Optimizing facility layout planning for reconfigurable manufacturing system based on chaos genetic algorithm

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ABSTRACT
In order to solve the problems associated with the organization of the dynamic facility layout in a manufacturing workshop, utilizing a chaotic generic algorithm with improved Tent mapping is proposed as a solution. The tent map is used to generate the initial population which is distributed throughout the solution space. Excellent individuals have the Genetic Algorithm optimization with elitist strategy applied to them. Partially matched crossover and mutation operations for single-period-layout encoding string are executed, and adaptive chaotic disturbance is increased to the superior individual. This method is an important innovation in the field of layout optimization by chaotic genetic algorithm. Finally, the paper compares several algorithms by analyzing sample outcomes of their respective implementations. It is also more convenient to verify the T-CGA method, which is better than the traditional method in solving the accuracy and the efficiency.

1. Introduction
The change in market demand has forced the enterprises to adopt a more flexible production mode in order to stay competitive. This flexibility should be established across different varieties, large, many few varieties and small batches. In this case, new equipment acquisition, shop layout adjustment or reconstruction inevitably become more frequent. Frequent changes in the workshop layout will inevitably bring equipment disassembly and relocation, as well as the cost of downtime and tardiness. The quality of a layout has impacts on material handling costs, production efficiency and safety. In flexible production environments, the traditional static facility layout, which does not consider the dynamic characteristics of the market, is more costly and can hardly satisfy the requirements of the enterprise. Therefore, it is imperative to study the dynamic facility layout problem. Due to the complexity and diversity of the actual layout problem, a complete set of optimization models and methods for handling dynamic facility layout problems is urgently needed. The dynamic equipment layout problem (DFLP) is imperative in the total planning time to optimize the equipment
layout problem. This is on the basis of the SFLP from the perspective of multi-periods (Li & Qiu, 2007). The study of the problem has important theoretical significance and practical value in engineering.

2. Literature review

In dynamic facilities layout, studies can be grouped mainly under two tracks, studies that used exact optimization models and those that used heuristic layout models. By implementing an exact optimization approach to assign the facilities in the site layout, literature (Baykasoglu, Dereli, & Sabuncu, 2006; Şahin, Ertoğral, & Türkbey, 2010; Zhu & Ye, 2009) research on dynamic layout problems is based on discrete layouts. In the study of the large-scale DFLP problem, Baykasoğlu and Gindy (2001) proved that the proposed algorithm was effective by the simulated annealing algorithm. McKendall, Shang, and Kuppusamy (2006) designed a forward and backward two-stage SA algorithm to solve the DFLP problem. Wang, Hu, and Ku (2005) and Garcia-Hernandez, Pierreval, and Salas-Morera et al. (2013) have used the improved genetic algorithm to optimize the unequal area facilities layout problem. In addition to GA and SA, the construction, improvement and consummation of other intelligent algorithms are also the focus of DFLP research. Hosseini-Nasab and Emami (2013) proposed the use of a hybrid particle swarm algorithm to solve the problem by coding and decoding method specially applied to DFLP. This was so that the discreet solution spaces could correspond to the continuous solution spaces on a one on one basis in the particle swarm. Pourvaziri and Pierreval (2017) have used an analytical approach which uses open queuing network theory and is based on a quadratic assignment problem formulation. Moslemipour, Lee, and Loong (2018) proposed a novel hybrid algorithm in which simulated annealing algorithm starts with a population of good initial solutions constructed by combining ant colony, clonal selection, and robust layout design approaches. Al Hawarneh, Bendak, and Ghanim, (2019) proposed a grid layout model to accommodate safety as a design parameter beside cost using a grid system for layout design based on the safety proximity level between facilities.

Applying these algorithms with the aim of to optimizing the dynamic facility layout problem can meet the workshop application requirements and result in profit value. Most studies in layout optimization only consider material handling fees, a few discuss equipment movement fees, and a few others consider equipment replacement costs. It is extremely important and urgent to form complete and systematic dynamic layout optimization theories and methods, because of the characteristics of combination optimization of large-scale dynamic layout and the defects of heuristic algorithms.

