Research Article

Layout Optimization of Flexible Manufacturing Cells Based on Fuzzy Demand and Machine Flexibility

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Layout flexibility is critical for the performance of flexible manufacturing cells, especially in dynamic production environment. To improve layout flexibility, layout optimization should consider more flexible factors based on existed models. On the one hand, not only should the current production demands be covered, but also the future uncertain demands should be considered so that the cell can adapt to the dynamic changes in a long term. On the other hand, the flexibility of machines should be balanced in the layout in order to guarantee that the cell can deal with dynamic new product introduction. Starting from these two points, we formulate a layout optimization model based on fuzzy demand and machine flexibility and then develop a genetic algorithm with bilayer chromosome to solve the model. We apply this new model to a flexible cell of shell products and test its performance by comparing it with the classical two-stage model. The total logistics path of the new model is shown to be significantly shorter than the classical model. Then we carry out adaptability experiments to test the flexibility of the new model. For the dynamic situation of both the fluctuation of production demands and the introduction of new products, the new model shows obvious advantages to the classical model. The results indicate that this advantage becomes greater as the dynamics becomes greater, which implies that considering fuzzy demand and machine flexibility is necessary and reasonable in layout optimization, especially when the dynamics of the production environment is dramatic.

1. Introduction

With the intensification of market competition and the developing trend of the manufacturing system towards digitization, networking, and intelligence, the highly flexible manufacturing cells, especially numerically controlled (NC) manufacturing cells (MC), are becoming one of the most important manufacturing modes dealing with dynamic production environment [1, 2].

Due to the wide use of highly flexible manufacturing cells, the layout design optimization of the MC is an important problem faced by production managers. There are already plenty of layout optimization models that use various algorithms to achieve objectives such as the shortest logistic distance and lowest costs. However, layout flexibility is not considered sufficiently in current models, which is critical for the adaptiveness of flexible manufacturing cells. To improve cell adaptiveness from the aspects of dynamic volume and new product, two important factors need to be considered in the layout design: (1) the ambiguity of customer demand, where the layout should adapt to the unpredictable changes of future customer demand, and (2) the layout flexibility, where the layout should provide stable manufacturing performance even when new products are frequently introduced. This means that the flexible machines should be balanced in layout design, so that the total flexibility of the cell can be guaranteed.

Starting from these two factors, we build a new layout optimization model and design a genetic algorithm (GA) to solve the problem. In the model, the ambiguity function is used to describe the fuzzy production requirements, to ensure that the constructed MC can adapt to a larger range of production quantity changes. Furthermore, flexibility weight of the flexible machine is defined and a decentralized layout constraint of flexible machines is added in the model. Based on such new constrains of fuzzy demand and machine
flexibility, the model takes the shortest moving distance of products inter- and intra-MC as the objective. It is expected that the layout derived by this model can satisfy the production requirements not only for the current production situation, but also for future dynamic situations.

The remainder of this paper is organized as follows. In Section 2, we summarize the related research and identify the problems that will be solved. In Section 3, we construct the layout model including fuzzy demand and machine flexibility. The fuzzy technology of uncertain manufacturing demand and the consideration of machine flexibility are presented especially. In Section 4, we describe the designed GA in detail. In Section 5, a practical and comprehensive case study is given to verify the effectiveness of the proposed model, and a series of experiments are conducted to test the effectiveness of the model. Conclusions and future works are presented in Section 6.

2. Related Research

Many scholars have deeply studied the problem of MC layout, and have formed rich mathematical programming models and algorithms. The scope of MC layout covers intercell and intracell problems, in which intercell problem deals machine layout inside one cell and intracell problem deals with the layout of several cells. Our work dedicated to both intercell and intracell problems, in which cell formation (CF) and machine layout are considered simultaneously. The objectives of the MC layout problem mainly include shortest movement distance, minimal exceptional elements (EEs), lowest operational cost, and multiobjectives. As the problem can be described by a mixed integer programming model, many algorithms are developed to solve the problems, such as classical integer programming, two-stage approach, and GA-based approaches. As there are plenty of MC layout literatures, we summarized some close related literatures in Table 1, in which authors, methods, and objectives are compared.

The motivation of our work is to improve the layout of MCs from the viewpoint of flexibility. Although the research findings mentioned above can form reasonable and economical MCs, but the mathematical models are seldom consider flexibility factors such as production demand and machine flexibility. There are only four literatures considered production demands [4, 7, 8, 13], and the other literatures all take production demand of all products as the same. Although the production demands are considered in the above four literatures, they assume the demand as constant during the production process. However, the production demands of the cells will unavoidably change along with the change of customer requirements. If the production demands changed, the layout calculated by these models will not be optimal any more, which means the flexibility of the layout cannot be guaranteed.

To cope with such demand uncertainty, the following authors try to solve layout problem using fuzzy mathematical models and algorithms. Such models can improve the layout flexibility under the circumstance of demand uncertainty. Drira et al. [14] studied the dynamic layout of the MC under the condition of uncertain demand and put forward an effective solution method. Slomp et al. [15] designed a virtual MC system, which is composed of machines and related tasks and personnel. The virtual cell is changed according to the demand, considering the processing capability and the limit of cell size. Arikan and Güngör [16] put forward a multiobjective fuzzy mathematical model for MC design, aimed at minimizing cost and the number of cells, and maximizing machine utilization, fuzzy processing capacity, and demand.

