

Retraction

Retracted: Research on Automobile Assembly Line Optimization Based on Industrial Engineering Technology and Machine Learning Algorithm

Wireless Communications and Mobile Computing

Received 11 July 2023; Accepted 11 July 2023; Published 12 July 2023

Copyright © 2023 Wireless Communications and Mobile Computing. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their

agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] X. Shi, W. Cui, P. Zhu, and Y. Yang, "Research on Automobile Assembly Line Optimization Based on Industrial Engineering Technology and Machine Learning Algorithm," *Wireless Communications and Mobile Computing*, vol. 2021, Article ID 2658090, 9 pages, 2021.

Research Article

Research on Automobile Assembly Line Optimization Based on Industrial Engineering Technology and Machine Learning Algorithm

Xiaorui Shi,¹ Wei Cui,¹ Ping Zhu,¹ and Yanhua Yang^{ID}²

¹Engine Factory of Sinotruk Jinan Power Co., Ltd, China National Heavy Duty Truck Group (China), Jinan 250220, China

²School of Control Science and Engineering Shandong University, Jinan 250012, China

Correspondence should be addressed to Yanhua Yang; yangyanhua@stu.ahu.edu.cn

Received 28 October 2021; Revised 16 November 2021; Accepted 18 November 2021; Published 20 December 2021

Academic Editor: Alireza Souri

Copyright © 2021 Xiaorui Shi et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Aiming at the lack of search depth of traditional genetic algorithm in automobile assembly line balance optimization, an improved genetic algorithm based on bagging integrated clustering is proposed for balance optimization. Through the integrated learning of several K -means algorithm based learners through bagging, a population clustering analysis method based on bagging integrated clustering algorithm is established, and then, a dual objective automobile assembly line balance optimization model is established. The population clustering analysis method is used to improve the intersection link of genetic algorithm to improve the search depth. The effectiveness and search performance of the improved genetic algorithm in solving the double objective assembly line balance problem are verified in an example.

1. Introduction

In today's global economy, every manufacturing company is competing fiercely in an open, continuously changing, and unpredictable global market. In the face of individualized and diversified customer needs and rapidly changing market demands, manufacturing companies must make every effort to continuously shorten product delivery times, improve product quality, reduce product prices, and provide the highest quality services to improve competitiveness, which is particularly evident for automotive manufacturers.

To improve the competitiveness of enterprises, automotive OEMs have commonly adopted the mixed-flow manufacturing technology, whose production operation control is based on the famous Just In Time (JIT) system [1] and Toyota Production System (TPS) [2]. The mixed-flow manufacturing system adopts a series of advanced management methods and technologies such as flexible process routes and kanban mechanisms to reduce production assistance time, improve production efficiency, reduce indirect costs such as logistics and inventory in production, enable the system to respond quickly to changes in market demand,

and make timely adjustments by using order-driven production and JIT methods to reduce work-in-process inventory.

Improving the productivity of the assembly line is the main focus of research in the actual production. Assembly is a process that combines manufacturing and information control, and a well-designed assembly line balancing solution can make the assembly line operate efficiently and reliably, thus improving productivity and increasing enterprise efficiency. Assembly line balancing problems are divided into three categories according to different optimization objectives [3]: (1) the optimal number of workstations with a certain production rate, (2) the optimal production rate with a fixed number of workstations, and (3) the optimal smoothing factor with a known number of workstations. The assembly line balancing problem is a typical nondeterministic polynomial problem with high requirements for the solution algorithm, which is mainly based on genetic algorithms and other heuristic algorithms in recent years.

Although the mixed-flow manufacturing system has improved and upgraded the traditional manufacturing system in many aspects such as flexible process routes, equipment layout, and inventory reduction, in order to adapt to

the changing market demand, the production mode adopts a multivariety and small-lot approach, and the system must be constantly adjusted according to the changes in demand, so the system cannot remain stable for a long time, and the production varieties brought by the production of new products and discontinuation of old products are inevitable [4]. Therefore, the system cannot remain stable for a long time, and the changes in production varieties, process flow adjustment, layout changes of assembly line stations and equipment, and material distribution system adjustment and upgrade are inevitable. Therefore, this paper takes the automotive mixed-flow assembly workshop as the application object, which is aimed at reducing costs and improving efficiency, and focuses on key issues such as the balance of the assembly and bilateral distribution lines and the optimization of internal logistics in the production workshop.

In summary, scholars have improved the genetic algorithm in terms of coding, decoding, crossover, variation, and selection, but they have not considered the improvement of the algorithm from the biological point of view that inbreeding cannot reproduce. In order to improve the search depth of the genetic algorithm, I established a bagging integrated clustering method to analyze the kinship between individuals in the population, and based on this method, I improved the crossover link of the genetic algorithm to improve the search depth of the algorithm and obtain a better feasible solution in the biobjective assembly line equilibrium optimization problem.

