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ОПТИМИЗАЦИЯ ПЛАНИРОВКИ ИНТЕЛЛЕКТУАЛЬНЫХ ПРОИЗВОДСТВЕННЫХ ЦЕХОВ С ИСПОЛЬЗОВАНИЕМ КОМБИНАЦИИ ЦИФРОВОГО ДВОЙНИКА С МНОГОЦЕЛЕВОЙ МОДЕЛЬЮ SLP-GA НА ПРИМЕРЕ КЕЙСА PCB

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Аннотация

В эпоху смарт-производства оптимизация планировки производственных цехов играет ключевую роль в повышении эффективности производства и снижении логистических затрат. В настоящем исследовании предлагается многоцелевая модель оптимизации планировки, основанная на интеграции метода систематического планирования размещения (SLP) и генетического алгоритма (GA), дополненная технологией цифрового двойника. Модель направлена на достижение баланса между логистической эффективностью и нелогистическими взаимосвязями в рамках комплексного процесса оптимизации. На примере цеха по производству печатных плат (PCB) предложенная модель SLP-GA была проверена с помощью цифрового двойника, реализованного в AnyLogic, что позволило выполнить динамическую оценку материальных потоков и занятости персонала. Результаты показывают, что оптимизированная планировка снижает логистическое расстояние на 28,8%, уменьшает потребность в транспортном персонале на 11 человек и увеличивает годовой выпуск продукции более чем на 120% по сравнению с исходной конфигурацией. Предложенный подход эффективно поддерживает концепцию бережливой трансформации и служит воспроизводимой методологической основой для интеллектуального, основанного на данных проектирования производственных цехов в контексте Индустрии 4.0.

КЛЮЧЕВЫЕ СЛОВА: смарт-производство, оптимизация планирования, SLP-GA, цифровой двойник производства.

OPTIMIZING SMART MANUFACTURING WORKSHOP LAYOUTS USING A DIGITAL TWIN-ENHANCED SLP-GA MULTI-OBJECTIVE MODEL: A PCB CASE STUDY

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Abstract

In the era of smart manufacturing, optimizing workshop layouts plays a pivotal role in enhancing production efficiency and reducing logistics costs. This study proposes a digital twin-enhanced multi-objective layout optimization model that integrates Systematic Layout Planning (SLP) with a Genetic Algorithm (GA). The model aims to balance logistics efficiency and non-logistics relationships through a comprehensive optimization process. Using a PCB manufacturing workshop as a case study, the proposed SLP-GA model was verified via digital twin simulation built in Anylogic, which enabled dynamic evaluation of production flow and personnel utilization. Results demonstrate that the optimized layout reduces logistics distance by 28.8%, decreases transport personnel by 11, and increases annual output by over 120% compared with the original configuration. The proposed approach *effectively supports lean transformation and provides a replicable framework for intelligent, data-driven workshop design in the context of Industry 4.0.*

KEYWORDS: smart manufacturing, layout optimization, SLP-GA, digital twin.

1. Introduction

Manufacturing is a pillar industry of the national economy. Against the backdrop of profound changes in the global industrial pattern, smart manufacturing has become the main direction for the transformation and upgrading of the manufacturing industry. As the basic unit of manufacturing activities, the level of intelligence, leanliness, and efficiency of workshops directly determines the core competitiveness of enterprises. Traditional workshop layout methods often have problems such as fragmented regional functions, tortuous logistics paths, and low resource utilization efficiency, which cannot meet the needs of modern production models with multiple varieties and small batches.

In this context, this study focuses on the optimization of manufacturing workshops, proposes a comprehensive scheme integrating improved YOLOv11 and SLP-GA coupled algorithm, and emphasizes the role of digital twin simulation verification in the optimization process. Its goal is to align with the national "lean production" concept, improve the overall operational efficiency and quality of workshops, reduce manual dependence, and provide a practical technical path for achieving the goals of smart manufacturing and high-quality development of the manufacturing industry.