Chaos is the inherent characteristic of nonlinear systems, which have randomness, ergodicity and sensitivity to initial values. At present, a lot of research results are very rich in the chaotic genetic algorithm. The earliest chaotic neural network utilizing chaotic initial value sensitivity and other chaotic dynamic properties were proposed by Aihara, Takabe, and Toyoda (1990). It is usually used to solve combinatorial optimization problems such as traveling traders and maintenance scheduling Jovanovic and Kazerounian (1998) have developed a method has been applied to mechanical engineering
design. This method uses a Chaos Fractal optimization algorithm combined with the initial sensitivity and fractal nature of chaos to achieve its results. Wang Yong-Feng, Yu, and Yongming et al. (2012) put forward the idea that the chaos genetic algorithm is applied to logistic distribution routing issue with the time window. Gao, Ge, and Wu (2016) utilize the infinite folding chaotic map, which is more homogeneous, to realize the particle initialization, and the cooperation between cloud genetic algorithm and PSO algorithm. Furthermore, they use it to verify the effectiveness of the algorithm through global convergence, time complexity and experimental analysis. Ye, Liu, and Jiang (2018) take advantage of the Logistic chaos sequence. The algorithm ensures the accuracy of the cross and variation points of Genetic Algorithm. The algorithm is applied to the experimental simulation of aeronautical planning in this dissertation. Simulation results showed that this method improved the precision of the genetic algorithm.

Thus, the hybrid algorithm inherits the inversion of the genetic algorithm and the ergodicity of the chaotic search, thereby mitigating the usual challenge of the genetic algorithm falling into the local optimum, and consequently, greatly improving the searching speed and global convergence. It is a very suitable algorithm for solving facility layout problems.

This paper has developed a dynamic layout model of unequal area equipment in multiple planning periods. This model uses the minimum cost of material transportation, the minimum cost of equipment replacement and the maximum area utilization of three targets. Chaos genetic algorithm is used to solve the optimal layout scheme in the whole production planning period.

The rest of the paper is organized as follows: Section 2 summarizes the model establishment. Algorithm design is explained in section 3. Section 4 compares the three algorithms and also provides a concrete workshop example. Section 5 summarizes the whole paper and gives some suggestions for future works.

3. Problem definition

The Dynamic layout optimization Model of workshop equipment is the optimal layout design under production planning periods in the precondition of the future.

The Dynamic layout optimization Model of workshop equipment is the optimal layout design under production planning periods in the precondition of the future. According to the relationship between the material flows of each sub-planning period, the best position of equipment in each period can be determined. This makes the total cost of workshop operation the smallest in the whole planning period. Use $S_t$ to indicate the layout scheme of $n$ units in the $t$ period of the sub-plan.

\[
S = \{S_1, S_2, \ldots, S_p\}
\]

\[
S_t = (x_{t1}, x_{t2}, \ldots, x_{tn}), t \in [1, p]
\]

Therefore, one of the plans for production planning periods can be expressed as:

\[
S = \{(x_{11}, x_{12}, \ldots, x_{1n}), (x_{21}, x_{22}, \ldots, x_{2n}), \ldots, (x_{p1}, x_{p2}, \ldots, x_{pn})\}
\]
3.1. Problem assumption

Based on ref. (Xu, Yang, & Li et al., 2011), the layout problem of the workshop is simplified to the layout of dynamic multi-line equipment under constraint conditions. Figure 1, below, shows the layout diagram of a single sub-planning period (L and H respectively indicate the length and width of the workshop).

According to the dynamic branch strategy, when the sum of the lengths of all the equipments and the spacing between the equipments in one row exceeds the workshop length L. The previous line must then be rearranged in order from left to right. Respectively mi, mj, mk indicate the need for the layout devicei, j, k. In the case of device i and j, xi(t) and yj(t) respectively represent the x-coordinate and the y-coordinate of the center point of the device i and j in the sub-plan period t. li, wi are the length and the width of equipment i respectively. hik indicates the minimum horizontal spacing between the device i and the adjacent device k. The hj0 indicates the minimum horizontal spacing between the device j and the workshop boundary, where the equipment is the same as the left and right boundary spacing of the workshop. v0 is the spacing between the first line of equipment and the shop floor, and v is the vertical line spacing between devices.