It is not enough to consider layout flexibility only from demand uncertainty. Layout flexibility means that the cell's layout can adapt to production dynamics. Production dynamics comes not only from demand uncertainty, but also from new product introduction. Flexible machines can be easily adjusted to the production dynamics by numerical controlled programming, reconfigurable tool storage, quick die changing system, etc. If the machines in MC have high flexibility, the MC can adapt to new product conveniently and effectively. However, high flexible machines are often expensive and scarce. So this kind of machine should be considered particularly in the layout design of MC, in order to improve the layout flexibility. Unfortunately, this character is not considered in all existing models.

In summary, layout optimization should consider not only the current production demand, but also the future requirements of products, in order that the cell can adapt to the demand changing in a long term. Meanwhile, the high flexibility of the numerically controlled machines should be balanced in the layout in order to guarantee the whole flexibility of the cell, so as to deal with frequent new product introduction. Starting from these two factors, we formulate a new layout optimization model based on fuzzy demand and machine flexibility and then develop a genetic algorithm with bilayer chromosome to solve the model.

3. Modeling of the Flexible Numerically Controlled MC

3.1. Problem and Parameter Descriptions

3.1.1. Problem Description. In general, there are several MCs in a workshop, so the problem is defined as the machine layout optimization to minimize the logistical route of all MCs in the workshop. The input of the optimization model is the machines number and features in these MCs, number of MCs in the workshop, and processing routes of all products. The output of the model is the machines groups in each MC and the detailed machines' location in these MCs. In order to standardize the problem, the model is formulated based on the following assumptions: (1) the processing route of all products to be processed has been determined in advance; (2) the MC and other equipment could be placed in multiple rows; (3) the number of MCs being constructed is known in advance; (4) the lower left corner of the layout area is the starting point of the layout of the MC and other equipment; (5) the equipment placed in the same line (x-axis) in the MC has the same y-axis ordinate; (6) the safety distance between the MC and the workshop boundaries has been determined, and all MCs are placed in accordance with safe distance requirements; and (7) the shape of the MC
Table 1: The summary of related models.

| Authors          | Solving method     | Objectives                                                   | Production demand |
|------------------|--------------------|--------------------------------------------------------------|-------------------|
| Chan et al. [3]  | two-stage GA-based | Minimizing both the intercellular and intracellular part movements. | No                |
| Wu et al. [4]    | GA                 | Minimizing the total cost of movement and exceptional elements (EEs). | Fixed demand      |
| Jolai et al. [5] | Lingo              | Minimizing total material handling cost and number of EEs.     | No                |
| Mahdavi et al. [6] | Lingo             | Minimizing handling costs.                                    | No                |
| Chang et al. [7] | HTSA               | Minimizing total intercellular movement distance and maximizing the consecutive forward flows. | Fixed demand      |
| Mahdavi et al. [8] | Lingo             | Minimizing intra- and inter-cell movements as well as EEs simultaneously. | Fixed demand      |
| Bagheri et al. [9] | LP-metric       | Minimizing inter-intra cell part trips, machine relocation cost and operator related issues. | No                |
| Mohammadi et al. [10] | GA              | Minimizing the total variable costs including the material handling, production and subcontracting costs. | No                |
| Aghajani et al. [11] | GA              | Minimizing system reconfiguration cost, penalty cost and the system failure rate. | No                |
| Mazinani et al. [12] | GA              | Minimizing the sum of material handling and rearrangement costs. | No                |
| Mehdizadeh et al. [13] | MOVDO and MOSA | Minimizing inter-intra cell part movements and machine relocation, machine and operator related costs, maximizing consecutive forward flows ratio. | Fixed demand      |
| Presented study  | GA                 | Minimizing both the intercellular and intracellular part movements. | Fuzzy demand      |

Table 2: The indices in the MCs model.

| Indices | Description |
|---------|-------------|
| t       | Evaluation item number, \( t = 1, 2, \ldots, \alpha \) |
| s       | Evaluation indices number, \( s = 1, 2, \ldots, \gamma \) |
| i       | Product number, \( i = 1, 2, \ldots, \iota \) |
| k, k'   | Equipment number, \( k = 1, 2, \ldots, \mu \), \( k' = 1, 2, \ldots, \nu \) |
| f       | Highly flexible numerically controlled MC number, \( f = 1, 2, \ldots, \alpha \) |
| j       | Technics Number, \( j, j' = 1, 2, \ldots, \rho \) |
| R       | The number of rows in the MC layout |
| g       | The row number of a MC, \( g = 1, 2, \ldots, \Omega \) |
| l, l'   | MC number, \( l, l' = 1, 2, \ldots, \zeta \) |

and other equipment is rectangular with known size. For the equipment with a nonrectangular shape, its size is the maximum circumscribed outer circle of the equipment.

3.1.2. Parameter Descriptions. Figure 1 illustrates a layout example of MCs of complex mechatronic products. The indices and variables used in the model are shown in Tables 2 and 3. The decision variables and their implications on the MCs model are shown in Table 4.

3.2. Model Building. When building the model of highly flexible numerically controlled MCs, we take the minimum moving distance inter- and intra-MCs as the goal, simultaneously considering the fuzzy manufacturing demand and the equipment flexibility.