In existing research, the classical Systematic Layout Planning (SLP) method analyzes logistics and non-logistics relationships among work units but relies heavily on expert experience and struggles with complex constraints [1–3]. Genetic Algorithms (GA) have been widely adopted for their strong global search capabilities, and combining SLP with GA has been shown to improve layout quality and reduce logistics costs [4–9]. Meanwhile, digital twin simulation has emerged as an effective tool for evaluating and refining layout designs, with recent studies demonstrating its value in early flaw detection and production system optimization through simulation platforms and mathematical models [10–13].

2. SLP-GA Layout Optimization Method

2.1. Layout Optimization Method Based on SLP

The core of the SLP method is to analyze the logistics and non-logistics relationships between work units. Logistics relationships are classified into levels (A, E, I, O, U, X) based on process flow and material flow volume. Non-logistics relationships consider 7 factors including process connection and environmental compatibility. The comprehensive mutual relationship is obtained through weighted synthesis (logistics weight 0.6, non-logistics weight 0.4), and a work unit position relationship diagram is drawn to provide a basis for subsequent optimization.

2.2 Layout Optimization Method Based on Genetic Algorithm (GA)

Coding Scheme

A parameter cascading coding method is adopted. Real number coding defines the center position of the manufacturing area, where different real numbers correspond to different centers; binary coding (0 for horizontal direction and 1 for vertical direction) defines the length and width direction of the area. Manufacturing units are arranged in rows with an automatic line feed strategy: if the current arrangement exceeds the workshop boundary in length or width, it automatically feeds to the starting position of the next row. The overall arrangement follows the order from left to right and top to bottom.

Objective Function Design

The objective function of the genetic algorithm model is set to minimize handling costs and maximize non-logistics relationships. Assuming the layout scheme is *X, i* and *j* are the work units of the scheme, the distance between them is denoted asd_{ij}, and the handling volume is denoted asf_{ij} The distance matrix and logistics volume matrix can be obtained, and then the material handling cost expression is derived as follows:

$$C_i' = \frac{\sum_{i=1}^{m}\sum_{j=1}^{m} c_{ij} f_{ij} d_{ij}}{\sum_{i=1}^{m}\sum_{j=1}^{m} c_{ij} f_{ij} d_{max}}, \tag{1}$$

where. C_i' is the total handling cost, and c_{ij} is the handling cost between each unit.

The non-logistics relationship expression is as follows:

$$C_2' = \frac{\sum_{i=1}^{m}\sum_{j=1}^{m} T_{ij} b_{ij}}{\sum_{i=1}^{m}\sum_{j=1}^{m} T_{ij}}, \tag{2}$$

where. C_2' is the sum of non-logistics relationships, T_{ij} is the closeness degree of non-logistics relationships between work units, with levels A, E, I, O, U, X corresponding to values 4, 3, 2, 1, 0, -1 respectively; b_{ij} is the correlation factor between non-logistics relationship levels and distance.

The final objective function expression C is obtained as:

$$minC = V_1 C_1' - V_2 C_2', \tag{3}$$

To conform to actual implementation conditions, corresponding constraints are imposed on the objective function. Firstly, the non-overlapping constraint of work units is set:

$$\left|x_i - x_j\right| \geq \frac{L_i+L_j}{2} + \Delta x_{ij},\ \left|y_i - y_j\right| \geq \frac{w_i+w_j}{2} + \Delta y_{ij}\ , \tag{4}$$

Secondly, the boundary constraint is set:

$$\left|x_i - x_j\right| + \frac{L_i+L_j}{2} \leq L,\ \left|y_i - y_j\right| + \frac{w_i+w_j}{2} \leq W, \tag{5}$$

where x_i, x_j are the X-axis center coordinates of work units; y_i, y_j are the Y-axis center coordinates of work units; L, W are the length and width of the workshop respectively; L_i, L_j and W_i,W_j are the length and width of work units i and j respectively; Δx_{ij} and Δy_{ij} are the horizontal and vertical distances between work units i and j respectively. Constraints are limited by penalty functions.