3.2. Mathematical model

3.2.1. Model constraints

During each planning period, the rectangular equipment is laid out in a continuous shop floor. The constraints that need to be met for each period are:

1. Spacing constraints: to ensure that a certain distance between adjacent equipment is kept. The equipment logistics direction is parallel to the workshop center line, logistics costs are only related to the distance, regardless of the direction.
(2) Boundary constraints: This is the layout of the device in the axis. The axis cannot exceed the limits of the shop floor. Because the layout uses a dynamic line feed strategy, the device layout in the axis direction does not exceed the shop area, without the need to repeat the constraints. As long as the equipment is in the direction of the arrow to ensure that the arrangement will not exceed the workshop area.

(3) Re-layout constraints: in any two consecutive planning periods, if the center of the device changes, you can determine the equipment in the next issue of re-layout. That satisfies the following formula:

\[ |X(t)i - X(t-1)i| \neq 0 \text{ or } |y(t)i - y(t-1)i| \neq 0 \]

3.2.2. Objective function

In this paper, the mathematical model of the multi-objective optimization problem in a dynamic layout is as follows:

(1) the minimum material handling costs

\[ \text{C is the total cost of material handling,} p \text{ is the planned period, and } n \text{ is the number of equipment to be arranged in the workshop. } P_{tij} \text{ is the handling cost per unit distance between units } i \text{ and } j \text{ in sub-period } t. Q_{tij} \text{ is the material handling frequency between units } i \text{ and } j \text{ in sub-period } t. D_{tij} \text{ is the distance between devices between units } i \text{ and } j \text{ in sub-period } t, \text{ and } s \text{ is the total number of rows in the device layout. The following formula shows:} \]

\[ \min C = \min \sum_{t=1}^{p} \sum_{i=1}^{n} \sum_{j=1}^{n} (P_{tij} Q_{tij} D_{tij}) \tag{1} \]

\[ i, j = 1, 2, \ldots, n; t = 1, 2, \ldots, p \]

\[ D_{tij} = |x(t)i - x(t)j| + |y(t)i - y(t)j| \tag{2} \]

The solution formulas for the horizontal and vertical coordinates between adjacent equipment in each sub-plan period t are as follows:

\[ x(t)k \geq x(t)i + (l_i + l_k) / 2 + h_{ik} \tag{3} \]

\[ y(t)k = (s - 1) v + v_0, s = 1, 2, \ldots, n \tag{4} \]

(2) Minimum equipment replacement cost

\[ R \text{ as the cost of equipment replacement, it can be simplified for the device mobile cost and installation, removal costs. And } c_i \text{ is equipment a per unit distance of the mobile costs. } U(t)(t+1)i \text{ is the distance moved for the location of the device } i \text{ from sub-period } t \text{ to } t + 1, \text{ which is the distance between the center points of this device between adjacent sub-planning periods. } r \text{ is the number of cycles in which the device’s position has changed, and } T_r \text{ is the loss of devices caused by installation or disassembly each time, and can be reduced to a fixed value.} \]
\[
\min R = \min \left( \sum_{i=1}^{n} \sum_{t=1}^{r} c_i U_{(t)(t+1)i} + rT_r \right)
\]  
(5)

\[U_{(t)(t+1)i} = |x_{(t) i} - x_{(t+1) i}| + |y_{(t) i} - y_{(t+1) i}|\]
(6)

(3) Maximum utilization of workshop area

\[S_l = \max \left( x_{(t) i} + \frac{l_i}{2} - \min \left( x_{(t) i} - \frac{l_i}{2} \right) \right) \times \left\{ \max \left( y_{(t) i} + \frac{w_i}{2} \right) - \min \left( y_{(t) i} - \frac{w_i}{2} \right) \right\} \]
(7)

\[A_{max} = \max \frac{1}{P} \sum_{l=1}^{p} \frac{S_l}{S_l}\]
(8)

The total floor space of \( n \) equipment is a certain value, so the maximum utilization of the workshop area can also be expressed as

\[A_{max} = \min \frac{1}{P} \sum_{l=1}^{p} S_l\]
(9)

From the above analysis, we can get the combined optimization objective function of the dynamic layout of workshop equipment.

\[F_{min} = \alpha_1 \beta_1 \sum_{t=1}^{p} \sum_{i=1}^{n} \sum_{j=1}^{n} P_{tij}Q_{tij}D_{tij} + \alpha_2 \beta_2 \left( \sum_{i=1}^{r} \sum_{t=1}^{n} c_i U_{(t)(t+1)i} + rT_r \right) + \alpha_3 \beta_3 \frac{1}{P} \sum_{i=1}^{p} S_l\]
(10)

