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An Improved Pigeon-inspired Optimization Algorithm for Solving Dynamic Facility Layout Problem with Uncertain Demand

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Abstract

In the layout planning, changes in product demand and uncertainty caused by demand prediction need to be considered simultaneously to cope with the market changes. To this end, a dynamic facility layout problem (DFLP) is studied to optimize cost and area utilization considering the uncertain product demands. An improved multi-objective pigeon-inspired optimization algorithm (IMOPIO) is proposed. A global collaboration mechanism is structured to balance the global and local search. The validity of the proposed approach is demonstrated by an industrial case. The results suggest that the search ability of IMOPIO is better than compared algorithms in solving the proposed problem.

Keywords: Dynamic facility layout; Improved PIO algorithm; Multi-objective optimization; Uncertain demand; Unequal area;

1. Introduction

Facility layout problems (FLPs) are determining the allocation of a set of facilities within some objectives or criteria while satisfying placement restrictions. It is estimated that about 20% ~ 50% production costs can be attributed to facility planning and material handling, and an effective layout design can reduce such costs by 10%–30% [1]. Since the FLP belongs to the NP-hard problem, many researchers have developed a lot of approaches to find solutions to the FLP.

As the material flows between facilities are assumed to be constant during all planning periods, this problem is known as the static facility layout problem (SFLP). However, material flows may vary by reasons such as changes in product design, removal or addition of a product from/to the production line, changes in the production amount because of the changes of demand [2]. These situations in real life make it necessary to consider the dynamic facility layout problem (DFLP). The DFLP method divides the planning horizon of the layout into several production periods and carries on the facilities rearrangement among the production periods. The DFLP has been widely concerned by researchers for its dynamic adaptation to market demands and effective reduction of production costs. Based on the facilities with equal-area and unequal-area, the DFLP can be classified into two categories: equal-area DFLP and unequal-area DFLP. In most applications and real-world scenarios, equal-area facilities are a very poor assumption. Therefore, more and more researchers focus on the unequal-area DFLP.

Heuristic algorithms have been widely used to solve the FLPs because of their good performance in complex problems. Pourhassan MR et al. [3] combined simulation method and non-dominated sorting genetic algorithm (NSGA-II) to deal with the DFLP. Liu J [4] combined the Wang-Landau sampling algorithm and some heuristic strategies to solve the unequal-area DFLP. Turanoğlu B et al. [5] proposed a hybrid simulated annealing algorithm based on bacterial foraging optimization (SABFO) to solve the DFLP. Guan C et al. [6] formulated a

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mixed integer linear programming model and the multi-objective particle swarm optimization (PSO) was employed to search for feasible solutions. Liu J et al. [7] studied multi-objective unequal-area FLP with the flexible bay structure and developed the configuration space evolutionary (CSE) algorithm to solve the unequal-area FLP. Garcia-Hernandez L et al. [8] combined the simultaneous consideration of both quantitative and qualitative features and proposed a novel approach for the unequal-area FLP based on an interactive coral reefs optimization (ICRO) algorithm. The above algorithms give a good performance in solving FLPs, but they also have their own disadvantages. For example, the local search ability of GA is weak, and the quality of the solution depends on the coding method of the gene. The main advantage of PSO is its rapid convergence rate but it is susceptible to premature convergence.

Pigeon-inspired optimization (PIO) algorithm, proposed by Duan and Qiao [9], has proven itself as a valuable competitor in optimization problems. Some studies modified the PIO algorithm to solve multi-objective optimization problems. Qiu H [10] proposed a distributed flocking control algorithm based on the modified PIO to coordinate unmanned aerial vehicles to fly in a stable formation. Chen G et al [11] put forward a modified PIO algorithm to optimize the active power loss, emission, and fuel cost of power system. The PIO algorithm has not yet been applied in FLPs, and more efficient variants of PIO need to be explored to solve real-world problems.

Demand information directly affects the amount of material flow between facilities, which seriously impact stability layout performance. Zha S et al. [12] described the uncertainty of demand as fuzzy random variables and proposed a robust layout model with unequal-area departments. Izadinia N et al. [13] considered that material flows between departments are uncertain and developed a robust MILP model for multi-floor layout problem. Balakrishnan et al. [14] studied the prediction error of product demands in dynamic layout and proved that the uncertainty of product demand had a great impact on the stability of layout performance. Hence, the impact of demand uncertainty on DFLP is considered in this study.