2. Related Work

An improved genetic algorithm based on multilevel random assignment coding is proposed for the large-scale mixed-flow U-shape assembly line balancing problem, which can accurately find the better solution of the problem while reducing the computational complexity [5]. For the assembly line balancing problem, a multiple population genetic algorithm based on feasible job sequences is proposed to expand the search space and effectively avoid the local optimum situation. The improved genetic algorithm based on hormone regulation mechanism and the selection, crossover, and variation operators are designed to solve the model of mixed assembly line balancing problem with one station and multiple products, which improves the performance of the algorithm [6]. Combined with the characteristics of genetic algorithm and mixed-flow assembly line, the initial population generation, visualization operation, crossover, and variation operation and probability setting of genetic algorithm are improved, and the population expansion mechanism is proposed to improve the global search capability of the algorithm. [7] analyzed the problem of premature maturity of traditional genetic algorithms with limited population size and proposed and implemented a hybrid genetic algorithm incorporating improved genetic operator strategy and the idea of simulated annealing. [8] designed an improved genetic algorithm based on natural number sequence and topological sorting to protect good genes by improving crossover and mutation operations when solving the model and proposed a population expansion mecha-

nism, which achieved significant results in terms of solution efficiency and solution quality. [9] proposed a stochastic assembly line equilibrium optimization method based on the station complexity measure and used an improved genetic algorithm based on the dynamic step method to optimize the solution. [10] proposed a two-population genetic algorithm and designed the coding and decoding based on the priority association matrix, as well as the fitness design, cross-selection, and variation operators, which were effective in solving the assembly line balancing problem. [11] proposed an improved bipopulation genetic algorithm for product family assembly line and also proposed a new decoding algorithm to make up for the shortcomings of traditional decoding methods, which accelerates the search speed of the algorithm.

In [12], the TALBP problem was first proposed in 1993, and a TALBP mathematical model considering the underlying constraints was given, and a heuristic algorithm using the "first adaptation principle" was designed for the model solution. In [13], a biobjective 0-1 integer programming model was proposed to solve the U-shaped bilateral assembly line balancing problem. A genetic encoding and decoding scheme for the class I bilateral assembly line balancing problem was designed, as well as a genetic operator suitable for this problem, and its applicability and scalability were discussed.

[14] developed an efficient task assignment procedure for the bilateral assembly line balancing problem, assigning a group of tasks at a time instead of one task, emphasizing maximizing work relevance, and maximizing work slack, which is particularly relevant for bilateral assembly lines. [15] developed a mathematical model for the class II bilateral assembly line balancing problem and proposed a heuristic algorithm that first groups task together based on graph depth-first search and then use a series of heuristic rules to select the group for assignment. In [16], the original genetic algorithm was improved by introducing sequences, tasks, and their operational orientations to improve the method of encoding combinations, designing crossover and variational operators adapted to the bilateral assembly line balancing problem, adjusting the encoding according to the order constraint before and after the tasks, making the solution space of the algorithm all feasible solutions, improving the efficiency of the search, and verifying the algorithm with basic arithmetic examples. [17] proposed a branch-and-bound method for the exact solution of the bilateral assembly line balancing problem. [18] designed a new branch-and-bound algorithm to solve the first class of bilateral assembly line balancing problems by first defining two opposite pairs of stations as positions, then relaxing the bilateral assembly line (TAL) to a single-sided assembly line (OAL), computing some new lower bounds for the positions, and extending the first class (OALB-1) of the one-sided assembly line balancing problem with dominant and approximate rules and incorporated them into a workstation-oriented assignment procedure for the TALB-1 problem, and experimental results show that the algorithm is effective.

[19] proposed a new ant colony-based heuristic algorithm to solve the first class of bilateral assembly line balancing problems and showed how to solve the TALB problem

using the ant colony heuristic algorithm. [20] established a mathematical model for the second type of TALBP problem and proposed a new genetic algorithm for model solving, in which local search and steady-state reproduction strategies are used to promote population diversity and improve the efficiency of the search.

[21] proposed a forbidden search algorithm that integrates two optimization objectives, line efficiency, and smoothness, for the TALBP problem, and computational results show that the algorithm performs well. [22] established a mathematical planning model to formally describe the bilateral assembly line balancing problem and proposed an ant colony optimization algorithm to solve this problem, in which two ants work simultaneously on both sides of the line to obtain a solution that verifies the sequential order, operation orientation, area, and synchronization constraints in the assembly process, and the computational results of numerical examples demonstrate its superior performance. [23] studied that in real life, especially in manual assembly lines, tasks may have different execution times and task time variations may be caused by machine failures, loss of motivation, lack of training, unqualified operators, complex tasks, environments, etc. The stochastic task time bilateral assembly line balancing problem is investigated, a chance constrained segmented linear mixed integer programming (CPMIP) is proposed to model it, a simulated annealing algorithm is designed to solve it, and the computational results show the effectiveness of the CPMIP and SA algorithms.