Among them, \( \alpha_1, \alpha_2, \alpha_3 \) are normalization factors, the first two are cost units, and the last one is an area unit, in order to ensure the unity of the dimensions, and make the minimum of their optimal results close to 1, so

\[\alpha_1 = \frac{1}{\sum_{t=1}^{p} \sum_{i=1}^{n} \sum_{j=1}^{n} P_{tij}Q_{tij}D_{tij}}, \quad \alpha_2 = \frac{1}{\sum_{i=1}^{r} \sum_{t=1}^{n} c_i U_{(t)(t+1)i} + rT_r}, \quad \alpha_3 = \frac{1}{\frac{1}{P} \sum_{i=1}^{p} S_l}\]
(11)

\( \beta_1, \beta_2, \beta_3 \) are weighting factors and must satisfy \( \beta_1 + \beta_2 + \beta_3 = 1 \). To ensure that the device in the last row in the \( Y \)-direction is placed within the size of the shop floor; the penalty function is set as shown in the following equation. \( P_k \) is the penalty for the \( Y \) direction beyond the workshop area, and \( T \) is the positive large penalty value \( M \).

\[P_k = \begin{cases} 0, \text{ others} \\ T, (s - 1) \nu + \nu_0 + 0.5 \max(w_i) > H \end{cases}\]
(12)

\[T = M\]
The fitness function is defined as
\[ fit(x) = \frac{1}{F_{\text{min}} + P_k} \] (13)

4. Solution methodology

4.1. Proposed solution method

Chaos refers to the seemingly random irregular motion in the deterministic system, the pseudorandomness, the ergodic and extreme sensitivity to the initial conditions which is the basic characteristic of chaos mapping output. It can be used in the genetic algorithm to design and maintain the diversity of the evolution of groups (Cui & Zhao, 2007). Based on the chaos search and the inversion of genetic algorithm optimization, this paper proposes a chaotic genetic algorithm (T_CGA) based on Tent mapping. The main idea is to use the ergodic merit of chaotic motion to select the initial population and improve the quality of the solution by applying the chaotic small perturbation to the current optimal solution.

In the Logistic map space \([0, 1]\), there are 0.25, 0.5 and 0.75 discontinuous points. The uneven distribution of the mapping points which is ‘high sides and low middle’ will directly affect the convergence speed of the whole iteration and reduce the efficiency of the algorithm. Tent mapping, also known as tent map, is a one-dimensional mapping method that is sensitive to initial values. The mapping equation is:

\[
x^{(u+1)}_i = \begin{cases} 
2x^{(u)}_i, & 0 \leq x^{(u)}_i \leq 0.5 \\
2(1 - x^{(u)}_i), & 0.5 < x^{(u)}_i \leq 1 
\end{cases} \] (14)

In the formula, \(i\) represents the serial number of the chaotic variable, \(u\) represents the serial number of the population, and \(u = 0, 1, 2, \ldots\) represents the chaotic variable which is in the interval \([0, 1]\). Due to the finite length of computer word, the Tent mapping iterations fall into the fixed point or small-period cycle (Ye et al., 2018), which greatly reduces the diversity of population. The following improvements have been made to the sequence generation method:

Step1: Take the initial value \(x_0\) (avoid falling into the fixed point or the small cycle point);
Step2: Iterate through Equation (1) to generate the \(x\) sequence;
Step3: If the iteration reaches the maximum number of times, go to step5; Else If \(x^{(k)} = \{0, 0.25, 0.5, 0.75\}\) \(x^{(k)} = x^{(k-i)}, i = \{1, 2, 3, 4\}\) Go to step4; else go back to step2;
Step4: re-assignment, \(x^{(k)} = x^{(k)} \text{rand}(0, 1)\), return to step2;
Step5: Terminate the operation and save the \(x\) sequence.