The objective function \( f \) is expressed as

\[
\begin{align*}
\min f &= \sum_{i=1}^{n} \sum_{j=1}^{r} \sum_{m=1}^{c} d_{ij} X_{ijkl} m_{ijkl} X_{k'} m_{ijkl} d_{kk'} + \sum_{i=1}^{n} \sum_{j=1}^{r} \sum_{m=1}^{c} d_{ij} X_{ijkl} m_{ijkl} X_{k'} m_{ijkl} d_{kk'} \tag{1}
\end{align*}
\]

The constraints are

\[
\begin{align*}
\sum_{f=1}^{d} Z_{fkl} X_{kl} &\leq c, \quad N_f \leq c, \quad \forall l
\end{align*}
\]

\[
\begin{align*}
\sum_{f=1}^{d} Z_{fkl} X_{kl} &\geq c, \quad N_f \geq c, \quad \forall l,
\end{align*}
\]

\[
\begin{align*}
mt_k &\geq \varepsilon
\end{align*}
\]

\[
\begin{align*}
\sum_{k=1}^{m} m_{ijkl} &= 1, \quad \forall i, j, l
\end{align*}
\]

\[
\begin{align*}
\sum_{g=1}^{G} Y_{lg} &= 1, \quad \forall l
\end{align*}
\]

\[
\begin{align*}
\sum_{j=1}^{r} r_{ij} &= 1, \quad \forall i
\end{align*}
\]

\[
\begin{align*}
d_{kk'} &= |x_{k} - x_{k'}| + |y_{k} - y_{k'}|, \quad \forall k \neq k'
\end{align*}
\]
Equation (1) indicates the moving distance of produce intra- and inter-MCs. Equation (2) represents the distribution constraint of highly flexible numerically controlled machines. When the quantity of the machines is larger than that of the MCs, it is guaranteed that each MC has at least one highly flexible numerically controlled machine. When the quantity of highly flexible numerically controlled machines is less than that of the MCs, it is necessary to ensure that they cannot be arranged in the same MC at the same time. Equation (3) means that the same equipment can only be located in one MC. Equation (4) means that a MC can only be located in one row. Equation (5) means that the same product can only be produced in one technic. Equation (6) is the distance of equipment within the MC. Equation (7) is the distance of equipment between MCs. Equations (8) and (9) mean that the equipment cannot be overlapped, and the minimum distance of equipment should be kept. Equations (10) and (11) mean that the equipment should be located in the MC. Equations (12) and (13) mean that the MC should be located in the layout area. The size constraints of MCs can be determined by (8)–(13). Equation (14) is the production demand of the MC. Equation (15) is the layout constraint of numerically controlled machines. Equation (16) is the nonnegative constraints of variables.

According to the mathematical model established, the layout of the MCs can still ensure that the logistics path is in the optimized state when the number of products of the MCs changes within a certain range, as it considers the uncertainty of demand in the model. When new products are introduced...
for triangular fuzzy numbers and uncertain demand, while the triangular ambiguity function is the minimum possible value of the objective function $f(x, \xi)$ when the confidence level is no less than $\alpha$, $g(x, \xi)$ is the constraint function with fuzzy parameters, pos(•) is the possibility of an event in [•], and $\alpha$ and $\beta$ are confidence levels that need to be given in advance.

According to (19) and (20), (1) and (14) can be transformed into (21)–(23).

$$\min \hat{f}_{\theta} = \left\{ \begin{array}{l} \sum_{i=1}^{n} \sum_{j=1}^{r} \sum_{k=1}^{m} \sum_{l=1}^{c} \bar{q}_{ij} X_{ik} m_{ijk} X_{kl} m_{ikl}^{'d_{kl}}/\delta_{kl}^{'t} \leq f_{0} \quad (21) \\ \sum_{i=1}^{n} \sum_{j=1}^{r} \sum_{k=1}^{m} \sum_{l=1}^{c} \bar{q}_{ij} X_{ik} m_{ijk} X_{kl} m_{ikl}^{'d_{kl}}/\delta_{kl}^{'t} \leq f_{0} \quad (22) \end{array} \right.$$  

$$\text{pos} = \left\{ \begin{array}{l} \sum_{i=1}^{n} \sum_{j=1}^{r} \sum_{k=1}^{m} \sum_{l=1}^{c} \bar{q}_{ij} X_{ik} m_{ijk} X_{kl} m_{ikl}^{'d_{kl}}/\delta_{kl}^{'t} \leq f_{0} \quad (23) \end{array} \right.$$  

By the properties of (17) and (18), we know that (21) is still a triangular fuzzy number.

To simplify (21) and (22), we assume that $g(x)$ is

$$g(x) = \left\{ \begin{array}{l} \sum_{i=1}^{n} \sum_{j=1}^{r} \sum_{k=1}^{m} \sum_{l=1}^{c} r_{ij} X_{ik} m_{ijk} X_{kl} m_{ikl}^{'d_{kl}^{'t}} \leq f_{0} \quad (24) \end{array} \right.$$  

Therefore, (21) and (22) can be simplified, respectively, as

$$\min f_{0} = g(x) \bar{q}_{ij}, \quad (25)$$  

and

$$\text{pos} \{ g(x) \bar{q}_{ij} \leq f_{0} \} \geq \alpha \quad (26)$$  

According to the above analysis, the objective function of the highly flexible numerically controlled MCs becomes (25), and the constraint conditions are added with (23) and (26), without changes to the rest of the constraints.

### 4. Algorithm Design

#### 4.1. Calculating the Objective Function

According to the existing literatures, GA can solve many problems, such as...
multiobjective optimization, nonlinear programming and constrained function optimization [17, 18]. In recent years, GA has successfully implemented CF and layout problems [19–22]. Since the fuzzy parameters are included in the model of the flexible numerically controlled MCs, fuzzy simulation is used to obtain the optimal solution. For the GA that contains fuzzy simulation, the main concern is the calculation of the fuzzy objective function. To get min $f_0$ with satisfied conditions, it can obtain the minimum value $f_0$ on the basis of the layout variables $g(x)$ of the equipment and MC: first, setting up $f_0 = 0$ and then generating $\alpha^0$ uniformly by the vector $\tilde{\alpha}$, of the product fuzzy demand to make $u(\alpha^0) \geq \alpha$. If $f < f(x, \alpha^0)$, then $f = f(x, \alpha^0)$. The process is iterated until the termination condition of the GA is satisfied.

