (A3) |
|-------|------------------|------------------|------------------|
|       | Level 11 (L11)   | Level 12 (L12)   | Level 13 (L13)   |
|       | (L11)            | (L12)            | (L13)            |
|       | Level 21 (L21)   | Level 22 (L22)   | Level 23 (L23)   |
|       | (L21)            | (L22)            | (L23)            |
|       | Level 31 (L31)   | Level 32 (L32)   | Level 33 (L33)   |
|       | (L31)            | (L32)            | (L33)            |
|       |                  |                  |                  |
| Individual 1 | 2 (0.20) | 3 (0.30) | 5 (0.50) |
| Individual 2 | 2 (0.33) | 3 (0.50) | 1 (0.17) |
| Individual 3 | 4 (0.36) | 2 (0.18) | 5 (0.45) |

Table 4. Utility of different products

|       | A1 | A2 | A3 | Individual 1 | Individual 2 | Individual 3 |
|-------|----|----|----|--------------|--------------|--------------|
| Product 1 | L13 | L23 | L31 | 1.06         | 0.69         | 1.23         |
| Competitive product 1 | L12 | L22 | L33 | 1.16         | 1.24         | 0.84         |
| Competitive product 2 | L11 | L23 | L32 | 1.03         | 0.95         | 0.69         |
| Competitive product 3 | L13 | L22 | L31 | 1.18         | 0.91         | 1.34         |
| Probability $PROB_i$ |  |  |  | 0.24         | 0.19         | 0.30         |
| Demand $D_i$ $(S = 300)$ |  |  |  | 73            |  |  |

and the weak ones collapse. In the end, a unique empire will just remain. In brief, ICA mainly consists of four parts, i.e., the formation of empires, the movement of colonies, the imperialist competition, and the collapse of empires.

This evolutionary optimization strategy has shown high performance and applicability not only in convergence rate but also in global optima achievement when solving different optimization problems [33]. However, it is just suitable for the continuous optimization problems. Therefore, we develop a revised imperialist competitive algorithm to solve the proposed discrete optimization problem. In RICA, the
solution representation, empire formation, movement strategy (colonial assimilation and revolution), competition strategy, collapse strategy, and deep convergence strategy are designed in the following.

4.1. **Solution representation.** The structure of each country should reflect two aspects of information. One is the relationship among products, cells and machines (or components). The other is the relationship among product schemes, attributes and levels. Therefore, we design a scheme containing two ingredients.

The first ingredient, related to the assignment of components to cells, is named matrix $Pr_{Op}Ce$, and shown in Equation (8). The elements of this $J \times M \times C$ matrix are variables $x_{jmc}$ which are either 0 or 1. For example, the term $x_{213} = 1$ means that component 1 of product type 2 is assigned to cell 3 for processing. While completing the matrix, constraint (3) should be satisfied.

$$Pr_{Op}Ce = \begin{bmatrix}
  x_{1MC} & \cdots & x_{JMC} \\
  \vdots & \ddots & \vdots \\
  x_{1M1} & x_{1C} & \cdots & x_{1C} \\
  \vdots & \vdots & \ddots & \vdots \\
  x_{111} & \cdots & x_{J11} 
\end{bmatrix}$$

The second ingredient, related to the selection of attribute’s levels for product scheme, is named matrix $Pr_{At}Le$, and shown in Equation (9). The elements of this $J \times A \times L$ matrix are variables $y_{jal}$ which are either 0 or 1. For example, the term $y_{231} = 1$ means that attribute 3 of product type 2 is level 1. While completing the matrix, constraint (2) should be satisfied.

$$Pr_{At}Le = \begin{bmatrix}
  y_{1AL} & \cdots & y_{JAL} \\
  \vdots & \ddots & \vdots \\
  y_{1A1} & y_{1L} & \cdots & y_{1L} \\
  \vdots & \vdots & \ddots & \vdots \\
  y_{111} & \cdots & y_{J11} 
\end{bmatrix}$$

Combining the above-mentioned two ingredients, the solution representation is $(Pr_{Op}Ce | Pr_{At}Le)$. Figure 1 shows the encode scheme for an example solution.

4.2. **Implementation of RICA.** Some notations used in RICA are summarized as follows.
### Table 1: Product and Component Data

| Product | Component | Cell (C) | Data |
|---------|-----------|----------|------|
| C1      | X11       | X111     | 0 1 0 |
|         | X12       | X121     | 0 0 1 |
|         | X13       | X131     | 1 0 0 |

### Table 2: Product and Attribute Data

| Product | Attribute | Level (L) | Data |
|---------|-----------|-----------|------|
|         | Y11       | L1        | 0 1 0 |
|         | Y12       | L1        | 1 0 0 |
|         | Y13       | L2        | 0 1 0 |
|         | Y14       | L2        | 1 0 0 |
|         | Y15       | L3        | 0 0 1 |
|         | Y16       | L3        | 1 0 0 |
|         | Y17       | L3        | 0 0 1 |
|         | Y18       | L3        | 1 0 0 |
|         | Y19       | L3        | 0 0 1 |