Fitness Setting

The selection of the fitness function directly affects the convergence speed of the genetic algorithm and whether an optimal solution can be found. It increases the probability of an individual producing the next generation by judging the superiority of the individual, thereby obtaining a better solution, i.e., a better target individual. Here, the reciprocal method is used to convert the objective function C into the fitness function $F(x)$:

$$F(x)=\frac{1}{1+C+f(x)}\ , \tag{6}$$

where $f(x)=C'_1-C'_2$; $C\geq 0$; $C+f(x)\geq 0$

Selection Method

The most commonly used iterative selection method in genetic algorithms is the roulette wheel method, also known as proportional selection method, where the probability of an individual being selected is proportional to its fitness value. The higher the fitness value, the larger the proportion, and the higher the probability of being selected as the next generation. Assuming the population size is k, the probability p_i of individual i being selected is:

$$p_i=\frac{F_i}{\sum_{i=1}^{k} F_i} \qquad i=1,2,3,\ldots,k, \tag{7}$$

where F_i is the fitness of each individual.

3. Practical Case Application

3.1. Case Background and Problem Analysis

The initial work unit layout of the PCB manufacturing workshop of Company Z is shown in Figure 3-1. The workshop is 31.3 meters long, 23.92 meters wide, with a total area of 748 m², and the actual production area accounts for approximately 450 m². To focus more clearly on the research problem, this study only considers the actual production area in the layout optimization process of the PCB manufacturing workshop.

3.2. SLP Method

This study determines the weighted values of logistics and non-logistics mutual relationships at a ratio of 3:2. According to the proportion of comprehensive mutual relationship level division, the comprehensive mutual relationship level is calculated. After considering factors such as material and personnel flow volume, process connection sequence, degree and convenience of information exchange, and the inability of two work units to be close due to equipment and environmental interference, the comprehensive mutual relationship level between work units is determined, and the work unit comprehensive mutual relationship diagram is obtained. After appropriately adjusting and modifying the work unit area relationship diagram, the final optimized layout scheme of the PCB production workshop of Company Z is determined. The optimized work unit layout diagram of the PCB manufacturing workshop is drawn, as shown in Figure 1.

3.3 SLP-Based GA Method

Two optimization schemes are generated using the SLP method, which together with random schemes form 50 initial populations. The GA algorithm parameters based on MATLAB are set as follows: maximum iterations 800, crossover probability 0.8, mutation probability 0.2, generation gap 0.9, penalty coefficient 10^5. The optimal solution of the workshop layout is obtained after 750 iterations of the genetic algorithm, thereby obtaining the optimal layout diagram. Since the scheme generated by the genetic algorithm pursues the optimal solution of the objective function, the layout diagram is often irregular. In the actual workshop layout optimization process, it is necessary to adjust the layout of work units slightly according to the on-site conditions and historical production experience to make it more in line with the actual production needs. Therefore, the final workshop layout of the SLP method optimization scheme based on the genetic algorithm is shown in Figure 2.

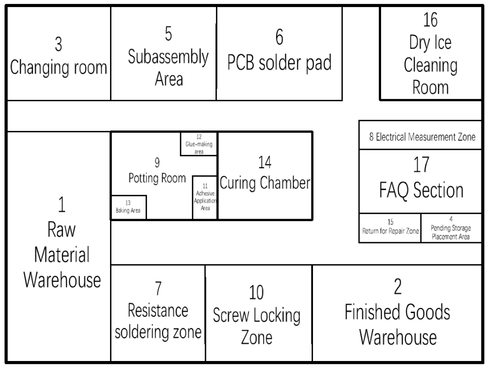

Fig. 1. SLP Method

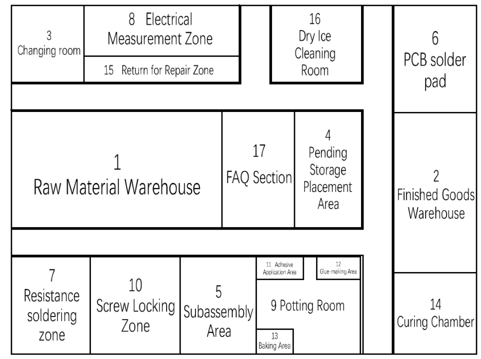

Fig. 2. SLP-GA method

3.4. Optimization Effect Evaluation

Quantitative analysis shows that the handling distance of the initial layout is 287.19m, which is reduced to 236.38m after SLP method optimization (a decrease of 17.69%) and to 204.45m after SLP-GA optimization (a decrease of 28.81%). Qualitative analysis indicates that the optimized layout reduces regional fragmentation and environmental interference, and improves space utilization.