### 4.2. Chromosome Coding Design

A good chromosome coding design can make the GA simple and efficient, with a strong execution and only a small probability of an invalid solution. Accordingly, we use MATLAB to encode for GA algorithm and use a double chromosome design method that combines the layout of the flexible numerically controlled MCs and the layout of equipment, setting the variable of the chromosome with integer encoding. The structure of the specific chromosome encoding is shown in Figure 2.

| Decision variable | Introducing 0-1 variables | Description |
|-------------------|---------------------------|-------------|
| $m_{ijkl}$        | $m_{ijkl}=1$              | indicating that the product family $i$ chooses the process $j$ to process on the equipment $k$ that is in the MC $l$; |
|                   | $m_{ijkl}=0$              | indicating that the product family $i$ doesn’t choose the process $j$ to process; |
| $X_{kl}$          | $X_{kl}=1$                | indicating that the equipment $k$ is in the MC $l$; |
|                   | $X_{kl}=0$                | indicating that the equipment $k$ is not in the MC $l$; |
| $Z_{fl}$          | $Z_{fl}=1$                | indicating that highly flexibility equipment $f$ is in the MC $l$; |
|                   | $Z_{fl}=0$                | indicating that highly flexibility equipment $f$ is not in the MC $l$; |
| $r_{ij}$          | $r_{ij}=1$                | indicating that the product family $i$ chooses the process $j$ to process; |
|                   | $r_{ij}=0$                | indicating that the product family $i$ doesn’t choose the process $j$ to process; |
| $Y_{lg}$          | $Y_{lg}=1$                | indicating that the MC $l$ locates in row $g$-th of layout area; |
|                   | $Y_{lg}=0$                | indicating that the MC $l$ doesn’t locate in row $g$ of layout area; |
| $d_{kk’l}$        | /                         | The distance between equipment $k$ and $k’$ in MC $l$; |
| $d_{kk’l’}$       | /                         | The distance between equipment $k$ in MC $l$ and equipment $k’$ in MC $l’$; |
| $x_{ii’}$, $y_{ii’}$ | /                         | The central point of equipment $k$ |
| $x_{ii’}$, $y_{ii’}$ | /                         | The central point of MC $l$ |

Figure 2: The scheme of chromosome encoding about MC.

As shown in Figure 2, there are two layers in the chromosome, and each layer contains three parts. The first layer contains the coding of the MC, equipment, and workpiece, which are encoded based on the respective methods of MC, equipment and workpiece. The second layer contains the row number, which is based on the line layout of the MC, and the coding of the MC and technics, which are encoded based on the respective representations of the MC and technics. This encoding allows the randomly chosen individual to satisfy (2) to (5). For example, the chromosome coding $[121331|211211]_{342}^{341256}$ means that the MC is composed of cells 1 to 3, equipment 1 to 9, and workpieces 1 to 6. Wherein, MCs 3 and 2 are arranged in the first row and MC1 is arranged in the second row. The equipment 3, equipment 1, equipment 5, and equipment 8 are placed in MC 1, while the equipment 4 and equipment 2 are placed in MC 2, and the equipment 6, equipment 9, and equipment 7 are placed in MC 3. The workpieces 1, 2, and 5 are processed by technics 1, while other workpieces are processed by technics 2. In addition, to meet the constraints of (8)–(13), the layouts of the equipment and MC adopt the word wrap strategy to the chromosome encoding, the constraints of equipment layout, and the MC layout. In the encoding scheme, the close degree of layouts between $C_{ij}$ and $C_{k’}$ depends on the degree of correlation between MCs. The close degree of layout between equipment $m_k$ and $m_{k’}$ in the MC depends on the processing path selected by the product.

### 4.3. The Design of Crossover and Mutation

#### 4.3.1. Chromosome Crossover Operation

Generally, there are three types of crossover operation: single point, two-point, and multipoint [23]. After the crossover of chromosome encoding, it cannot destroy the structure of the chromosome and generate any invalid solutions in the highly flexible numerically controlled MC model. Moreover, the chromosome of the MC is relatively short. Therefore, to avoid invalid
To avoid an ineffective solution, we use the method of variation, reverse variation and insertion variation, among commonly used methods in mutation operation are exchange gene in the chromosome, which is usually randomized. The mutation operation produces a new entity by changing a part of the chromosome. Each mutation operation on the chromosome must be carried out. In the process of general GA, the mutation probability of chromosomes is relatively small. To diversify the chromosome population, a general GA, the mutation probability of chromosomes is five.fitted./three.fitted./two.fitted. Chromosome Mutation Operation.

The specific method of crossover operation is as follows.

1. According to the length $N_i$ of chromosome encoding of the MCs, the layout of equipment, and the workpiece, multiple integers $N_{i1}, N_{i2}, \ldots, N_{in}$ ($0 < N_{i1} < N_{i2} < \cdots < N_{in} < N_i$) are randomly generated.
2. The same location and sequence of integers $N_{i1}, N_{i2}, \ldots, N_{in}$ generated by the parent chromosomes P1 and P2 are kept.
3. The remaining chromosomes that will cross in the parent chromosomes P1 and P2 in sequence to the parent P2 and P1, producing new chromosomes C1 and C2, are copied.

After the crossover method, the offspring chromosomes C1 and C2 are produced to generate new chromosome populations. The specific crossover process of chromosomes is shown in Figure 3. In the crossover process, the shaded part in Figure 3 demonstrates choosing the genes based on the sequence to cross.