**Figure 1.** The encode scheme for an example solution

- $N_{\text{pop}}$: Population size.
- $N_{\text{imp}}$: Number of imperialists.
- $N_{\text{col}}$: Number of colonies.
- $p_p$: Profit of imperialist $p$ ($p = 1, 2, \ldots, N_{\text{imp}}$).
- $P_k$: Profit of colony $k$ ($k = 1, 2, \ldots, N_{\text{col}}$).
- $p_i$: Profit of country $i$ ($i = 1, 2, \ldots, N_{\text{pop}}$).
- $P$: Mean profit of all countries.
- $P_{\text{min}}$: Minimum profit of all countries.
- $\mathcal{I}_1$: Profit of best country in the current generation.
- $\mathcal{I}_0$: Profit of best country in the last generation.
- $P_{\text{norm}}$: Power (normalized profit) of country $i$.
- $NP_p$: Normalized power of imperialist $p$.
- $N_p$: Number of colonies controlled by imperialist $p$ in the initial population.
- $S_p$: Set of colonies of empire $p$.
- $T$: Temperature.
- $\rho$: Cooling rate.
- $T_p$: Total power of empire $p$.
- $\xi$: Weight coefficient for colony profit.
- $\sigma$: Standard deviation of the profit of countries.
- $U$: Counter that keeps a record of the number of times for which the optimal profit remains unchanged.
- $\varepsilon$: A pre-given threshold indicating the deviation of the profit of countries.
The pseudocode of Algorithm 1 describes the implementation process of RICA, and its flowchart is shown in Figure 2. Because the structure of country designed in sub-section 4.1 is reasonable to reflect a solution of optimization problem, we can observe that RICA can obtain feasible offspring countries through crossover and mutation operators in this sub-section.

4.2.1. Initialization and empire formation. The revised imperialist competitive algorithm is a kind of search method based on population. A country in RICA is corresponding to a chromosome in genetic algorithm, and the world composed of all countries is corresponding to the population. The population size $N_{pop}$ in RICA includes $N_{imp}$ imperialists and $N_{col}$ subordinate colonies, i.e., $N_{pop} = N_{imp} + N_{col}$. These imperialists and colonies are divided into multiple empires. Every empire consists of one imperialist and several colonies. How many colonies each empire has depends on the power of its imperialist. The detailed process of forming the initial empires is displayed in step 3 of Algorithm 1.
Algorithm 1: Revised imperialist competitive algorithm

1. **Input parameters:** $N_{pop}$, $N_{imp}$, $\xi$, $\rho$, $U$, $\varepsilon$.
2. **Initial population:** Randomly generate $N_{pop}$ feasible countries.
3. **Initialization and empire formation:**
   3.1. Select $N_{imp}$ most powerful countries as imperialists, and the rest $N_{col}$ countries as colonies.
   3.2. Calculate the number of colonies controlled by each imperialist $p$:
   $$N_p = \text{round}(P_p \cdot N_{col}).$$
   3.3. For each imperialist $p$, randomly choose $N_p$ colonies to it.
4. **While** ($N_{imp} > 1$) **Do**
   4.1. **For** ($p = 1 \rightarrow N_{imp}$) **Do**
      Implement movement strategy for the colonies in the empire (**Algorithm 2**).
   4.2. Implement competition strategy among all empires (**Algorithm 3**).
5. **While** ($\sigma > \varepsilon$ or $U < 15$) **Do** (initialize $\sigma = 10$)
   5.1. Initial temperature $T = \frac{|OFV(X_i) - OFV(X_j)|}{\ln(0.5)}$, where $OFV(X_i)$ and $OFV(X_j)$ are the objective function values of random solutions $X_i$ and $X_j$, respectively [20];
   5.2. Record the value of $\Im_0$.
   5.3. Implement hybrid movement strategy for the countries in the sole empire (**Algorithm 4**).
   5.4. Implement development strategy for the countries in the sole empire (**Algorithm 5**).
   5.5. Record the value of $\Im_1$.
   5.6. **If** ($\Im_1 = \Im_0$) **Then**
      $$U := U + 1$$
   **Else**
   $$U = 0$$
   5.7. Calculate $\sigma = \sqrt{\frac{\sum_{i=1}^{N_{pop}} (p_i - \overline{P})^2}{N_{POP}}}$. 
   5.8. $T := T \times \rho$.
6. **Output:** The optimal solution with profit $\Im_1$. 
4.2.2. Colonial assimilation and revolution. Imperialists try to promote their own ideological pattern and cultural custom to their colonies in order to control them tightly, which is called assimilation. RICA simulates the process of assimilation by moving all colonies towards their imperialists (cf. step 1 in Algorithm 2). Because the proposed problem is discrete, we design a mutation operator to reflect the movement process (cf. Algorithm 7).

In real world, some revolutions are successful and beneficial to the society, and others may lead to resource depletion and invalid social change. The colonial revolution is a certain tremendous movement in the hope that the colony will be closer to the optimal solution. When a colony moves to a new position, its objective function value may be larger than that of its imperialist. At that time, the position of colony and imperialist is exchanged, i.e., the colony is upgraded to imperialist in the empire, while the original imperialist is relegated to colony (cf. steps 4 and 5 in Algorithm 2).

4.2.3. Empire competition. The mechanism of empire competition simulates the process that the strong empires occupy and control the colonies in the weak empires in real society. First, we need to calculate the total objective function value of the empire, i.e., the total power. The imperialist has greater influence on the power of whole empire than its colonies. Therefore, RICA calculates the total power of an empire by using the formula $T_p = \frac{p_{\text{norm}}}{\sum_{k \in S_p} p_{\text{norm}}}$ in step 4 of Algorithm 3, where $\xi$ determines the degree to which the colonies influence the total power of empire. The weakest colony in the weakest empire is chosen as a ruled country, and the more powerful an empire is, the more likely it possesses the colony (cf. steps 5 and 6 of Algorithm 3).

4.2.4. Empire collapse. The competition among empires makes the powerful empires become stronger and stronger by occupying the colonies of other empires, while the number of colonies in weak empires keeps decreasing. When an empire loses all its colonies, the empire collapses. Then the collapsing imperialist is relegated to a colony and seized by the most powerful empire. With the fall of more and more empires, only one empire is left eventually (cf. step 4 of Algorithm 1).