3. Overview of Automotive Mixed-Flow Production Systems

3.1. Definition and Characteristics of Mixed-Flow Production. Mixed-flow production is a scientific production method that takes into account the variety, equipment load, output, and working hours. It is able to arrange the production sequence scientifically on an assembly line for multiple product varieties with high similarity of process flow and production operation methods and implement rhythmic and proportional mixed continuous flow production. Compared with a single product line, the mixed-flow production system has higher flexibility and has been widely used in the automotive and home appliance industries.

The mixed-flow manufacturing model is generally based on the traditional Just-In-Time (JIT) ideological principle, which requires that the required parts arrive where they are needed, in the required quantity, at the required moment, with the following key features:

- (1) *Customer Demand Pull Drive.* In order to respond quickly to customer demand and improve the ability to adapt to changes in customer demand, the daily production schedule on the mixed-flow line is updated according to the amount of customer demand and variety combinations, and the daily production schedule is optimally sequenced to achieve balanced production line capacity, with the entire production pulled by the final assembly process.

- (2) *Linear Manufacturing.* This reduces the WIP queue, reduces production bottlenecks, and smooths out demand fluctuations.
- (3) *Beat-Based (TAKT) Production.* The production line beat is determined based on the production time on the mixed-flow line, and the production cycle time is the same for each station, thus smoothing production and eliminating production bottlenecks.
- (4) *Total Quality Management.* Total quality management is implemented on the production line, and quality inspection is performed by production personnel in the relevant processes. Quality inspection is closely integrated with the production process, enabling timely detection of problems, significantly reducing scrap and rework, and ensuring high quality products at the lowest cost.
- (5) *Just-In-Time Replenishment System.* Materials are sent directly to the consumption point on demand and on time, and material replenishment is driven by kanban signals, which can reduce the capital occupation of raw material inventory, ensure strategic partnership with suppliers, guarantee high quality and low cost, and significantly improve inventory turnover rate.

3.2. Process Flow of Automotive Mixed-Flow Production. The automotive assembly line system is generally an organic whole composed of conveying equipment (air suspension and ground) and specialized equipment (such as lifting, turning, press fitting, heating or cooling, testing, and bolt and nut fastening equipment), including complete vehicle assembly line (process chain, driven by multiple motors), body conveyor line, reserve line, and lift. The automotive mixed-flow assembly line is large in scale, with many stations, equipment, and personnel, and is generally divided into a main assembly line and several subassembly lines [24].

4. Clustering Analysis of Populations Based on Bagging Integrated Clustering

In order to improve the search depth of the genetic algorithm, the author proposes a bagging integrated clustering algorithm, which integrates several K -means algorithm-based learners with bagging, and after a voting mechanism, the class to which each population individual belongs.

4.1. K-Means Clustering Algorithm. The K -means algorithm is based on the principle of minimizing the sum of squares of the distances from all samples of the cluster to the cluster center and is the classical hard clustering algorithm.

The clustering criterion function used by the K -means clustering algorithm is the error sum-of-squares criterion:

$$J_k = \sum_{j=1}^K \sum_{k=1}^{n_j} \|x_k - m_j\|^2. \quad (1)$$

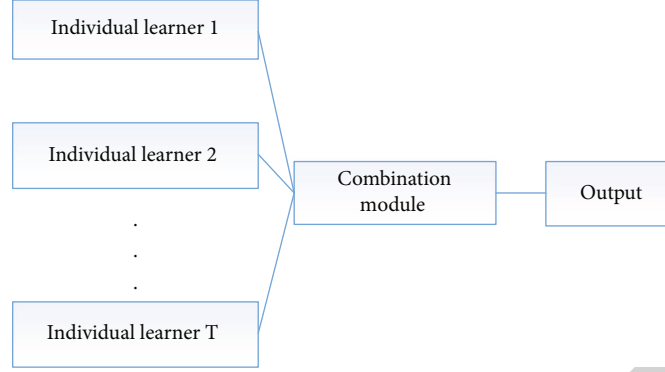


FIGURE 1: Structure of integrated learning.

To optimize the clustering results, the criterion should be minimized.

In the first step, given n mixed samples, let $I = 1$, which denotes the number of iterations, and K initial aggregation centers are selected $Z_j(I), j = 1, 2, \dots, K$.