4.3.2. Chromosome Mutation Operation. In the process of general GA, the mutation probability of chromosomes is relatively small. To diversify the chromosome population, a mutation operation on the chromosome must be carried out. The mutation operation produces a new entity by changing a gene in the chromosome, which is usually randomized. The commonly used methods in mutation operation are exchange variation, reverse variation and insertion variation, among others. To avoid an ineffective solution, we use the method of exchange variation to generate new individuals. According to the length $N_i$ of chromosome encoding of the MCs, the layout of equipment, and the workpiece, it randomly selects two exchange genes, $K_1$ and $K_2$, in each part ($0 < K_{i1} < K_{i2} < N_i$), getting a new chromosome after exchanging its position, as shown in Figure 4.

5. Case Study

5.1. The Basic Information of the MCs. The optimized layout model is applied to the layout design of a shell product's cell. The cell has 16 flexible numerically controlled machines (numbered M1–M16), producing 12 typical products (numbered E1–E12). Each product has a flexible process. In the layout of the MCs, the main considerations are the flexible process routes, the flexible processing capacity of equipment, the equipment sizes, and the product fuzzy demands of the 12 typical products. Specific equipment information is shown in Table 5. The flexible processing capacity of the equipment assessed by equipment experts is shown in Table 6. The input information for the number and size of the MCs is shown in Table 7. In this case, the triangular fuzzy number is used to describe the fuzziness of product requirements. The quantity of fuzzy demands within one year is obtained based on the historical product data and the market demand prediction. The process route and fuzzy demands of the product family are shown in Table 8.

In addition, through the evaluation of machine tools by equipment experts, we find that there are five highly flexible pieces of equipment in the highly flexible numerically controlled MCs, namely, M1, M3, M4, M7, and M9.

5.2. Result Analysis and Discussion

5.2.1. The Comparison of Optimization Results between the Classical Layout Model and the Highly Flexible Numerically Controlled MCs Model. The input of our optimization model is the machines number and features in these MCs, number of MCs in the workshop, and processing routes of all products. It is not possible to use literature instances in our research because there is no machine features description in these instances. As the information in our case study covers more parameters, we use the classical two-stage approach, which is widely used in many literatures, in our production circumstance to illustrate the effectiveness and advantages of our model.

Firstly, to reflect the difference between the classical model and the new model, we take the mathematical expectation to express the product demand in the new model and do not consider the flexibility of the equipment. The new model is constructed as follows. In the first stage, it solves the layout problem between MCs, which is taking the minimum moving distance of products between MCs as the optimization goal, to determine the location of the MCs and determine which equipment should be placed in the appropriate MCs. In the second stage, it solves the layout of the equipment in the MCs according to the layout results in the first stage. It takes the minimum logistics volume as the goal, to realize the reasonable arrangement of the equipment in the MCs. After building the model based on the above two stages and solving further with GA, we get the layout of the MCs as shown in Figure 5.

Secondly, using the layout planning model based on fuzzy demand and machine flexibility and taking the shortest moving distance of the product as the goal, we adopt the
### Table 5: The information of equipment (unit : m).

| Number | Size ($w \times l$) |
|--------|---------------------|
| M1     | 3.4 × 2             |
| M2     | 2 × 1.6             |
| M3     | 3 × 2               |
| M4     | 3.2 × 2.2           |

### Table 6: Equipment processing capacity.

| Equipment | Structure of Machine Tool | Control System | Machining Characteristics |
|-----------|---------------------------|----------------|---------------------------|
|           | Spindle speed | Tool speed | Tool library capacity | Axes | Controllable axes | Maximum size range | Dimensional accuracy |
| M1        | 0.67          | 0.52       | 0.46                  | 0.39 | 0.38             | 0.78               | 0.65                 |
| M2        | 0.26          | 0.72       | 0.43                  | 0.21 | 0.24             | 0.65               | 0.34                 |
| M3        | 0.82          | 0.73       | 0.18                  | 0.43 | 0.35             | 0.29               | 0.46                 |
| M4        | 0.24          | 0.36       | 0.46                  | 0.56 | 0.56             | 0.75               | 0.13                 |
| M5        | 0.36          | 0.28       | 0.75                  | 0.32 | 0.22             | 0.11               | 0.68                 |
| M6        | 0.12          | 0.12       | 0.86                  | 0.15 | 0.29             | 0.19               | 0.36                 |
| M7        | 0.85          | 0.76       | 0.35                  | 0.42 | 0.34             | 0.23               | 0.92                 |
| M8        | 0.35          | 0.36       | 0.42                  | 0.36 | 0.38             | 0.25               | 0.68                 |
| M9        | 0.43          | 0.42       | 0.11                  | 0.54 | 0.51             | 0.36               | 0.54                 |
| M10       | 0.36          | 0.35       | 0.12                  | 0.51 | 0.43             | 0.29               | 0.53                 |
| M11       | 0.28          | 0.24       | 0.16                  | 0.23 | 0.16             | 0.09               | 0.42                 |
| M12       | 0.37          | 0.28       | 0.21                  | 0.34 | 0.26             | 0.17               | 0.65                 |
| M13       | 0.74          | 0.64       | 0.26                  | 0.21 | 0.13             | 0.09               | 0.72                 |
| M14       | 0.36          | 0.27       | 0.34                  | 0.42 | 0.31             | 0.24               | 0.61                 |
| M15       | 0.23          | 0.16       | 0.39                  | 0.38 | 0.42             | 0.23               | 0.48                 |
| M16       | 0.19          | 0.14       | 0.42                  | 0.25 | 0.17             | 0.08               | 0.73                 |