4.2.5. Deep convergence. When there is only one empire, the ideal state is that all countries have the same positions and the same power. They peacefully coexist with each other to form a perfect new world without competition and plunder. The pretest of classical ICA shows that there are still some differences in the power of these countries within the left single empire due to the lack of subsequent evolution. Thus, in RICA, we add step 5 of Algorithm 1 to describe the process of deep convergence including hybrid movement strategy and development strategy. The former strategy encourages each colony to move continuously in the same direction up to 10 times, only if it can reach favorable positions. This behavior can be called swim vividly. Of course, even if the colony moves to an unfavorable position, it has to accept the reality with a decreasing probability along with dropping temperature (cf. Algorithm 4). The latter strategy provides a chance for all countries in the empire to learn from each other and develop their power (cf. Algorithm 5). The deep convergence method is implemented until the following two conditions are satisfied: 1) the standard deviation ($\sigma$) of the profit of countries in the population is not greater than a pre-given constant ($\varepsilon$), and 2) the optimal profit in the population remains unchanged for $U$ times continuously.
Algorithm 2: Movement strategy

1. For (each $k \in S_P$) Do
   1.1. Calculate current profit $P_k$ of colony $k$.
   1.2. Generate a number $d = 1$ or $d = 2$ randomly. Try to mutate in the $d^{th}$ ingredient of colony $k$ towards imperialist $p$, and then calculate the temporary $P'_k$.
   1.3. If ($P'_k > P_k$) Then
       Accept the movement, try to mutate in the previous ingredient, and then calculate the temporary $P'_k$: $P_k = P'_k$.
   Else
       Generate a random number $r$ in the interval $[0,1]$. If ($r > 0.7$) Then
       Accept the movement, and $P_k = P'_k$;
   Else
       Abandon the movement.

2. Try to mutate imperialist $p$, and then calculate the temporary profit $P'_p$.

3. If ($P'_p > P_p$) Then
   Accept the mutation, and $P_p = P'_p$;
   Else
   Abandon the movement.

4. Identify the colony $k^*$ with the maximum profit in $S_P$, $k^*: P_{k^*} = \max_{k \in S_P} P_k$.

5. If ($P_{k^*} > P_p$) Then
   Exchange the positions of colony $k^*$ and imperialist $p$, and update their profits.

5. Genetic algorithm. Although genetic algorithm (GA) has been proposed for a long time, it is still a very powerful intelligent optimization algorithm based on biological evolution theory, and has been applied to many optimization problems. It is also reasonable to use GA to solve the optimization problem in this paper. GA can act as a comparison benchmark to reflect the performance of RICA in the later experiments. Although the number of function evaluations (NFE) can approximately evaluate the time required for GA performance [18], it cannot be used to compare the effect of GA with RICA, because GA has not been exploited to solve the proposed new model and obtain associated solution by other scholars. Therefore,
Algorithm 3: Competition strategy

1. Record the minimum profit \( P_{\text{min}} \) of all countries in the population.
2. Calculate power of each imperialist \( p \): 
   \[ P_{\text{norm}}^p = P_p - P_{\text{min}} + 3. \]
3. Calculate power of each colony \( k \): 
   \[ P_{\text{norm}}^k = P_k - P_{\text{min}} + 3. \]
4. Calculate total power of each empire \( p \): 
   \[ T_p = P_{\text{norm}}^p + \xi \sum_{k \in S_p} P_{\text{norm}}^k. \]
5. The “roulette wheel” sampling is used to select a prior empire \( p^* \) according to \( T_p \).
6. Hand the weakest colony in the weakest empire to empire \( p^* \).
7. The imperialist with no colony is colonized by empire \( p^* \).
8. Update \( N_{\text{imp}} \) if necessary.

the following designed GA needs to be run within the same computational time of RICA.

- **Chromosome representation:** The chromosome representation is the same as the country representation in RICA, which facilitates the comparison between RICA and GA.
- **Initial population:** Randomly generate 20 initial chromosomes.
- **Fitness function:** \( F_g^k \) represents the fitness value of the \( k^{th} \) chromosome in the \( g^{th} \) generation before selection. Its fitness function is 
  \[ F_g^k = \psi_g^k - \min_{i \in \{1, \ldots, E\}} \psi_g^i + \delta, \]
  where \( \psi_g^i \) is the objective function value of the \( i^{th} \) chromosome in the \( g^{th} \) generation, \( E \) is the number of chromosomes in the \( g^{th} \) generation before selection, and \( \delta \) is a small constant (say 3).
- **Crossover:** All chromosomes cross over in pairs with a pre-given probability \( P_c = 90\% \). If the fitness value of the offspring chromosome generated after crossover is not less than a threshold \( h = \text{average } \psi_g^i + \frac{\max \psi_g^i - \min \psi_g^i}{DR} \) in the \( g^{th} \) generation, the new offspring will be added to the population with a 70% probability; Otherwise, it will be abandoned. Here, \( DR \) is used to adjust the value of \( h \), and is usually set to a fixed value based on experience (say 10). The crossover rule between two chromosomes refers to Algorithm 6 and Figure 3.
- **Mutation:** Each chromosome mutates with a pre-given probability \( P_m = 50\% \). The rule is to make two ingredients of the chromosome to mutate similar to Algorithm 7 (shown in Figure 4). All new chromosomes through mutation are added to the new generation.
- **Selection:** The “roulette wheel” sampling is one of the most common selection strategies. The probability that a chromosome is selected in a population is proportional to the chromosome’s fitness value. We need to add up the fitness values of all chromosomes in the population, and calculate each normalized fitness value \( \tilde{F}_g^k = F_g^k / \sum_{i=1}^E F_g^i \). Then we select each chromosome under the wheel’s marker on each spin until 20 chromosomes are selected,
Algorithm 4: Hybrid movement strategy