In the second step, calculate the distance of each sample from the aggregation center $D(x_k, Z_j(I)), k = 1, 2, \dots, n, j = 1$.

If $D(x_k, Z_j(I)) = \min$ and $D(x_k, Z_j(I)), k = 1, 2, \dots, n$, then $x_k \in w_i$.

In the third step, K new aggregation centers are calculated, $Z_j(I + 1) = 1/n \sum_{k=1}^{n_i} x_k^{(j)}, j = 1, 2, \dots, K$.

In the fourth step, determine if $Z_j(I + 1) \neq Z_j(I), j = 1, 2, \dots, K$; then, assign $I + 1$ to I and return to step 2; otherwise, the algorithm ends.

The author's K -means clustering algorithm adopts a batch processing method to select and adjust the initial classification, and the representative point is the clustering center. After selecting a batch of representative points, the distance from other samples to the clustering center is calculated, and all samples are grouped into the nearest center point to form the initial classification, and then, the clustering center is recalculated.

4.2. K-Means Integration Clustering

4.2.1. Integrated Learning. Integrated learning is a combination of learning using several learners. Several individual learners are selected first and then combined using some combination methods. Many classical machine learning algorithms, such as the random forest method, are built using integrated learning. The random forest method is integrated by several decision tree algorithms, and such individual learners are called base learners. The integration learning structure is shown in Figure 1.

4.2.2. Bootstrap. To obtain an integration with high generalization performance, the individual learners in the integration should be as independent as possible from each other. Bootstrap is a resampling technique in statistical learning, and this seemingly simple approach has had a profound impact on many subsequent techniques. Methods such as bagging and AdaBoost in machine learning actually embody the idea of Bootstrap.

In statistics, one is faced with a sample, which has significant uncertainty. It is because of the existence of uncertainty that statistics can live and die, and the meaning of statistics is to infer the total from the sample. The Bootstrap method was originally proposed by Efron, a professor of statistics at Stanford University, in 1977. As a new statistical method for augmenting samples, the Bootstrap method provides a good idea for integrated learning of sampling.

4.2.3. Bagging. Bagging is the most famous representative of the parallel integrated learning method. Given a data set with sample size n , a sample is first randomly taken out and put into the sampling set and then put back into the initial data set so that the sample may still be selected in the next sampling. Some samples in the initial training set appear in the sampling set several times, while some never appear. Repeating the sampling process T times, we obtain T Bootstrap samples with sample size ν , denoted as $D_i = (x_1, x_2, \dots, x_\nu), i = 1, 2, \dots, T$.

The basic process of bagging is to sample T sets of ν training samples, then train a base learner based on each set, and then combine these base learners. When combining the results, bagging usually uses the voting principle.

4.2.4. K-Means Integrated Clustering Algorithm. K -means clustering algorithms are unsupervised learning in machine learning, i.e., they use unlabeled data for learning. Integration learning uses multiple base learners to reduce the bias and variance in the generalization error of the model. Combining the above two concepts is unsupervised integration learning, i.e., using integration algorithms on unlabeled data.

Combining K -means with bagging to generate K -means integrated clustering algorithm, the specific flow of the algorithm is shown in Figure 2.

In the first step, the initial training set is randomly sampled ν times with put-back in a Bootstrap manner, and the sampling process is repeated $T - 1$ times to sample $T - 1$ bootstrap sets containing ν training samples, denoted as $D_i = (x_1, x_2, \dots, x_\nu), i = 1, 2, \dots, T - 1$.

In the second step, since there are unsampled samples, when each sample needs to be categorized, all the remaining unsampled w samples need to be taken out to form the last sample set, denoted as $D_T = (x_1, x_2, \dots, x_w)$; then, the total sample set is denoted as follows:

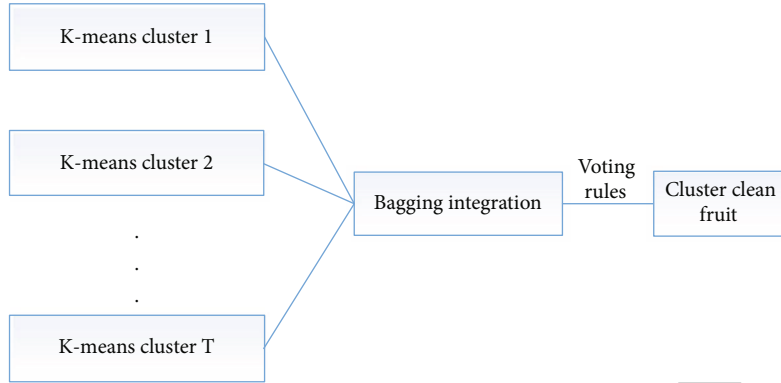


FIGURE 2: K-means integrated clustering algorithm flow.