### Table 7: The information of the MC (unit : m).

| Unit number | Size ($W \times L$) |
|-------------|---------------------|
| 1           | 11.5 × 7            |
| 2           | 9.5 × 7             |

| Layout area specification |
|---------------------------|
| D | 24 | F | 18 |

| Distance between adjacent units and equipment |
|----------------------------------------------|
| B | 1.5 | H | 3 |

By designing GA to solve the planning problem. With regard to the computer system configuration for solving problem, we use the computer with Intel Core i7-4790S CPU 3.20GHz, operating system 64 bit and computer memory 8192MB RAM. Since our research is focused on the layout of highly flexible MCs, which solves the problem at the workshop level and with relatively small scale. Therefore, we can solve planning problem efficiently and quickly. Based on the above description, in the new model, we set the population size to 100, the number of evolution generation to 1000, crossover probability to 0.9, and mutation probability to 0.05. The confidence levels $\alpha$ and $\beta$ are set as 0.85 and 0.8, respectively, according to the probability of crossover and mutation in the MCs. The optimal plane layout of the MCs is shown in Figure 6.

![Figure 5: The layout result of the model based on the classical two-stage model (layout A).](image)
Table 8: The process route and fuzzy demand of product family.

| product family | process route       | fuzzy demand     |
|----------------|---------------------|------------------|
| E1             | M1-M2-M5            | (70,143,268)     |
|                | M1-M2-M9            |                  |
| E2             | M3-M5-M8-M12        | (86,120,234)     |
|                | M6-M8-M11-M12       |                  |
| E3             | M1-M2-M10           | (56,195,310)     |
|                | M1-M9-M19           |                  |
| E4             | M9-M14-M15          | (107,204,416)    |
|                | M1-M10-M15          |                  |
| E5             | M4-M11-M14          | (87,95,109)      |
|                | M2-M7-M14           |                  |
| E6             | M11-M12-M13-M16     | (21,128,332)     |
| E7             | M1-M2-M6-M7-M8-M16  | (29,82,137)      |
|                | M3-M5-M6-M7-M9-M16  |                  |
| E8             | M4-M10-M11-M13-M14  | (98,130,256)     |
| E9             | M9-M10-M13-M14      | (68,203,420)     |
|                | M2-M5-M7-M14        |                  |

Figure 6: The layout results of the model based on fuzzy demands and machine flexibility (layout B).

the equipment placements in the MCs of the two models are quite different. By analyzing the objective function values of the two models, we find that the total logistics path of the MCs based on the new model is 52393 meters, while the total logistics path based on the classical model is 57976 meters, indicating that the optimization result of the new model is slightly better.

To make the comparison results statistically significant, we randomly sample 20 values within the fuzzy interval of product demand based on the classical model, to carry on the t-test with the optimization results of the new model. The test result is shown in Table 9. According to the P value test method, we can find that the value of probability P of the test statistic t is 2.76374E-05 which is far less than the significance level 0.05. Therefore, the null hypothesis of t-test should be rejected; that is, the results calculated by the two models have significant differences. It indicates that the new model can better optimize the production layout.

5.2.2. Adaptability Analysis of Equipment Layout to the Fluctuation of Product Demand Quantity. In this section, we consider the situation of the uncertainty of customer demand, to analyze the performance difference between the layout result of the classical model (layout A) and the layout result of the new model (layout B) when coping with the fluctuation of product quantity. The random function is used to automatically generate the 8 sets of random demand data for 9 products as shown in Table 10. The minimum quantity of each product does not exceed the lower limit of the triangular fuzzy function, and the maximum quantity does not exceed the upper limit of the triangular fuzzy function. The specific upper and lower limits are adopted by refer to the upper and lower limits of the fuzzy demand of products E1-E9.

After calculations based on Table 10, the differences of the product moving distance under the two layouts are shown in Figure 7.

Figure 7 shows that the moving distances of products in layout B are less than those in layout A. Through performing t-test analysis on the two layouts, we obtain the results as shown in Table 11. Based on the P value, we find that the probability P 4.76E-09 of the test statistic t is far less than the significance level 0.05. So the null hypothesis of t-test should be rejected; that is, the moving distances of the two layouts are significantly different. In addition, the variance difference is larger. It illustrates that the layout model of the MCs, which considers the fuzzy demand and the machine flexibility, has a good adaptability to the uncertainty of the product quantity.

5.2.3. Adaptability Analysis of the Constructed MCs When Introducing New Products. To further verify the effectiveness and adaptability of the new model, we simulate and analyze the situation where new products are introduced into the MCs.
Table 9: t-test: pairwise double sample mean analysis.

|                  | variable 1                  | variable 2                  |
|------------------|-----------------------------|-----------------------------|
| Mean             | 60936.375                   | 52133.08                    |
| Variance         | 113803039.9                 | 55492822                    |
| Observed value   | 20                          | 20                          |
| Poisson correlation coefficient | 0.753764137               | -                           |
| Hypothetical mean| 0                           | -                           |
| df               | 19                          | -                           |
| t Stat           | 5.478154126                 | -                           |
| P (T < t) Single tail | 1.38187E-05            | -                           |
| t Single tail critical | 1.729132812               | -                           |
| P (T < t) Double tail | 2.76374E-05            | -                           |
| t Double tail critical | 2.093024054               | -                           |

Table 10: Product demand randomly produced.