1. For (each $k \in S_p$) Do
   1.1. Calculate current profit $\mathcal{P}_k$ of colony $k$.
   1.2. Try to mutate in the 2nd ingredient of colony $k$ towards
       imperialist $p$, and then calculate the temporary $\mathcal{P}_k'$.
   1.3. Let $h = 0$.
   1.4. While ($h < 10$) Do
       If ($\mathcal{P}_k' > \mathcal{P}_k$) Then
       Accept the movement, and $\mathcal{P}_k = \mathcal{P}_k'$;
       Try to mutate in the previous ingredient, and then
       calculate the temporary $\mathcal{P}_k'$;
       $h = h + 1$;
       Else
       Generate a random number $r$ in the interval $[0,1]$, and
       set $\Delta = \mathcal{P}_k - \mathcal{P}_k'$;
       If ($\exp(-\Delta / T) > r$) Then
       Accept the movement, and $\mathcal{P}_k = \mathcal{P}_k'$;
       Else
       Abandon the mutation;
       Break.
   2. Try to mutate imperialist $p$ in the 1st ingredient, and then calculate the temporary profit $\mathcal{P}_p'$.
      If ($\mathcal{P}_p' > \mathcal{P}_p$) Then
      Accept the mutation, and $\mathcal{P}_p = \mathcal{P}_p'$;
      Else
      Abandon the mutation.
   3. Identify the colony $k^*$ with the maximum profit in $S_p$, $k^* : \mathcal{P}_{k^*} = \max_{k \in S_p} \mathcal{P}_k$.
      If ($\mathcal{P}_{k^*} > \mathcal{P}_p$) Then
      Exchange the positions of colony $k^*$ and imperialist $p$, and update
      their profits.
Algorithm 5: Development strategy

1. Try to crossover each country $i$ with any other country in the population, generate a new temporary country $i'$, and calculate its profit $p_{i'}$. The crossover mechanism is described in Algorithm 6 and displayed in Figure 3.

2. If $(p_{i'} > p_i)$ Then
   Replace country $i$ with the new country $i'$;

   Else
   Abandon the new country $i'$.

Algorithm 6: Crossover operator

1. (Cf. Figure 3(a)): Randomly select the same position (dash plane) of $Pr\_Op\_Ce$ of two countries in the parent generation. The left part of dash plane in $Pr\_Op\_Ce$ of the first country and the right part of dash plane in $Pr\_Op\_Ce$ of the second country are combined to generate a feasible sub-offspring $Pr\_Op\_Ce$.

2. (Cf. Figure 3(b)): Similarly, a feasible sub-offspring $Pr\_At\_Le$ is generated through the method as in step 1. Sub-offsprings $Pr\_Op\_Ce$ and $Pr\_At\_Le$ form a new country.

3. If the fitness value of new country obtained from crossover is larger than the average fitness value of all countries in the parent generation, the new country is put into the new generation, and otherwise it is discarded.

Algorithm 7: Mutation operator

1. (Cf. Figure 4(a)): Randomly select two columns of $Pr\_Op\_Ce$ in the country, and swap their elements.

2. (Cf. Figure 4(b)): Randomly select two columns of $Pr\_At\_Le$ in the country, and swap their elements.

similar to rotating roulette wheel in the casino. Obviously, the probability that chromosome $k$ is selected is equal to $\bar{F}_q^k$.

• Stopping rule: GA is stopped when its runtime reaches that of RICA.
6. **Computational experiments.** Since appropriate design for parameters increases the efficiency of algorithms, we calibrate the parameters of proposed RICA using Taguchi method. This method is based on an orthogonal array (OA) that is provided to reduce the number of required experiments [5]. In the experiments, the considered control parameters and their different levels are shown in Table 5. According to the Taguchi standard arrays table, orthogonal array $L_{27}$ which requires 27 experiments is selected to tune the RICA parameters. The experiments are conducted under Minitab 18. Fig. 5 shows the mean and signal-to-noise ratio (S/N) for each level of each RICA control parameter. Therefore, we can obtain the best combination of RICA parameters: $N_{pop}(50)$, $N_{imp}(10)$, $\xi(0.2)$, $\rho(0.6)$, $U(15)$, and $\varepsilon(0.0001)$. 

![Diagram of crossover of Pr_Op_Ce and Pr_At_Le]
After executing Taguchi experimental design and recognizing the desirable values of parameters, we evaluate the performance of RICA in comparison with other meta-heuristic algorithms ICASA [47] and GA. The following experiments for performance comparison are performed on a Core-based Lenovo-compatible personal computer with 1.50 GHz clock-pulse and 8.00 GB RAM. RICA, ICASA and GA are coded in C++, compiled with the Microsoft Visual C++ 6 compiler, and tested under Microsoft windows 7 operating system.

A typical example is given to better demonstrate the optimization problem. Suppose the company produces two types of vacuum toughened glass, each of which is made up of three components. Each product type has nine attributes, and each attribute has three different candidate levels. There are three types of machines distributed in three cells. Each component of a product type is performed on a dedicate type of machine. There are five competitive product types in the market.
for each company’s product type. We conduct a questionnaire survey to obtain customers’ preferences for the types of vacuum glass in construction and transportation. Two questionnaires are shown in the Appendix. Each questionnaire is answered by 100 sample consumers. According to the feedback we can calculate the probability that consumers choose the product type. The weight of preference score for each attribute is randomly generated in the integer interval $[1,3]$. The main parameters of this example are listed in Table 6. This example problem is solved by RICA, ICASA and GA, and Figure 6 shows their convergence within the same runtime.