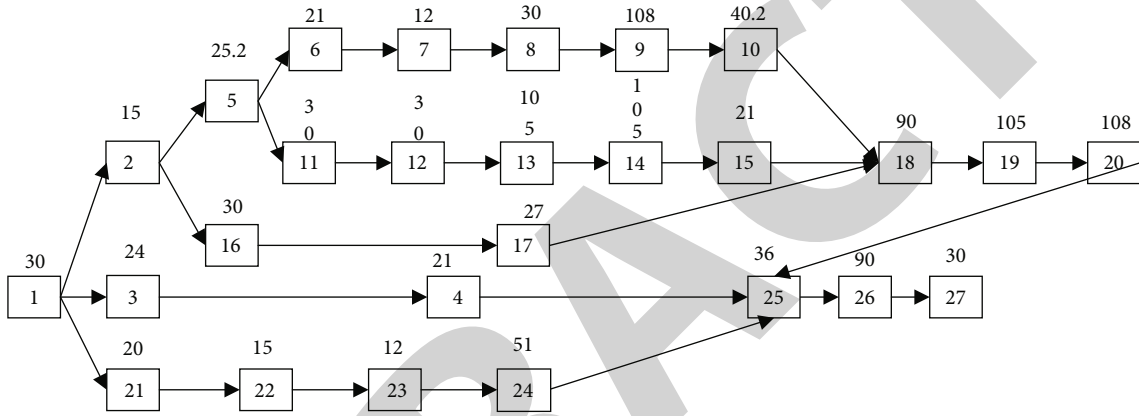


FIGURE 3: Priority relationship of automobile gearbox assembly.

$$D_i = \begin{cases} (x_1, x_2, \dots, x_v) & i = 1, 2, \dots, T - 1, \\ (x_1, x_2, \dots, x_w) & i = T. \end{cases} \quad (2)$$

In the third step, the T sample sets are individually trained with K -means base learners for clustering; let the initial training set sample number be z and the number of clustering categories be K . A $z \cdot K$ dimensional matrix is established to record the voting of each individual learner for each sample clustering category, and the number s in column j of row i indicates that there are s base learners classifying the i th sample as the j th category.

In the fourth step, the final clustering category of each sample is decided according to the established $z \cdot K$ dimensional matrix according to the voting rule. The final category of the sample is determined by the category with the highest number of votes, and if there are categories with the same number of votes, one of them is randomly selected as the final clustering category of the sample.

5. Mathematical Model for Biobjective Assembly Line Equilibrium Optimization

The author establishes a biobjective assembly line equilibrium optimization model with the constraints of fixed num-

ber of workstations and priority relationship of job elements and the assembly line production beat and smoothing factor as the optimization objectives.

5.1. Binding Conditions. C is the production beat, I is the set of job elements, J is the set of workstations, n is the number of job elements, m_i is the actual number of workstations for the i th individual in the population, M is the number of identified workstations, j_k is the set of job elements for the k th workstation, and $k \in (1, M)$.

X is a one-dimensional vector, which represents the ordering of each assembly operation element. If $\mathbf{x} = [x_1, x_2, \dots, x_n]$, x_i satisfying all constraints is the feasible solution. X is an $n \cdot m$ -dimensional matrix, representing the allocation of each assembly operation element on the workstation. For $X(i, k) \in \mathbf{X}$, if $X(i, k) = 1$, it means that the assembly operation element I is allocated on the workstation K . If $X(i, k) = 0$, it indicates that the assembly operation element I is not assigned to workstation K . \mathbf{P}_{Pred} is $n \times 2$ -dimensional priority relation set, and $\mathbf{P}_{\text{Pred}}(i, 1)$ is the preorder operation element of $\mathbf{P}_{\text{Pred}}(i, 2)$. P is the $n \cdot n$ -dimensional priority relation matrix. For $p(k, i) \in p$, if $p(k, i) = 1$, it means that K is the preorder operation element of I . If $p(k, i) = 0$, it indicates that K is a subsequent job element of I . t_i is the operation time of the i th operation element.