In summary, this paper proposes an improved MOPIO algorithm to solve the unequal-area DFLP considering demand uncertainty, which aims to minimize the total cost of material handling and rearrangement and maximize the area utilization. The rest of this paper is organized as follows. Section 2 develops the unequal area facility layout model. Section 3 introduces the improved MOPIO algorithm. An industrial case is provided in Section 4 and the results are discussed. Section 5 concludes and looks forward to the next study.

2. Problem description and formulation for DFLP

2.1. Problem description

In multi-variety processing workshops, the planned service life of workshop layout is divided into several production periods, and the output demand of each product in each period is obtained by prediction. The layout of facilities with unequal area is carried out at each period, and the facility rearrangement is allowed between periods. The problem studied in this paper is to obtain a practical dynamic layout scheme considering the uncertainty of the predicted demand. The objective is to minimize the total cost of material handling and facility rearrangement and maximize the area utilization.

2.2. Approach for demand uncertainty

For a product p, the demand d_t in a certain production period t is distributed between the minimum predicted value $d_{pt}^{\min}$ and the maximum predicted value $d_{pt}^{\max}$ according to a certain probability and the most reliable predicted value is d_{pt}^{pr}. In this paper, Triangular fuzzy number(TFN) is used to describe the information of predictive demand d_t, which denoted as $\tilde{D}_{pt}\left(d_{pt}^{\min}, d_{pt}^{pr}, d_{pt}^{\max}\right)$.

In the process of solving DFLP, it mainly involves arithmetic addition and multiplication. According to [15], for two TFNs, $\tilde{A}_1=\left(a_1, b_1, c_1\right)$ and $\tilde{A}_2=\left(a_2, b_2, c_2\right)$,their addition and multiplication is defined as:

$$\tilde{A}=\tilde{A}_1+\tilde{A}_2=\left(a_1+a_2, b_1+b_2, c_1+c_2\right) \tag{1}$$

$$\tilde{A}=k\tilde{A}=\left(ka_1, kb_1, kc_1\right) \tag{2}$$

According to the above definition of TFN operation, the object value obtained by each scheme is a triangular fuzzy number, which should be converted to determined values for comparison and ordering. According to Palacios et al. [16], the objective value is defined as the expected value of the triangle fuzzy number, which is implemented by Eq. (3).

$$E(\tilde{A}_1)=\left(a_1+2b_1+c_1\right)/4 \tag{3}$$

In our research, the predicted demand of production is defined as the most reliable predicted value d_{pt}^{pr}. The $d_{pt}^{\min}$ and $d_{pt}^{\max}$ of TFN expression $\tilde{D}_{pt}\left(d_{pt}^{\min}, d_{pt}^{pr}, d_{pt}^{\max}\right)$ is randomly generated from interval $\left[d_{pt}^{pr}(1-\alpha), d_{pt}^{pr}\right]$ and interval $\left[d_{pt}^{pr}, d_{pt}^{pr}(1+\alpha)\right]$ respectively.

2.3. Mathematization of DFLP problems

The model is based on the following premise:

- All facilities and the workshop are rectangular in shape.
- The orientation of each facility is determined.
- Each facility is placed parallel to x and y axis.
- The product varieties of production and the unit material flow of each product have been known.
- The origin coordinate is in the bottom left of the workshop, and the coordinates of each facility are located at its center.

Nomenclature

$\left(x_i^t, y_i^t\right)$	centroid coordinate of facility i at period t
T	number of periods in planning horizon
M	number of facilities

U	number of varieties of part
$\tilde{f}_{jk}^{t}$	fuzzy number of total material handling between facility j and facility k at period t
α_{jk}^{p}	unit material flow of part p between facility j and facility k
$\tilde{D}_{pt}$	fuzzy number of demands of part p at period t
c_{jk}^{t}	unit cost of material handling between facility j and facility k at period t
d_{jk}^{t}	the Manhattan Distance between facility j and facility k at period t
τ_k	unit cost of relocation of facility k
u_k^t	relocation distance of facility k between period $t-1$ to period t
S_l	rectangular area enveloped by the boundary of facilities
A	area utilization
δ_x, δ_y	the minimum gap between facilities in the x-axis and y-axis.
Δ_x, Δ_y	minimum distance of facilities from the boundary in the x-axis and y-axis.
L, W	length and width of workshop
l_k, w_k, h_k, S_k	length, width, weight and area of facility k