4.2. Chaotic genetic algorithm based on Tent mapping

The proposed steps of the chaotic genetic algorithm are as follows:
Step 1. The chaotic variables are initialized, and the Logistic mapping is selected, as shown in the formula (14)

\[ x_i^{(u+1)} = \mu_i x_i^{(u)} (1 - x_i^{(u)}) \]  

(15)

In the formula, \( i \) represents the sequence number of the chaotic variable, the \( u \) denotes the population ordinal, \( u = 0, 1, 2, \ldots, C \); \( x_i \) represents the chaotic variable, \( 0 \leq x_i \leq 1 \); the \( \mu_i \) represents the attractor, \( \mu_i = 4 \). The \( x_i \) is transformed into the variable optimization interval. Then, the result is the C-group solution of \( n \) equipment arrangement in \( p \) plan periods.

By calculating the fitness value of each group, the feasible solution of the first \( N \) (population size) with large fitness value is selected to form the initial population, and each individual in the initial population is encoded by the device serial number.

Step 2. We calculate the fitness value of the first \( N \) populations, and in descending order, find out the average fitness, and compare it with the maximum value. If the average fitness value and the maximum fitness value satisfy the formula (16), then the optimization process is concluded and the optimal value is output, otherwise, move to the next step.

\[ \left| \frac{1}{n} \sum_{i=1}^{n} \text{fit}(x_i') - \text{fit}(x_i')_{\text{max}} \right| < \varepsilon \]  

(16)

(\( s \) is one of the minor positive numbers which is given in advance).

Step 3. The 10% of groups with the greatest adaptability in the previous generation adopt a retention mechanism while the other 90% is selected, crossed and mutated by these genetic manipulations.

In order to avoid the generation of illegal offspring and to ensure the new individuals obtained through genetic manipulation are feasible solutions, the single parent genetic algorithm is used to select, cross and mutate the layout string, respectively, in each period. This then ensures a whole chromosome is formed by concatenation of the layout string of the sub-individual in each period. The operation is as follows:

1. Selection.
   The pair of chromosomes which are the layout string of the father’s generation in each period is selected by Roulette Law.
   Each period layout string of the father’s generation selects a pair of chromosomes by roulette. They choose the individual with high adaptability and repeat the election so far.

2. Crossover.
   Two intersection points ‘|’ are randomly set for the first layout string of two parent individuals, one matching segment is determined, and then the first-period layout string of two sub-individuals are generated according to the mapping relationship given by the middle segment between the two intersection points in the two parent individuals. The crossover strategy is shown in Figure 2:

   ↓ ↓ Intersection points
   parent individual A (2 8 7 5 1 3 4 6)
   parent individual B (3 1 4 2 8 5 7 6)
   ↓ Matching
   sub-individual A'(x x | 4 2 8 | x x x)
By means of this crossover strategy, it is a valid and feasible solution to concatenate the various period layout strings of the obtained sub-individual.

(3) Variation. Randomly select a certain layout string and use the mutation operator to perform the mutation operation.

Finally, the new solution is added to the population. With the elitist retention strategy, the optimal solution for each iteration is preserved. When the number of terminations $G$ is exceeded or the convergence condition is satisfied, the optimal value is output.

STEP4. Add a chaotic perturbation to each variable according to formula (17) for the optimal solution of the current generation. $\delta^*$ is the vector of the current optimal solution where individual $(S_1^*, S_2^*, \ldots, S_p^*)$ maps to the interval $[0,1]$, and $\delta_k$ is the chaotic vector after iteration $k$ times. $\delta'_k$ is the chaotic vector after perturbation, which can be calculated by formula (17). The value of $\theta$ in the formula (18) is between $(0,1)$, and it decreases as the number of iterations increases. $m$ is an integer, that depends on the objective function. The range of chaotic perturbation decreases with increases in algebra. This can guarantee both a large-scale search at the initial stage of the iteration, which ensures that the optimal solution appears in the range, and the convergence of the later acceleration to the global optimal solution. In this paper, the chaotic perturbation parameter $m$ is chosen to be $3$. $k$ is the number of chaotic iterations. ($k = 1, \cdots$)

$$\delta'_k = (1 - \theta)\delta^* + \theta\delta_k$$  \hspace{1cm} (17)

$$\theta = 1 - \left\lfloor \frac{k - 1}{k} \right\rfloor^m$$  \hspace{1cm} (18)
STEP5. Calculate the fitness of the newly generated population. If Equation (19) is satisfied, the optimal solution is output; otherwise, return to STEP3.

\[
|f_k(x'_i) - f_{k+1}(x'_j)| < \varepsilon'
\]

(\varepsilon' is a small positive number given in advance).