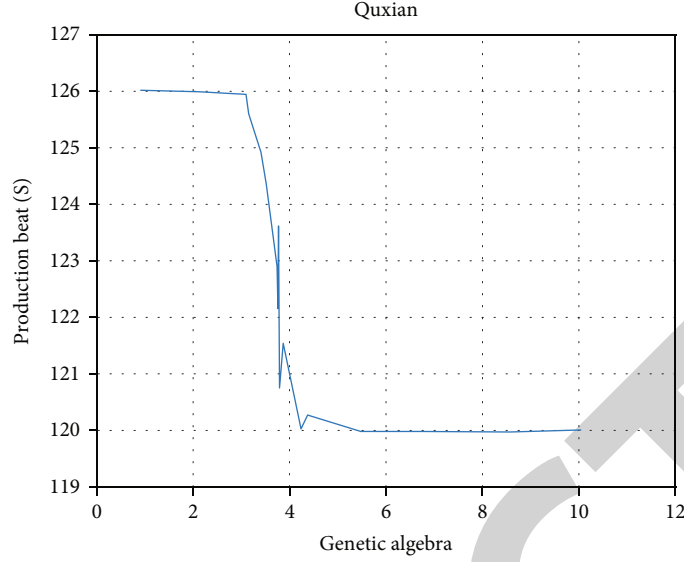


FIGURE 4: Production beat optimization process.

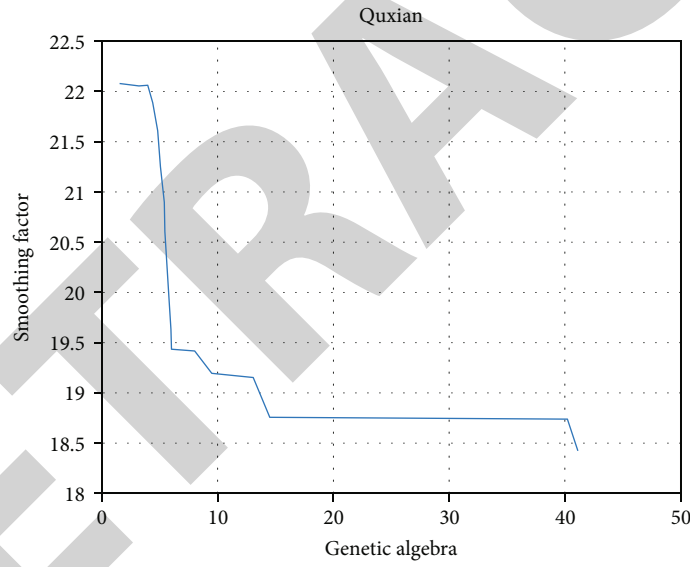


FIGURE 5: Smoothing factor optimization process.

In the actual production of enterprises, the assembly line has often been established. If it is reconstructed or expanded, the cost is high, so the number of workstations is certain.

Each job element can only be assigned to one workstation, i.e.,

$$\sum_{k=1}^M X(i, k) = 1 \quad i = 1, 2, \dots, n. \quad (3)$$

To allocate job elements under the condition of meeting the priority relationship, i.e.,

$$\sum_{k=1}^M k[X(a, k) - X(b, k)] \leq 0 \quad \forall (a, b) \in \mathbf{P}_{\text{Pred}}. \quad (4)$$

The total operation time of each workstation is less than or equal to the production beat, i.e.,

$$\sum_{i=1}^n t_i X(i, k) \leq C \quad k = 1, 2, \dots, M. \quad (5)$$

The number of workstations is certain, i.e.,

$$m_i = M \quad \forall i \in (1, 2, \dots, n). \quad (6)$$

TABLE 1: Assignment scheme for job element 1.

Workstation	Contains job elements	Optimized production beat/S	Smoothing factor
1	1, 2, 16, 5		
2	11, 21, 22, 12		
3	17, 6, 7, 8		
4	13		
5	14		
6	9		
7	10, 3, 15, 23	120	18.3573
8	18		
9	19		
10	20		
11	24, 4, 25		
12	26, 27		

5.2. *Optimization Goals.* The author chooses the optimization objectives as the production beat C and the smoothing factor s_i , because reducing the production beat C can play a role in reducing the total idle time, while the smoothing factor s_i is an index to evaluate the load balance of the assembly line, which serves to improve the utilization of personnel and equipment. The optimization objective is defined as $\min c, \min s_i$.

The production beat C is defined as the maximum value of the workstation operating time and is the operating time of the k th workstation; then, we have T_k .

$$C = \max T_k \quad k \in (1, M). \quad (7)$$

The smoothing factor s_i is as follows:

$$S_I = \sqrt{\frac{\sum_{k=1}^M [T(k) - C]^2}{M}}. \quad (8)$$

6. Example Analysis

In order to verify the depth search capability of the author's algorithm, an automotive transmission assembly line is used as an example for the equilibrium optimization of this assembly line. The automobile transmission assembly body consists of three main parts, the number of operational elements $n = 27$, and the priority relationship is shown in Figure 3. The workstations of the assembly line are already established, with the number of workstations $M = 12$, which would be costly to modify or expand. The equilibrium optimization of this assembly line is carried out with the constraint that the number of workstations is fixed at $M = 12$, and the production beat C and the smoothing factor SI are used as the optimization objectives, and the proposed improved genetic algorithm is used to solve the problem and improve the search depth.