The mathematical model for DFLP is described as follows:

$$\tilde{f}_{jk}^{t} = \sum_{p=1}^{U} \alpha_{jk}^{p} \tilde{D}_{pt} \tag{4}$$

$$\min F = \sum_{t=1}^{T}\sum_{k=1}^{M}\sum_{j=k+1}^{M}\left(\tilde{f}_{jk}^{t} c_{jk}^{t} d_{jk}^{t}\right) + \sum_{t=2}^{T}\sum_{k=1}^{M}\tau_k h_k u_k^t \tag{5}$$

$$\mathrm{d}_{jk}^{t} = \left|x_j^t - x_k^t\right| + \left|y_j^t - y_k^t\right|,\ u_k^t = \left|x_k^t - x_k^{t-1}\right| + \left|y_k^t - y_k^{t-1}\right| \tag{6}$$

$$\max A = \sum_{k=1}^{M} S_k / S_l \tag{7}$$

According to Eq. (7), maximization of area utilization can be converted to minimization of envelope area S_l as Eq. (8).

$$S_l = \left[\left(x_{j\max} + \frac{l_j}{2}\right) - \left(x_{k\min} + \frac{l_k}{2}\right)\right]\left[\left(y_{j\max} + \frac{w_j}{2}\right) - \left(y_{k\min} + \frac{w_k}{2}\right)\right] \tag{8}$$

Facilities are not allowed to overlap and shall be kept at a minimum distance from one another.

$$P_{jk} \cdot Q_{jk} = 0, \forall j,k \tag{9}$$

$$P_{jk} = \max\left\{\left(\frac{l_j + l_k}{2} + \delta_{xjk}\right) - \left|x_j - x_k\right|, 0\right\} \tag{10}$$

$$Q_{jk} = \max\left\{\left(\frac{w_j + w_k}{2} + \delta_{yjk}\right) - \left|y_j - y_k\right|, 0\right\} \tag{11}$$

The facilities arranged in X and Y directions shall not be exceeding the overall length and width of the workshop, and a certain distance shall be kept between the facilities and the edge of the workshop for the convenience of material handling.

$$\frac{l_j}{2} + \Delta_x \le x_j,\ \frac{w_j}{2} + \Delta_y \le y_j, \forall j \tag{12}$$

$$L - \frac{l_j}{2} - \Delta_x \ge x_j,\ W - \frac{w_j}{2} - \Delta_y \ge y_j, \forall j \tag{13}$$

3. Pigeon inspired optimization algorithm

3.1. Basic PIO algorithm

PIO simulates two behaviors of pigeons. Map and compass operator is the first operator. The total number of pigeons is N. Their positions and velocities respectively are denoted as $X_i = [x_{i1}, x_{i2}, \cdots, x_{iD}]$ and $V_i = [v_{i1}, v_{i2}, \cdots, v_{iD}]$, where $i = 1, 2, \cdots, N$. Both the positions and velocities of the pigeons are updated in each iteration. The new position X_i^{nc} and velocity V_i^{nc} of the pigeon i at the nc-th iteration can be calculated as follows:

$$V_i^{nc} = V_i^{nc-1} e^{-R \times nc} + rand \cdot (X_{gbest} - X_i^{nc-1}) \tag{14}$$

$$X_i^{nc} = X_i^{nc-1} + V_i^{nc} \tag{15}$$

where R is the map and compass factor. nc is the current iteration. $rand$ is a random number within [0, 1]. X_{gbest} is the global best position, which can be obtained by comparing all the pigeons' positions after $nc-1$ iteration cycles.

Landmark operator is the second operator. The pigeons in the lower half of the line sorted by fitness values are abandoned. Then the center of pigeons' positions X_{center} is regard as the destination. The position X_i^{nc} is updated as follows:

$$X_{center}^{nc-1} = \frac{\sum_{i=1}^{N^{nc-1}} X_i^{nc-1} \cdot F\left(X_i^{nc-1}\right)}{N^{nc-1} \cdot \sum_{i=1}^{N^{nc-1}} F\left(X_i^{nc-1}\right)} \tag{16}$$

Where $F\left(X_i^{nc-1}\right) = 1/\left(\text{fitness}\left(X_i^{nc-1}\right) + \varepsilon\right)$ for the minimization problem, and $F\left(X_i^{nc-1}\right) = \text{fitness}\left(X_i^{nc-1}\right)$ for the maximization problem.

$$N^{nc} = \frac{N^{nc-1}}{2} \tag{17}$$

$$X_i^{nc} = X_i^{nc-1} + rand \cdot \left(X_{center}^{nc-1} - X_i^{nc-1} \right) \tag{18}$$

3.2. Improved multi-objective PIO algorithm

(1) Non-dominated sorting scheme.