4. Digital Twin Verification

4.1. Modeling Method

Combined with the process flow and the factory layout 2D CAD drawing, a digital twin model is constructed based on Anylogic, with time scaled at 1:24 to simulate material flow and production links. The model integrates process data (such as the standard time of 14.74s for resistor installation), uses Service and Delay modules to represent the processing process, and sets the number of personnel through ResourcePool.

4.2 Operation Results

As can be seen from Figures 3 and 4, under the same production volume, transport efficiency depends on the peak and average number of transport personnel. This paper selects the operation results of the model in the first 150 seconds. From the perspective of the peak number of transport personnel, the peak number of transport personnel under the three layouts all reaches the maximum value of the resource pool. From the curve trend, the workshop layout optimized by the genetic algorithm reaches the peak in the least time within the same time, which can be initially considered to have the smallest transport load.

Table 1. Capacity Data

Item	Original Workshop	After SLP Improvement	After Genetic Algorithm Improvement
Actual Production Quantity	2304	4128	5088
Total Inspection Quantity	2304	5376	5472
Capacity Waste Rate	0.00%	30.23%	7.55%
Capacity Improvement Rate	-	79.17%	120.83%

In terms of production quantity, both the actual production quantity and the total inspection quantity satisfy: quantity after genetic algorithm improvement > quantity after SLP method improvement > quantity of the original workshop.

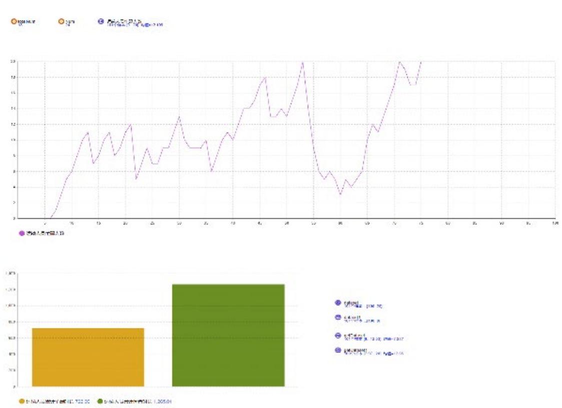

Fig. 3. Transport Personnel Idle Time Diagram

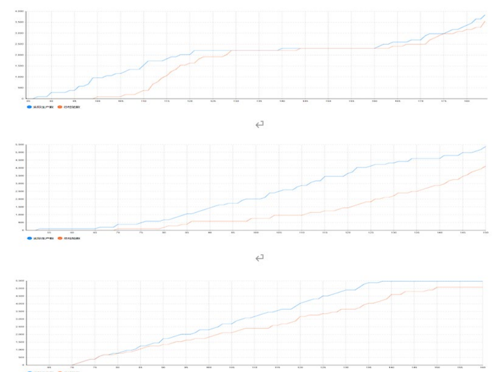

Fig. 4. Production Quantity Change Diagram

In addition, combined with the lowest personnel busy rate mentioned earlier, it can be inferred that the layout of the original workshop will cause congestion when transport personnel are transporting, thereby affecting transport efficiency.

Finally, checking the original production data shows that the daily production quantity of the original workshop is about 4190, and the original workshop reaches 4000 at the 190th second, which confirms that the model operation results are credible.