6.1. *Biobjective Optimization Solution.* MATLAB 2015b was used to program the solution, and the parameters of the

TABLE 2: Assignment scheme for job element 2.

Workstation	Contains job elements	Optimized production beat/S	Smoothing factor
1	1, 2, 5, 11		
2	16, 17, 3, 6		
3	21, 12, 7, 8		
4	9		
5	13		
6	14		
7	10, 22, 23, 15	120	18.3899
8	18		
9	19		
10	20		
11	24, 4, 25		
12	26, 27		

TABLE 3: Comparison of solutions.

Parameter	Production beat/S	Smoothing factor
$T = 5, v = 60, K = 3$	120	18.3573
$T = 5, v = 80, K = 5$	120	18.2672
$T = 7, v = 60, K = 5$	120	18.4307
$T = 7, v = 80, K = 3$	120	18.4062
Not improved	120	19.7127

mathematical model were set as follows: fixed number of workstations $M = 12$, crossover probability $P_c = 0.6$, variation probability $P_m = 0.05$, number of genetic generations $G = 50$, number of populations $S = 200$, and initial value of production beat $C = 130$ s.

When $T = 5, v = 60$, and $K = 3$ are set, the optimization processes of production beat C and smoothing factor SI are shown in Figures 4 and 5, respectively. The optimization process records the optimal values of C and SI in each generation of the population.

As can be seen in Figures 4 and 5, both objectives are optimized. The production beat optimization is relatively easy, and the final optimized value is obtained within 5 generations. The smoothing factor is continuously optimized and converges after 40 generations without premature convergence. Some representative and excellent solutions are selected and shown in Tables 1 and 2.

As can be seen from Tables 1 and 2, both the production beat C and the smoothing factor SI are optimized to improve the assembly efficiency and reduce the total idle time, and the algorithm performs a deep search for feasible solutions and optimizes several better solutions.

6.2. *Program Comparison.* The improved genetic algorithm based on bagging integrated clustering has different search depths for different settings of the main parameters, including T, v , and K . To demonstrate that the improved genetic algorithm does improve the search depth, a comparison test is performed with different settings of the parameters. The

first is to optimize the genetic algorithm given different T , v , and K , and the second is to use the unimproved genetic algorithm to solve the problem. The solution with the smallest sum of the two objective values is taken as the representative for multiple comparison tests, and the comparison results are shown in Table 3.

From the analysis in Table 3, it can be seen that the optimized solution of production beat C is the same for each group of experiments, while the optimized solution of smoothing factor SI is different, which indicates that from the perspective of a single optimization objective, the optimization of production beat is easier, while the optimization of smoothing factor is more difficult, and the search depths are different for different parameter settings. Comparing the results of each group of experiments, the optimized solutions with the improved genetic algorithm do not have the same results under different parameter settings, and the search depths are different; on the whole, the optimized solutions with the improved genetic algorithm are significantly better than the unimproved genetic algorithm. In summary, the improved genetic algorithm based on bagging integrated clustering has a deeper search depth and can obtain better solutions than the unimproved genetic algorithm.

7. Conclusions

The author established a population clustering analysis method based on the bagging integrated clustering algorithm from the perspective of the fact that close relatives cannot cross over in biology, used this method to determine whether two individuals in a population are close relatives, and then improved the crossover rule of the genetic algorithm. A dual-objective assembly line balancing model was developed with production beat and smoothing factor as the optimization objectives, and the improved genetic algorithm was applied to the dual-objective assembly line balancing example. The example shows that the improved genetic algorithm effectively improves the depth-seeking ability of the algorithm compared with the unimproved genetic algorithm.

Data Availability

The datasets used during the current study are available from the corresponding author on reasonable request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