The non-dominated sorting scheme is introduced to deal with this multi-objective optimization problem. Pigeons will be divided into different sets(S_1, S_2, etc.) by the non-dominated sorting scheme. The surface formed by solutions in the best non-dominated set S_1 is known as the Pareto frontier. In multi-objective optimization, X_{gbest} and X_{center}^{nc-1} need to be redefined. An elite archive A is used to store the non-dominated solutions. The elite archive selects the pareto optimal solution from S_1 by non-dominant sorting scheme and is updated in each iteration. X_{gbest} is randomly selected in elite archive A. X_{center}^{nc-1} can be obtained by the following equation:

$$X_{center}^{nc-1} = \frac{\sum_{i=1}^{N_A^{nc-1}} X_i^{nc-1} \cdot F\left(X_i^{nc-1}\right)}{N_A^{nc-1} \cdot \sum_{i=1}^{N_A^{nc-1}} F\left(X_i^{nc-1}\right)} \tag{19}$$

Where N_A^{nc-1} is the number of pigeons in A at $(\mathrm{nc}-1)$-th iteration. $F\left(X_i^{nc-1}\right) = 1/\left(\sum_k^n f_k^*\left(X_i^{nc-1}\right) + \varepsilon\right)$, where $f_k^*\left(X_i^{nc-1}\right)$ is the normalized value of k-th objective function of X_i^{nc-1}.

(2) Modified map and compass factor.

The function of map and compass factor R is to search the whole space and increase the diversity of pigeons, which represents the global searching ability of PIO algorithm. To increase the global search ability and avoid falling into local optimal, the modified map and compass factor adopted linear-decreasing mutation strategy [14] is put forward in, which is implemented by Eq. (20).

$$R = \left(R_{\min} + \left(R_{\max} - R_{\min} \right) \frac{nc}{Nc} \right) \times \left(1 + P_m \cdot (rand - 1) \right) \tag{20}$$

where $R_{\min}$ and $R_{\max}$ are the minimum and the maximum of R respectively, P_m is the mutation probability and Nc is the maximum iteration number.

(3) Global collaboration mechanism.

In order to increase the population collaboration among pigeons, two operators are combined. Namely, landmark operator navigation is conducted after each map compass operator. To balance in global search and local search, a cognitive factor u and a compression factor v as Eq. (21) are adopted in map and compass operator and landmark operator respectively. The global collaboration mechanisms is beneficial to the increase of population diversity in the prophase and get more precise solution carefully in the late. The updating equation Eq. (14) and Eq. (18) is modified as Eq. (22) and Eq. (23).

$$u = \mathrm{e}^{-\frac{(nc-Nc/2)^2}{Nc^2/10}}, \quad v = 1 \Big/ \left(1 + e^{-\frac{nc-Nc/2}{Nc/10}} \right) \tag{21}$$

$$V_i^{nc} = V_i^{nc-1} e^{-R \times nc} + u \cdot rand \cdot (X_{gbest} - X_i^{nc-1}) \tag{22}$$

$$X_i^{nc} = X_i^{nc-1} + v \cdot rand \cdot \left(X_{center}^{nc-1} - X_i^{nc-1} \right) \tag{23}$$

(4) Crossover operator.

The Crossover operator is introduced to improve the global search ability (as shown in Fig. 1) and the steps are as follows:

- Randomly select a pigeon and swap the coordinates of two facilities randomly for each production period.
- Randomly select a pigeon, and randomly select two production periods, swap the coordinates of all its facilities.
- Randomly select two production periods of two pigeons and swap the coordinates of all its facilities.

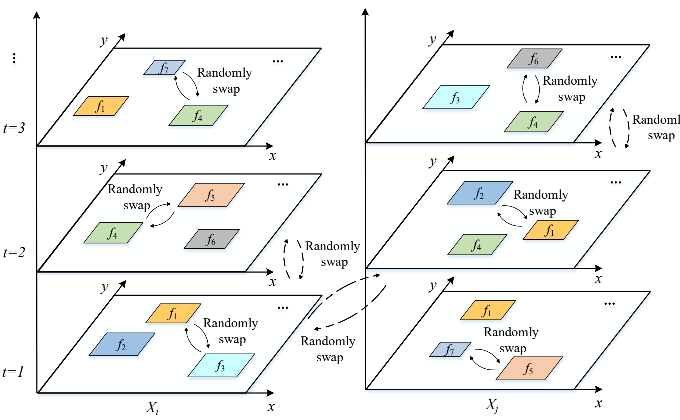

Fig. 1. Crossover operator.