5. Conclusion

In summary, from the model operation results, the logistics distance is reduced by 28.8% after optimization. After removing outliers, the workshop layout optimized by the genetic algorithm has the lowest personnel busy rate and the highest output within the same time, so it is the optimal among the three layouts. Among them, the personnel busy rate is only 36%, which means that under reasonable capacity arrangement, only 36% of the current personnel are needed to complete the transport task. Considering factors such as personnel fatigue and rest, it is appropriately relaxed to 80%, so the actual number of personnel needed is 20*36/0.8=9, that is, the workshop layout optimized by the genetic algorithm can reduce 11 transport personnel per day. This indicates that our SLP-GA optimization model can realize workshop optimization.

References

1. Alom, M. Z., Taha, T. M., Yakopcic, C., Westberg, S., Sidike, P., Nasrin, M. S., Hasan, M., Van Essen, B. C., Awwal, A. A. S., & Asari, V. K. (2019). A State-of-the-Art Survey on Deep Learning Theory and Architectures. Electronics, 8(3), 292. https://doi.org/10.3390/electronics8030292
2. Boysen, N., Fliedner, M., & Scholl, A. (2006). A classification of assembly line balancing problems. European Journal of Operational Research, 183(2), 674–693. https://doi.org/10.1016/j.ejor.2006.10.010
3. Yiqiong, W. A. N. G., & Zhiwei, M. I. (2010). Method of systematic layout planning improved by genetic algorithm and its application in facility layout. Computer Engineering and Applications, 46(5), 211-213.
4. Zhao, Y., Lu, J., Yan, Q., Lai, L., & Xu, L. (2019). Research on cell manufacturing facility layout problem based on improved NSGA-II. Computers, Materials & Continua/Computers, Materials & Continua (Print), 62(1), 355–364. https://doi.org/10.32604/cmc.2020.06396
5. Turanoğlu, B., & Akkaya, G. (2018). A new hybrid heuristic algorithm based on bacterial foraging optimization for the dynamic facility layout problem. Expert Systems With Applications, 98, 93–104. https://doi.org/10.1016/j.eswa.2018.01.011
6. Khajemahalle, L., Emami, S., & Keshteli, R. N. (2020). A hybrid nested partitions and simulated annealing algorithm for dynamic facility layout problem: a robust optimization approach. INFOR Information Systems and Operational Research, 59(1), 74–101. https://doi.org/10.1080/03155986.2020.1788328
7. Tayal, A., & Singh, S. P. (2016). Integrating big data analytic and hybrid firefly-chaotic simulated annealing approach for facility layout problem. Annals of Operations Research, 270(1–2), 489–514. https://doi.org/10.1007/s10479-016-2237-x
8. Zuniga, E. R., Moris, M. U., Syberfeldt, A., Fathi, M., & Rubio-Romero, J. C. (2020). A Simulation-Based Optimization Methodology for facility layout design in manufacturing. IEEE Access, 8, 163818–163828. https://doi.org/10.1109/access.2020.3021753.

9. DENG Bing, LIN Guang-chun . Workshop Facility Layout Optimization by Using Improved SLP and Genetic Algorithm. Combination Machine Tool and Automation Processing Technology, 2017(8):148-151+156.
10. Tao, F., Zhang, H., Liu, A., & Nee, A. Y. C. (2019). Digital twin in industry: State-of-the-Art. IEEE Transactions on Industrial Informatics, 15(4), 2405–2415. https://doi.org/10.1109/tii.2018.2873186
11. Zhang, Z., Wang, X., Wang, X., Cui, F., & Cheng, H. (2018). A simulation-based approach for plant layout design and production planning. Journal of Ambient Intelligence and Humanized Computing, 10(3), 1217–1230. https://doi.org/10.1007/s12652-018-0687-5 .
12. Damiani L, Demartini M, Giribone P, Maggiani M, Revetria R, Tonelli F (2018) Simulation and digital twin based design of a production line: A case study. In Proceedings of the International MultiConference of Engineers and Computer Scientists (Vol. 2).
13. Wang B, et al. Construction and Optimization of Digital Twin Model for Hardware Production Line. Proceedings of IEEE IECON. 2020.