**Table 6. Parameters of the proposed problem**

| Parameter | Value | Min | Max |
|-----------|-------|-----|-----|
| $M$ : Number of components of each product type (or number of machines in each cell) | 3 | |
| $C$ : Number of cells | 3 | |
| $A$ : Number of attributes of each product type | 9 | |
| $L$ : Number of levels of each attribute | 3 | |
| $J$ : Number of company’s product types | 8 | |
| $J'$ : Number of competitive product types for each company’s product type | 5 | |
| $I$ : Number of sample consumers | 100 | |
| $S$ : The size of represented population in the market | 1000 | |
| $\phi$ : Fixed cost per unit time | 3 | |
| $p_{jsa}$ : Price of an attribute’s level | 10 | 20 |
| $h_{jsa}$ : Material cost of an attribute’s level | 1 | 3 |
| $k_{jsa}$ : Processing cost of an attribute’s level | 1 | 2 |
| $\theta_j$ : Material handling cost each time | 25 | 40 |
| $\Omega_j$ : Unit assembly cost of each product type | 2 | 5 |
| $\tau_{jsa}$ : Processing time of an attribute’s level | 3 | 8 |
| $\varphi$ : Preference score for an attribute’s level | 1 | 5 |

Extensive numerical experiments are conducted to further verify RICA, ICASA and GA. Their performance is to be evaluated by the use of four key impact factors, including the number of machine types ($M$), the number of cells ($C$), the number of attributes ($A$), and the number of levels ($L$). Thus, we design 4 sets of sub-experiments, each of which changed an impact factor. For instance, in the first set, $M$ is allowed to vary from 6 to 24 in order to test its impact effect, given $C = 6$, $A = 9$, and $L = 3$. The performance of each algorithm is compared by the sum of the calculated objective functions for each sub-experiment.
A = 5, and L = 5. They form 4 groups of parameters. The other three sets test the effects of varying C, A, and L, respectively. The other parameters for the randomly generated instances are listed in Table 6.

We use each group of parameters to randomly generate 10 instances. $\bar{V}_{RICA}$, $\bar{V}_{ICASA}$ and $\bar{V}_{GA}$ represent the average objective function values using RICA, ICASA and GA, respectively. $\Delta \bar{V}_{RICA}$ represents the increasing percentage of RICA over ICASA, $\Delta \bar{V}_{GA}$ represents the increasing percentage of RICA over
Figure 6. Convergence diagram of a typical example

GA. CPU denotes the average runtime of an algorithm. From Table 7, we can notice that $\Delta \bar{V}_{RICA}^{RICA}$ reaches 13-19% and $\Delta \bar{V}_{RICA}^{ICASA}$ reaches 17-25% regardless of the variation of the four impact factors $M$, $C$, $A$, and $L$. Obviously, RICA performs better than ICASA and GA.

We further make paired-samples' t-test experiment in Statistical Product and Service Solutions (SPSS) 24.0 software to verify the significant superiority of RICA compared with ICASA and GA. The statistical results of experiment using samples of 16 entries in Table 7 are shown in Table 8.

The 2nd row of the 1st entry shows the following information. The mean, standard deviation, and standard error of the mean for ICASA is 335469, 24735 and 7822, respectively. The mean difference between RICA and GA is 76596. The lower and upper values of 99% confidence interval manifest that the true population mean lies between 46523 and 106669 with a 99% probability. The t-test results show that t-value is equal to 8.277 ($> t_{0.01}(9)=2.8214$), and p-value is equal to 0.000 ($< \alpha = 0.01$). Therefore, both t-value and p-value affirm that in comparison with ICASA and GA, RICA has significant increase in objective function value. Since each t-value and each p-value also satisfy the above constraints, it is evident that RICA has better global optimization ability than ICASA and GA in the sense of statistics.

There are some crucial reasons for the experimental results. Firstly, there are difference among the movement strategies in RICA and ICASA, and the mutation strategy in GA. In RICA, if a colony gets a better position after moving towards its imperialist, it will move in the previous direction again. This is likely to result in deeper exploration. In ICASA, however, the colony will not move further in the favourable direction. In GA, a chromosome only mutates once and then is added to
Table 7. Performance comparison between RICA, ICASA and GA for impact parameters

| \( M = 6 \), \( A = 5 \), \( L = 5 \) | \( \bar{V}_{RICA} \) | \( \bar{V}_{ICASA} \) | \( \bar{V}_{GA} \) | \( \Delta \bar{V}_{RICA}^{ICASA}(\%) \) | \( \Delta \bar{V}_{GA}^{RICA}(\%) \) | CPU (s) |
|---|---|---|---|---|---|---|
| 6 | 398720 | 335469 | 322124 | 19 | 24 | 130 |
| 12 | 607478 | 517620 | 489546 | 17 | 24 | 203 |
| 18 | 797091 | 673714 | 657481 | 18 | 21 | 353 |
| 24 | 1010046 | 860332 | 819408 | 17 | 23 | 519 |
| \( M = 14 \), \( A = 5 \), \( L = 5 \) | \( \bar{V}_{RICA} \) | \( \bar{V}_{ICASA} \) | \( \bar{V}_{GA} \) | \( \Delta \bar{V}_{RICA}^{ICASA}(\%) \) | \( \Delta \bar{V}_{GA}^{RICA}(\%) \) | CPU (s) |
| 3 | 1371713 | 1201124 | 1156277 | 14 | 19 | 308 |
| 6 | 1000975 | 863354 | 829463 | 16 | 21 | 344 |
| 9 | 963418 | 837029 | 796480 | 15 | 21 | 433 |
| 12 | 978119 | 831539 | 791116 | 18 | 24 | 593 |
| \( M = 12 \), \( A = 5 \), \( C = 10 \) | \( \bar{V}_{RICA} \) | \( \bar{V}_{ICASA} \) | \( \bar{V}_{GA} \) | \( \Delta \bar{V}_{RICA}^{ICASA}(\%) \) | \( \Delta \bar{V}_{GA}^{RICA}(\%) \) | CPU (s) |
| 3 | 459945 | 402027 | 388192 | 14 | 18 | 176 |
| 10 | 916115 | 788887 | 741580 | 16 | 24 | 283 |
| 17 | 1343335 | 1154694 | 1104538 | 16 | 22 | 418 |
| 24 | 1601637 | 1344834 | 1285988 | 19 | 25 | 819 |
| \( M = 17 \), \( A = 7 \), \( L = 3 \) | \( \bar{V}_{RICA} \) | \( \bar{V}_{ICASA} \) | \( \bar{V}_{GA} \) | \( \Delta \bar{V}_{RICA}^{ICASA}(\%) \) | \( \Delta \bar{V}_{GA}^{RICA}(\%) \) | CPU (s) |
| 3 | 1304929 | 1156539 | 1111787 | 13 | 17 | 294 |
| 18 | 1427445 | 1198392 | 1155033 | 19 | 24 | 541 |
| 13 | 1403110 | 1178416 | 1137835 | 19 | 23 | 813 |
| 18 | 1421519 | 1222470 | 1173408 | 16 | 21 | 801 |