The flowchart of the chaotic genetic algorithm is shown in Figure 3.

5. Instance validation

A manufacturing workshop is known to be 16 m long, and 12 m wide. According to the production process requirements and the principle of equipment adjacent placing, the layout of 10 units will be designed for three planning periods. If the equipments are redesigned, the transportation cost of unit distance is \(d_i\).

The size of the equipment is shown in Table 1. According to the calculated statistics, the cost of unit materials per unit distance between equipment \(i\) and equipment \(j\) is \(P_{ij}\);
and the logistics matrix between them in the sub-planning period is $Q_{tij}(t = 1, 2, 3)$; and the horizontal distance between them is $h_{ij}$. The equipment is the same distance from the right and left edge of the workshop.

$$d_i = [120 40 160 50 100 60 40 100 60 70] \text{Yuan}.$$
Using the Java-eclipse platform for programming, the basic parameter settings in the optimization process are shown in Figure 4. In this paper, the standard genetic algorithm, chaos genetic algorithm based on logistic mapping and T_CGA three methods are used to simulate and calculate this example. A computer with the frequency of CPU 2.6 GHz and a memory of 4 GB runs 50 random simulations. The comparison results are shown in Table 2.

It is known that the optimal solution refers to the operating cost of the workshop and the utilization of the workshop area from Table 2, including the cost of material transportation and the re-layout layout. It can be seen that the T_CGA method obtains the best solution performance, and the corresponding three planning periods for each
In this paper, the 3-phase material flow is integrated together, the total cost of calculating static layout is 24973 Yuan, and the workshop area utilization is 24.8%. The method reduces the total operating cost by 15% and the area utilization rate by 4.2%.

In addition, the examples in the text are solved simultaneously with the improved GM in the text (Guo, Xu, & Sun, 2011), the NSGA-II in the text (Huang, Ai-Ping, & Lei, 2014), and the ant colony algorithm in the text (Zhang, Kan, & Yue, 2007). A comparison of the results is shown in Table 3.

The above comparative analysis clearly shows that the T_CGA optimization algorithm designed in this paper is slightly better, than the other algorithms, at solving the problems of accuracy and speed. T_CGA optimization algorithm also proved to have reliable search ability and search speed. Results of the calculation show that the T_CGA optimization algorithm has obvious advantages in reducing the operating cost of the workshop. However, cost reduction in the dynamic layout is not always as much as in the static layout. When the device handling cost is too high, the device replacement cost increases, thereby increasing the total cost of the dynamic layout. In such cases, improving efficiency would depend on the actual situation of the workshop layout.

Table 2. Performance comparison of three optimization algorithms.

| Optimization method | Optimal solution | Number of times convergence to global optimal solution | The number of average iterations to produce the optimal solution | Average iterations | Calculation Time/s |
|---------------------|------------------|--------------------------------------------------------|--------------------------------------------------------------|-------------------|-------------------|
| GA                  | 23775, 26.7%     | 18                                                     | 121                                                          | 8.92              |
| L_CGA               | 23312, 27.3%     | 50                                                     | 83                                                           | 8.02              |
| T_CGA               | 21207, 29.0%     | 50                                                     | 55                                                           | 7.98              |

Figure 4. The basic parameter settings in the optimization process.
6. Conclusion

The Chaos algorithm works on multiple fronts. It synthesizes the inversion of the genetic algorithm and the ergodicity of the chaos search as well as the crossover mutation operator and the elitist retention strategy based on the single parent genetic algorithm, which has the advantage of wide search space and fast convergence with the global optimum when solving combinational optimization and multi-objective optimization problems. This paper has developed the steps of designing the algorithm, then it carried out the layout optimization of 10 unequal area equipment in three planned periods, furthermore, a concrete workshop example was put forward. The simulation results show the superiority of the chaotic genetic algorithm over the genetic algorithm because it has the advantage of wide search spaces high efficiency and global convergence. Thus, providing a new way solves the problem of dynamic continuous equipment layout.

The shop floor layout problem solved in this paper is a medium-scale, single-layer, dynamic workshop floor layout, but further research can be done for more complex multi-layer facility layout. This paper does not pay much attention to a series of other constraint indicators such as the balance of the production line during the operation of the system and the processing time of the parts. For more insightful research on efficient production, the next study will have to consider turnaround time.
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