The pseudocode of the IMOPIO is shown as follows:

Algorithm 1 Framework of the IMOPIO

initialize population X, V, A
evaluate the pigeon positions by Eq. (5) and Eq. (8)
non-dominated sorting in X and add S_1 to archive A
while nc < maximum number of iterations **do**
  if mod (nc , 2) = 1
    X_{gbest} ← Randomly select X_i in A
    for each $X_i \in X$ **do**
      update velocities and positions by Eq. (22) and Eq. (23)
    end for
  else
    X_{center} ← obtained by Eq. (19)
    for each $X_i \in X$ **do**
      update positions by Eq. (18)
    end for
  end if
  crossover operator in X
  non-dominated sorting in S and add S_1 to archive A
  non-dominated sorting in A and $A \leftarrow A_1$
  $nc \leftarrow nc+1$
end while

Fig. 2. Pseudocode of the IMOPIO.

4. Case study

4.1. Case description

An engine cylinder head processing workshop is used to verify the effectiveness and practicability of the proposed model and algorithm. The engine plant is planned to build a new processing workshop, which needs to determine the layout location of 12 facility groups. The size and weight parameters of the facility group are shown in Table 1. The workshop is planned to produce three types of cylinder heads (p_1, p_2, p_3) and the unit material flow matrix of three products is known. The entire period of production is made up of three different periods and the predicted demand of product p at each predictable period t is shown in Table 2, which is defined as the most reliable predicted value d_{pt}^{pr} . The new assembly workshop had a large planning area with its length $L = 60m$ and its width $W = 50m$. The minimum gap of facilities with each other $\delta_x = 1.5m$, $\delta_y = 2m$. The minimum distance of facilities from the boundary $\Delta_x = \Delta_y = 2m$.

Table 1. Facility size.

	Facility number					
	1	2	3	4	5	6
Length	5.8	5.8	5.0	5.6	5.0	5.3
Width	4.0	4.0	4.0	4.5	4.0	4.8
Weight	1300	1234	1189	1213	1159	900

	Facility number					
	7	8	9	10	11	12
Length	5.5	6.0	6.0	8.0	6.0	4.0
Width	4.5	3.5	3.2	3.0	4.0	3.5
Weight	1125	1369	1245	1329	1420	1190

Table 2. Predicted demand of products

Product	Period		
	t = 1	t = 2	t = 3
p1	1000	100	2100
p2	2100	1200	100
p3	100	2000	1200

4.2. Parameter setting and Analysis

In the improved MOPIO algorithm, map, and compass factor $R_{\min}$ and $R_{\max}$, mutation probability P_m of R determine the global search capability, which has a great influence on the performance of the algorithm. In addition, the cognitive factor u and compression factor v both affect the local search ability of the algorithm. Experiment results show that the smaller R is valid to improve the global search ability, while the search velocity will get decreased with R declining. Set the parameters as follows: $R_{\min}$=0.05 , $R_{\max}$=0.2 , P_m=0.25 , maximum iterations Nc=100 . According to Eq.(21) and Eq.(22), set $w = e^{-R \times nc}$, the curve graph of $w - nc$, $u - nc$, $v - nc$ is shown as follows:

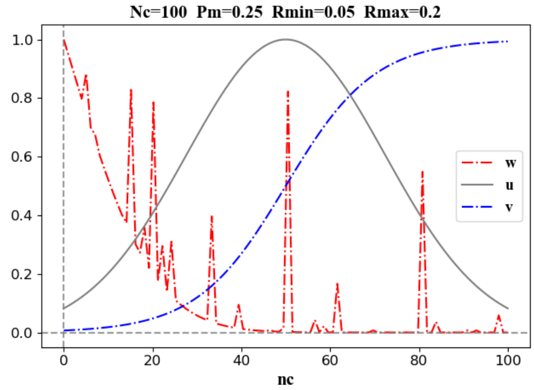

Fig. 3. Graph of parameter.

As shown in Fig.3, The global search capability of the proposed algorithm is guaranteed by a higher value w in the early stage. With the increase of iteration times, the value of cognitive factor u increases. The increased u ensures that the population performs a local search near the current optimal location. In the later stage of iteration, the cognitive factor u gradually decreased and the compression factor v gradually increased, making the population search more carefully around all optimal locations.