the population regardless of the outcome of mutation. Secondlty, RICA supplements a deep convergence strategy after a unique empire is left, which contains a hybrid movement strategy and a development strategy. The hybrid movement strategy can accept inferior movements with decreasing probability along with the dropping temperature, which helps RICA to jump out of local optima. The development strategy impels every county to learn from other. Consequently, not only all counties can be possible to move towards better positions, but also the whole population can maintain the diversity. However, ICASA lacks of this deep convergence strategy, and thus cannot perform well than RICA.

7. Conclusions. This paper proposes a new optimization model for cellular manufacturing system based on product line design, which takes into account customer preference from the perspective of market and analyzes task dispatching from the perspective of production. The objective is to maximize the profit, i.e., maximize the income, as well as minimize the material cost, processing cost, transportation cost, assembly cost and fixed cost. In addition, we develop a revised imperialist competitive algorithm to solve the proposed discrete problem. The imperialist competition algorithm in this paper is improved from the following three aspects.
### Table 8. Statistical t-test results from SPSS for samples of entries 1-16

| Sample Size of Each Pair | N = 10 | Degree of Freedom df = 9 | Significance Level α = 0.01 |
|-------------------------|-------|--------------------------|-----------------------------|
| Mean Difference         |       |                          |                             |

#### Sampling Distribution

| Pair | Mean of Paired Differences | Std. Deviation of Paired Differences | Std. Error of Mean | Paired Differences 99% Confidence Interval | T-Value | P-Value |
|------|---------------------------|-------------------------------------|--------------------|--------------------------------------------|---------|---------|
| 1    | RICA 398720, ICASA 30994  | 9801                                |                    | 43515, 36983, 89520                       | 7.825   | 0.000   |
| 2    | RICA 607478, GA 335469    | 89520                               |                    | 76996, 40523, 96909                       | 8.477   | 0.000   |
| 3    | RICA 767414, ICASA 673714 | 20801                               |                    | 139610, 112754, 166466                    | 15.344  | 0.000   |
| 4    | RICA 850966, GA 517620    | 106669                              |                    | 117932, 96715, 139150                     | 19.064  | 0.000   |
| 5    | RICA 997832, ICASA 860332 | 20340                               |                    | 123937, 101520, 145235                    | 18.544  | 0.000   |
| 6    | RICA 1157966, GA 797392   | 20240                               |                    | 123507, 101520, 145235                    | 20.491  | 0.000   |
| 7    | RICA 130713, ICASA 1201124| 30152                               |                    | 139610, 112754, 166466                    | 15.344  | 0.000   |
| 8    | RICA 143533, ICASA 1455944| 106669                              |                    | 143533, 106669, 143533                    | 19.064  | 0.000   |
| 9    | RICA 158487, ICASA 1242366| 27822                               |                    | 1455944, 1242366, 1455944                 | 20.491  | 0.000   |
| 10   | RICA 173280, ICASA 1242366| 35320                               |                    | 173280, 1242366, 1455944                  | 20.491  | 0.000   |
| 11   | RICA 180098, ICASA 158487 | 34359                               |                    | 173280, 1242366, 1455944                  | 19.064  | 0.000   |
| 12   | RICA 197165, ICASA 130713 | 20340                               |                    | 197165, 130713, 20340                     | 18.544  | 0.000   |
| 13   | RICA 20801, ICASA 850966  | 106669                              |                    | 20801, 850966, 20340                      | 15.344  | 0.000   |
| 14   | RICA 223929, ICASA 158487 | 35320                               |                    | 223929, 158487, 35320                     | 20.491  | 0.000   |
| 15   | RICA 242448, ICASA 143533 | 106669                              |                    | 242448, 143533, 106669                    | 19.064  | 0.000   |
| 16   | RICA 253271, ICASA 180098 | 35320                               |                    | 253271, 180098, 35320                     | 20.491  | 0.000   |

Note: Sample size of each pair N=10, degree of freedom df = 9, significance level α = 0.01
• Considering the discrete characteristic of the problem, in the movement strategy, we design a mutation method to represent the process of colonial assimilation into imperialists. If a colony gets better assimilation result, it can further assimilate into its imperialist in the last direction. Otherwise, it accepts the unfavorable result with a given probability. This method can help the world to preserve versatile and reach the optimum at a faster speed in the end.