| Product family | Demand quantity |
|----------------|-----------------|
|                | 1   | 2   | 3   | 4   | 5   | 6   | 7   | 8   |
| E1             | 12  | 37  | 31  | 28  | 33  | 29  | 30  | 23  |
| E2             | 85  | 9   | 2   | 6   | 60  | 71  | 8   | 82  |
| E3             | 40  | 46  | 56  | 24  | 40  | 41  | 15  | 36  |
| E4             | 103 | 167 | 35  | 47  | 96  | 146 | 24  | 83  |
| E5             | 52  | 79  | 12  | 18  | 4   | 58  | 31  | 27  |
| E6             | 8   | 20  | 48  | 23  | 9   | 42  | 57  | 87  |
| E7             | 20  | 20  | 6   | 13  | 10  | 4   | 16  | 9   |
| E8             | 11  | 20  | 133 | 21  | 117 | 185 | 65  | 101 |
| E9             | 5   | 67  | 24  | 41  | 45  | 53  | 60  | 48  |

![Figure 7: Comparison of product moving distance between layouts A and B in Experiment 2.](image)

We first simulate a situation where 12 new products are imported into the MCs. Each product has 3–6 processes. The number of specific processes is generated randomly, with at least one process being of a complex nature. The complex process needs to be processed by at least one flexible numerically controlled machine. It follows the random principle about which the flexible numerically controlled machine processes the complex process. However, the machines must be part of M1, M3, M4, M7, and M9. Beyond that, the manufacture machines that are used in other processes are also randomly generated, as shown in Table 12. To eliminate the impact of product demand on production, the number of all product demands is set to 1.

After calculating based on Table 12, we find the differences between the product moving distances between the two layouts, as shown in Figure 8.

As a whole, the moving distances of a new product in layout B are less than that in layout A, which indicates that the new model has good adaptability for the frequent importing of new products. Through further analysis of the causes of this result, we find that the highly flexible numerically controlled machines are relatively centralized in the MCs constructed by layout A, based on the classical two-stage approach, and, in the production, new products need to be produced across the cells more frequently, resulting in longer moving distances. In layout B, obtained by the new model, due to adding the constraints of a decentralized arrangement on flexible equipment, most new products can be produced in one cell. This reduces the situation of crossing cells during production, thus reducing the total moving distance. Summing up all results leads to the conclusion that the new model and method we propose are effective.

![Figure 8: The difference of moving distance between new products.](image)
Table 11: t-test: pairwise double sample mean analysis.

|                  | variable 1 | variable 2 |
|------------------|------------|------------|
| Mean             | 156669.9   | 139797.2   |
| Variance         | 6.58E+08   | 7.49E+08   |
| Observed value   | 20         | 20         |
| Poisson correlation coefficient | 0.962036 | -         |
| Hypothetical mean| 0          | -          |
| df               | 19         | -          |
| t Stat           | 10.06289   | -          |
| P (T < t) Single tail | 2.38E-09 | -          |
| t Single tail critical | 1.729133 | -          |
| P (T < t) Double tail | 4.76E-09 | -          |
| t Double tail critical | 2.093024 | -          |

Table 12: Process route of new products.

| Product | Process route |
|---------|---------------|
| E10     | M5-M1-M3-M15-M2-M6 |
| E11     | M7-M2-M8-M6-M10 |
| E12     | M1-M14-M11-M12-M6-M3 |
| E13     | M10-M11-M9-M2-M3 |
| E14     | M7-M5-M3 |
| E15     | M4-M13-M14 |

| Product | Process route |
|---------|---------------|
| E16     | M7-M13-M16 |
| E17     | M9-M12-M14 |
| E18     | M9-M6-M7-M3 |
| E19     | M8-M12-M6-M1 |
| E20     | M2-M8-M3-M7-M11-M14 |
| E21     | M1-M4-M5-M14 |

6. Conclusions

Layout flexibility has significant influence on the performance of flexible MCs, especially when the production environment is dynamic. Therefore, layout optimization should consider not only the current production situations, but also the future dynamics of the production environment. Starting from this point, we formulated a layout optimization model based on fuzzy demand and machine flexibility. Then, we designed a genetic algorithm with bilayer chromosome to solve the model. The proposed model and algorithm were applied to a realistic flexible cell of shell products, and further experiments were conducted to verify the advantages of the model. The results indicate that layout optimization considering fuzzy demand and machine flexibility is necessary and reasonable, especially when the dynamics of the production environment are dramatic.

Compared with existing models, our proposed layout model of the MCs has the following highlights:

1. Most existing models of the MCs assume that there is no difference in the volume of products, or the models adopt a fixed quantity of products as input for layout optimization. In this paper, we use fuzzy trigonometric function to describe the fuzzy demand of products, to make the constructed layout of the MCs maintain an optimal state in a larger range of changing product quantities.

2. The existing models of the MCs mainly consider the equipment size and processing routes, without considering the different levels of equipment flexibility. In this paper, we fully consider the manufacturing flexibility of equipment, describing it quantitatively using equipment weights. In the layout optimization model of the MCs, a constraint of the decentralized arrangement of flexible equipment are added, thus making the cell layout can adapt to the changes in product kinds. Our case study proves that the new model achieves the expected effect and can effectively improve the layout flexibility of the MCs.

It is worth noting that the model is especially suitable for the multispecies and variable batch manufacturing, in which the flexibility is critical for the production performance. For MCs with relatively stable production batches and narrow variety of products, the advantage of the model proposed in this paper may not obvious as expected.

In the future work, the equipment reconfiguration should be considered. In the case of reconfiguration, logistics and restructuring costs should be included in the objective function, and new algorithms should be developed to deal with the higher complexity of the model.

Data Availability

The data used to support the findings of this study come from an enterprise. We have to comply with a non-disclosure agreement. Therefore, the data are not released.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

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References

[1] O. Durán, N. Rodríguez, and L. A. Consalter, "Collaborative particle swarm optimization with a data mining technique for manufacturing cell design," Expert Systems with Applications, vol. 37, no. 2, pp. 1563–1567, 2010.