4.3. Problem solving and Experiments

According to the constraints of the workshop, the DFLP model was constructed in accordance with Section 2.3. The object fuzzy number is converted into a definite value by using the method in Section 2.2. To verify the performance of the proposed IMOPIO algorithm in this paper, it is compared with the multi-objective particle swarm optimization (MOPSO) [17] and MOPIO which introducing the non-dominating sorting scheme to the basic PIO algorithm. The parameters set for three algorithms were chosen by using the Taguchi method [18]. The values in Table 3 present the best parameters set. The population size of the above three algorithms is uniformly set as N=80 . Two metrics include numbers of non-dominated solutions (NS) and the hypervolume (HV) are introduced to evaluate the algorithm performance [20]. To eliminate the impact of random factors, all the algorithms run for thirty times and Table 4 shows the average value.

Table 3. Parameters for algorithms

Algorithm	Parameters	Value
IMOPIO	minimum map and compass factor $R_{\min}$	0.05
	maximum map and compass factor $R_{\max}$	0.2
	mutation probability P_m	0.25
MOPIO	map and compass operator times T_1	70
	landmark operator times T_2	30
	map and compass factor R	0.1
MOPSO	inertia weight w	0.4
	acceleration coefficients c_1 , c_2	1.0
	number of hypercubes in each dimension N_h	10

	repository size S	100

Table 4. Averaged value of different algorithms

Metrics	Algorithms		
	MOPIO	MOPSO	IMOPIO
NS	5.644	5.591	5.720
HV	0.617	0.629	0.683

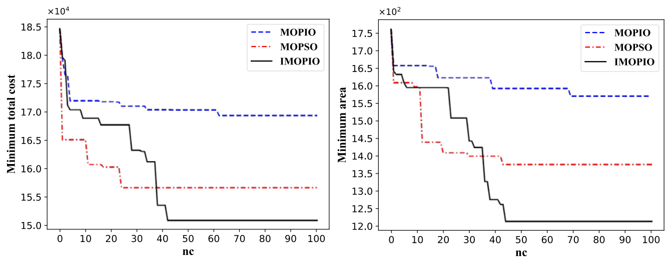

Fig. 4. The iterative process comparison

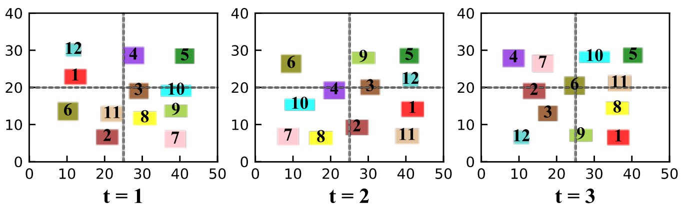

Fig. 5. Dynamic layout of optimal solution

It can be seen from Table 4 that the NS and HV values of IMOPIO are both higher than those of MOPIO and MOPSO. A larger NS and HV value have a better performance of the algorithm. The results demonstrate that the closeness and diversity of solutions obtained by IMOPIO are better than those of the other two algorithms. Hence, the superiority of IMOPIO exists regarding NS and HV, which proves the effectiveness of our improved approaches in this paper. The iterative process is presented in Fig.4. The dynamic layout of the optimal solution is shown in Fig.5. It can be observed from Fig.4 that MOPIO and MOPSO are easy to fall into local optimum prematurely. In addition, the convergence speed of IMOPIO is slightly lower than that of MOPSO, but far better than that of MOPIO. It can be concluded that the search ability of IMOPIO is better than that of the other two algorithms. Fig.5 shows that the algorithm proposed in this paper can effectively solve the DFLP considering the uncertainty of product demand.

5. Conclusions

In this research, a mathematical model for unequal-area dynamic facility layout problem is built. The triangular fuzzy number theory is introduced to describe the demand uncertainty on facility layout. An improved PIO algorithm is proposed to solve this model. The non-dominated sorting scheme is introduced, and a global collaboration mechanism is structured to balance the global and local search by introducing a cognitive factor and a compression factor. In addition, modified map and compass factor and crossover operator are adopted to enhance the algorithm performance. The superiority of the algorithm is proved by an industrial case finally.

However, this paper simplifies the problem of facility rearrangement. In order to make the model more practical, detailed facility rearrangement process need to be considered, such as setting up a facility buffer and considering path planning for facility rearrangement. In addition, the performance of the IMOPIO can be evaluated by applying it to other types of facility layout problems. For example, applying the algorithm to the multi-floor layout problem can be tried.

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