• In the collapse mechanism, when all colonies of an empire are occupied by other empires, the imperialist does not directly die out, but turns into a colony, and then is occupied by other powerful empire.

• When there is only one empire left, the procedure does not terminate, but goes ahead for deep convergence. In the process, hybrid movement strategy is dedicated to make the colonies to swim along an advantageous path and reach a much profitable status in the solution space. Because of the possible negative influence of swimming (i.e., trapping into local optima), the colonies are also allowed to move to unprofitable positions conforming to a rigorous standard. In addition, development strategy is set to enhance mutual learning between any two countries through a certain mechanism to make all countries to reach more favorable positions with stronger power than before.

Therefore, the proposed approach exhibits superior optimization capability, and outperforms ICASA and GA significantly in the sense of statistics. It has promising application in industrial scale cellular manufacturing, such as spare product processing, fiber connector manufacturing, and assembly production of metallic case parts. The limitation of this research is that it is difficult to acquire the real production data because of its confidentiality in many enterprises. We will try to gather some data that does not involve trade secrets for production research in the future. Fortunately, we have obtained the real data of customers’ preferences through some surveys, so that the model can calculate the real market demand.

The future valuable research direction is to study the ambiguous expression of consumers’ needs. The consumers living in the big data era are facing various marketing attraction, and often express their drifting ideas in the forms of text, image, audio and video in social media. We can apply big data technology to analyze these ideas to obtain consumers’ potential needs for product line design. Since the consumers’ needs are vague and uncertain, the manufacturing system should be more flexible and dynamic to match them. Company managers can invest multi-functional machines and train multi-skilled workers to strengthen flexible ability. It is also worth to consider employing virtual cells to enhance dynamic ability, which possess rapid adaption to product specification changes without physical reconfiguration of cells.

Appendix.

Questionnaire 1 about customer preference for the type of vacuum glass in construction

The type of vacuum glass in construction can be applied in doors, windows, glass curtain wall, soundproof room, observation room, sunshine room, self-service convenience store and so on. Kindly respond to the given questions below and tick mark accordingly.
1. What is your gender?
   □ Male
   □ Female

2. What is the highest level of education you have completed:
   □ Primary school or below
   □ Junior school
   □ Senior school
   □ Junior college
   □ University
   □ Graduate school

3. Do you know about vacuum glass?
   □ Know a lot
   □ Know something
   □ Know nothing

Survey scale: 1=Strongly disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly agree

4. For the attribute of thickness of vacuum glass, the level of thin is more attractive to me.
   □ 1 □ 2 □ 3 □ 4 □ 5

5. For the attribute of thickness of vacuum glass, the level of thick is more attractive to me.
   □ 1 □ 2 □ 3 □ 4 □ 5

6. For the attribute of thickness of vacuum glass, the level of super thick is more attractive to me.
   □ 1 □ 2 □ 3 □ 4 □ 5

7. For the attribute of support shape of vacuum glass, the level of cylindrical is more attractive to me.
   □ 1 □ 2 □ 3 □ 4 □ 5

8. For the attribute of support shape of vacuum glass, the level of spherical is more attractive to me.
   □ 1 □ 2 □ 3 □ 4 □ 5

9. For the attribute of support shape of vacuum glass, the level of oval is more attractive to me.
   □ 1 □ 2 □ 3 □ 4 □ 5

10. For the attribute of glass shape of vacuum glass, the level of square is more attractive to me.
    □ 1 □ 2 □ 3 □ 4 □ 5

11. For the attribute of glass shape of vacuum glass, the level of circular is more attractive to me.
    □ 1 □ 2 □ 3 □ 4 □ 5

12. For the attribute of glass shape of vacuum glass, the level of rhombic is more
attractive to me.

□ 1  □ 2  □ 3  □ 4  □ 5

13. For the attribute of color of vacuum glass, the level of blue is more attractive to me.

□ 1  □ 2  □ 3  □ 4  □ 5

14. For the attribute of color of vacuum glass, the level of gray is more attractive to me.

□ 1  □ 2  □ 3  □ 4  □ 5

15. For the attribute of color of vacuum glass, the level of green is more attractive to me.

□ 1  □ 2  □ 3  □ 4  □ 5

16. For the attribute of light transmission of vacuum glass, the level of transparent is more attractive to me.

□ 1  □ 2  □ 3  □ 4  □ 5

17. For the attribute of light transmission of vacuum glass, the level of translucent is more attractive to me.

□ 1  □ 2  □ 3  □ 4  □ 5

18. For the attribute of light transmission of vacuum glass, the level of opaque is more attractive to me.

□ 1  □ 2  □ 3  □ 4  □ 5

19. For the attribute of thermal insulation performance of vacuum glass, the level of general is more attractive to me.

□ 1  □ 2  □ 3  □ 4  □ 5

20. For the attribute of thermal insulation performance of vacuum glass, the level of great is more attractive to me.

□ 1  □ 2  □ 3  □ 4  □ 5

21. For the attribute of thermal insulation performance of vacuum glass, the level of excellent is more attractive to me.