[2] C. R. Shiyas and V. Madhusudanan Pillai, "A mathematical programming model for manufacturing cell formation to develop multiple configurations," Journal of Manufacturing Systems, vol. 33, no. 1, pp. 149–158, 2014.

[3] F. T. S. Chan, K. W. Lau, P. L. Y. Chan, and K. L. Choy, "Two-stage approach for machine-part grouping and cell layout problems," Robotics and Computer-Integrated Manufacturing, vol. 22, no. 3, pp. 217–238, 2006.

[4] X. Wu, C.-H. Chu, Y. Wang, and W. Yan, "A genetic algorithm for cellular manufacturing design and layout," European Journal of Operational Research, vol. 181, no. 1, pp. 156–167, 2007.

[5] F. Jalali, R. Tavakkoli-Moghaddam, A. Golmohammadi, and B. Javadi, "An Electromagnetism-like algorithm for cell formation and layout problem," Expert Systems with Applications, vol. 39, no. 2, pp. 2172–2182, 2012.

[6] I. Mahdavi, A. Aalaei, M. M. Paydar, and M. Solimanpur, "Designing a mathematical model for dynamic cellular manufacturing systems considering production planning and worker assignment," Computers & Mathematics with Applications, vol. 60, no. 4, pp. 1014–1025, 2010.

[7] C.-C. Chang, T.-H. Wu, and C.-W. Wu, "An efficient approach to determine cell formation, cell layout and intracellular machine sequence in cellular manufacturing systems," Computers & Industrial Engineering, vol. 66, no. 2, pp. 438–450, 2013.

[8] I. Mahdavi, E. Teymourian, N. T. Baher, and V. Kayvanfar, "An integrated model for solving cell formation and cell layout problem simultaneously considering new situations," Journal of Manufacturing Systems, vol. 32, no. 4, pp. 655–663, 2013.

[9] M. Bagheri and M. Bashiri, "A new mathematical model towards the integration of cell formation with operator assignment and inter-cell layout problems in a dynamic environment," Applied Mathematical Modelling: Simulation and Computation for Engineering and Environmental Systems, vol. 38, no. 4, pp. 1237–1254, 2014.

[10] M. Mohammadi and K. Forghani, "A novel approach for considering layout problem in cellular manufacturing systems with alternative processing routings and subcontracting approach," Applied Mathematical Modelling, vol. 38, no. 14, pp. 3624–3640, 2014.

[11] A. Aghajani, S. A. Didehvari, M. Zadahmad, M. H. Seyedrezaei, and O. Mohsenian, "A multi-objective mathematical model for cellular manufacturing systems design with probabilistic demand and machine reliability analysis," The International Journal of Advanced Manufacturing Technology, vol. 75, no. 5–8, pp. 755–770, 2014.

[12] M. Mazinani, M. Abedzadeh, and N. Mohebali, "Dynamic Facility Layout Problem based on Flexible Bay Structure and Solving by Genetic Algorithm," International Journal of Advanced Manufacturing Technology, vol. 65, no. 5–8, pp. 929–943, 2013.

[13] E. Mehdizadeh and V. Rahimi, "An integrated mathematical model for solving dynamic cell formation problem considering operator assignment and inter/intra cell layouts," Applied Soft Computing, vol. 42, pp. 325–341, 2016.

[14] A. Drira, H. Pierreval, and S. Hajri-Gabouj, "Design of a robust layout with information uncertainty increasing over time: A fuzzy evolutionary approach," Engineering Applications of Artificial Intelligence, vol. 26, no. 3, pp. 1052–1060, 2013.

[15] J. Slomp, B. V. Chowdary, and N. C. Suresh, "Design of virtual manufacturing cells: A mathematical programming approach," Robotics and Computer-Integrated Manufacturing, vol. 21, no. 3, pp. 273–288, 2005.

[16] F. Arikan and Z. Gungör, "Modeling of a manufacturing cell design problem with fuzzy multi-objective parametric programming," Mathematical and Computer Modelling, vol. 50, no. 3–4, pp. 407–420, 2009.

[17] J. Balakrishnan and C. Hung Cheng, "The dynamic plant layout problem: Incorporating rolling horizons and forecast uncertainty," Omega, vol. 37, no. 1, pp. 165–177, 2009.

[18] A. Drira, H. Pierreval, and S. Hajri-Gabouj, "Facility layout problems: a survey," Annual Reviews in Control, vol. 31, no. 2, pp. 255–267, 2007.

[19] M. A. El-Baz, "A genetic algorithm for facility layout problems of different manufacturing environments," Computers & Industrial Engineering, vol. 47, no. 2–3, pp. 233–246, 2004.

[20] E. Vila Goncalves Filho and A. J. Tiberti, "A group genetic algorithm for the machine cell formation problem," International Journal of Production Economics, vol. 102, no. 1, pp. 1–21, 2006.

[21] M. Solimanpur, P. Vrat, and R. Shankar, "A multi-objective genetic algorithm approach to the design of cellular manufacturing systems," International Journal of Production Research, vol. 42, no. 7, pp. 1419–1441, 2004.

[22] T.-H. Wu, S.-H. Chung, and C.-C. Chang, "Hybrid simulated annealing algorithm with mutation operator to the cell formation problem with alternative process routings," Expert Systems with Applications, vol. 36, no. 2, pp. 3652–3661, 2009.

[23] A. Tariq, I. Hussain, and A. Ghafoor, "A hybrid genetic algorithm for machine-part grouping," Computers & Industrial Engineering, vol. 56, no. 1, pp. 347–356, 2009.