□ 1  □ 2  □ 3  □ 4  □ 5

22. For the attribute of edge banding material of vacuum glass, the level of metallic is more attractive to me.

□ 1  □ 2  □ 3  □ 4  □ 5

23. For the attribute of edge banding material of vacuum glass, the level of plastic is more attractive to me.

□ 1  □ 2  □ 3  □ 4  □ 5

24. For the attribute of edge banding material of vacuum glass, the level of rubber is more attractive to me.

□ 1  □ 2  □ 3  □ 4  □ 5
25. For the attribute of decoration style of vacuum glass, the level of retro is more attractive to me.
   □ 1 □ 2 □ 3 □ 4 □ 5

26. For the attribute of decoration style of vacuum glass, the level of fashion is more attractive to me.
   □ 1 □ 2 □ 3 □ 4 □ 5

27. For the attribute of decoration style of vacuum glass, the level of chinoiserie is more attractive to me.
   □ 1 □ 2 □ 3 □ 4 □ 5

28. For the attribute of welding process of metallic layer of vacuum glass, the level of metal brazing is more attractive to me.
   □ 1 □ 2 □ 3 □ 4 □ 5

29. For the attribute of welding process of metallic layer of vacuum glass, the level of gastight welding is more attractive to me.
   □ 1 □ 2 □ 3 □ 4 □ 5

30. For the attribute of welding process of metallic layer of vacuum glass, the level of laser welding is more attractive to me.
   □ 1 □ 2 □ 3 □ 4 □ 5

Questionnaire 2 about customer preference for the type of vacuum glass in transportation

The type of vacuum glass in transportation can be applied in high-speed railway, subway, ship, aircraft, airport lookout and so on. Kindly respond to the given questions below and tick mark accordingly.

1. What is your gender?
   □ Male
   □ Female

2. What is the highest level of education you have completed:
   □ Primary school or below
   □ Junior school
   □ Senior school
   □ Junior college
   □ University
   □ Graduate school

3. Do you know about vacuum glass?
   □ Know a lot
   □ Know something
   □ Know nothing

   Survey scale: 1=Strongly disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly agree
4. For the attribute of thickness of vacuum glass, the level of thin is more attractive to me.
   □ 1 □ 2 □ 3 □ 4 □ 5
5. For the attribute of thickness of vacuum glass, the level of thick is more attractive to me.
   □ 1 □ 2 □ 3 □ 4 □ 5
6. For the attribute of thickness of vacuum glass, the level of super thick is more attractive to me.
   □ 1 □ 2 □ 3 □ 4 □ 5

7. For the attribute of support shape of vacuum glass, the level of cylindrical is more attractive to me.
   □ 1 □ 2 □ 3 □ 4 □ 5
8. For the attribute of support shape of vacuum glass, the level of spherical is more attractive to me.
   □ 1 □ 2 □ 3 □ 4 □ 5
9. For the attribute of support shape of vacuum glass, the level of oval is more attractive to me.
   □ 1 □ 2 □ 3 □ 4 □ 5

10. For the attribute of glass shape of vacuum glass, the level of square is more attractive to me.
    □ 1 □ 2 □ 3 □ 4 □ 5
11. For the attribute of glass shape of vacuum glass, the level of circular is more attractive to me.
    □ 1 □ 2 □ 3 □ 4 □ 5
12. For the attribute of glass shape of vacuum glass, the level of rhombic is more attractive to me.
    □ 1 □ 2 □ 3 □ 4 □ 5

13. For the attribute of color of vacuum glass, the level of blue is more attractive to me.
    □ 1 □ 2 □ 3 □ 4 □ 5
14. For the attribute of color of vacuum glass, the level of gray is more attractive to me.
    □ 1 □ 2 □ 3 □ 4 □ 5
15. For the attribute of color of vacuum glass, the level of green is more attractive to me.
    □ 1 □ 2 □ 3 □ 4 □ 5

16. For the attribute of light transmission of vacuum glass, the level of transparent is more attractive to me.
    □ 1 □ 2 □ 3 □ 4 □ 5
17. For the attribute of light transmission of vacuum glass, the level of translucent is more attractive to me.
18. For the attribute of light transmission of vacuum glass, the level of opaque is more attractive to me.

☐ 1  ☐ 2  ☐ 3  ☐ 4  ☐ 5

19. For the attribute of thermal insulation performance of vacuum glass, the level of general is more attractive to me.

☐ 1  ☐ 2  ☐ 3  ☐ 4  ☐ 5

20. For the attribute of thermal insulation performance of vacuum glass, the level of great is more attractive to me.

☐ 1  ☐ 2  ☐ 3  ☐ 4  ☐ 5

21. For the attribute of thermal insulation performance of vacuum glass, the level of excellent is more attractive to me.

☐ 1  ☐ 2  ☐ 3  ☐ 4  ☐ 5

22. For the attribute of edge banding material of vacuum glass, the level of metallic is more attractive to me.

☐ 1  ☐ 2  ☐ 3  ☐ 4  ☐ 5

23. For the attribute of edge banding material of vacuum glass, the level of plastic is more attractive to me.

☐ 1  ☐ 2  ☐ 3  ☐ 4  ☐ 5

24. For the attribute of edge banding material of vacuum glass, the level of rubber is more attractive to me.

☐ 1  ☐ 2  ☐ 3  ☐ 4  ☐ 5

25. For the attribute of decoration style of vacuum glass, the level of retro is more attractive to me.

☐ 1  ☐ 2  ☐ 3  ☐ 4  ☐ 5

26. For the attribute of decoration style of vacuum glass, the level of fashion is more attractive to me.

☐ 1  ☐ 2  ☐ 3  ☐ 4  ☐ 5

27. For the attribute of decoration style of vacuum glass, the level of chinoiserie is more attractive to me.

☐ 1  ☐ 2  ☐ 3  ☐ 4  ☐ 5

28. For the attribute of welding process of metallic layer of vacuum glass, the level of metal brazing is more attractive to me.

☐ 1  ☐ 2  ☐ 3  ☐ 4  ☐ 5

29. For the attribute of welding process of metallic layer of vacuum glass, the level of gastight welding is more attractive to me.

☐ 1  ☐ 2  ☐ 3  ☐ 4  ☐ 5

30. For the attribute of welding process of metallic layer of vacuum glass, the level of laser welding is more attractive to me.

☐ 1  ☐ 2  ☐ 3  ☐ 4  ☐ 5
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