References

- [1] Y. Wang and O. Yang, "Research on industrial assembly line balancing optimization based on genetic algorithm and witness simulation," *International Journal of Simulation Modelling*, vol. 16, no. 2, pp. 334–342, 2017.
- [2] S. R. Yadav, N. Mishra, V. Kumar, and M. K. Tiwari, "A framework for designing robust supply chains considering product development issues," *International Journal of Production Research*, vol. 49, no. 20, pp. 6065–6088, 2011.
- [3] J. R. Jadhav, S. S. Mantha, and S. B. Rane, "Development of framework for sustainable Lean implementation: an ISM approach," *Journal of Industrial Engineering International*, vol. 10, no. 3, p. 72, 2014.
- [4] J. Wang, Y. Di, and X. Rui, "Research and application of machine learning method based on swarm intelligence optimization," *Journal of Computational Methods in Sciences and Engineering*, vol. 19, no. 2, pp. 179–187, 2019.
- [5] M. Busogi and N. Kim, "Analytical modeling of human choice complexity in a mixed model assembly line using machine learning-based human in the loop simulation," *IEEE Access*, vol. 5, pp. 10434–10444, 2017.
- [6] Z. Dan, "Part recognition method based on visual selective attention mechanism and deep learning," *Journal of Fiber Bioengineering & Informatics*, vol. 8, no. 4, 2018.
- [7] M. Fathi, M. J. Alvarez, F. Hassani Mehraban, and V. Rodriguez, "A multiobjective optimization algorithm to solve the part feeding problem in mixed-model assembly lines," *Mathematical Problems in Engineering*, vol. 2014, Article ID 654053, 12 pages, 2014.
- [8] S. A. Torabi, S. M. T. Fatemi Ghomi, and B. Karimi, "A hybrid genetic algorithm for the finite horizon economic lot and delivery scheduling in supply chains - ScienceDirect," *European Journal of Operational Research*, vol. 173, no. 1, pp. 173–189, 2006.
- [9] T. Xie, C. Zhang, Z. Zhang, and K. Yang, "Utilizing active sensor nodes in smart environments for optimal communication coverage," *IEEE Access*, vol. 7, pp. 11338–11348, 2019.
- [10] W. Zhang and M. Gen, "An efficient multiobjective genetic algorithm for mixed-model assembly line balancing problem considering demand ratio-based cycle time," *Journal of Intelligent Manufacturing*, vol. 22, no. 3, pp. 367–378, 2011.
- [11] Z. Yang, W. Xu, P. K. Wong, and X. Wang, "Modeling of RFID-enabled real-time manufacturing execution system in mixed-model assembly lines," *Mathematical Problems in Engineering*, vol. 2015, Article ID 575402, 15 pages, 2015.
- [12] B. Nelson and M. Donath, "Optimizing the location of assembly tasks in a manipulator's workspace," *Journal of Robotic Systems*, vol. 7, no. 6, pp. 791–811, 1990.
- [13] Q. Tang, Y. Liang, L. Zhang, C. A. Floudas, and X. Cao, "Balancing mixed-model assembly lines with sequence-dependent tasks via hybrid genetic algorithm," *Journal of Global Optimization*, vol. 65, no. 1, pp. 83–107, 2016.
- [14] Z. Zhang, C. Zhang, M. Li, and T. Xie, "Target positioning based on particle centroid drift in large-scale WSNs," *IEEE Access*, vol. 8, pp. 127709–127719, 2020.
- [15] C. H. Cao, Y. N. Tang, D. Y. Huang, W. M. Gan, and C. Zhang, "IIBE: an improved identity-based encryption algorithm for WSN security [J]. Security and Communication," *Networks*, vol. 2021, article 8527068, 8 pages, 2021.
- [16] D. Wu, C. Zhang, L. Ji, R. Ran, H. Wu, and Y. Xu, "Forest fire recognition based on feature extraction from multi-view images," *Traitement du Signal*, vol. 38, no. 3, pp. 775–783, 2021.
- [17] L. Wang, C. Zhang, Q. Chen et al., "A communication strategy of proactive nodes based on loop theorem in wireless sensor networks," in *2018 Ninth International Conference on Intelligent Control and Information Processing (ICICIP)*, pp. 160–167, Wanzhou, China, 2018.

- [18] H. Li, D. Zeng, L. Chen, Q. Chen, M. Wang, and C. Zhang, "Immune multipath reliable transmission with fault tolerance in wireless sensor networks," in *International Conference on Bio-Inspired Computing: Theories and Applications*, pp. 513–517, Singapore, 2016.
- [19] S. Zhong, Z. Yan, Y. Li, J. Luo, and H. Zhang, "Research on optimization of mining substitution in Wangzhuang mine based on system dynamics," *Advances in Civil Engineering*, vol. 2021, no. 8, 17 pages, 2021.
- [20] D. K. Kwak and J. K. Ryu, "A study on the dynamic image-based dark channel prior and smoke detection using deep learning," *Journal of Electrical Engineering & Technology*, pp. 1–9, 2021.
- [21] J. S. Yoon, B. C. Min, S. O. Shin, W. S. Jo, and D. H. Kim, "GA-based optimal waypoint design for improved path following of mobile robot," *Adv. Intell. Syst. Comput.*, vol. 274, pp. 127–136, 2014.
- [22] C. Zhang, T. Xie, K. Yang et al., "Positioning optimisation based on particle quality prediction in wireless sensor networks," *IET Networks*, vol. 8, no. 2, pp. 107–113, 2019.
- [23] N. Boysen, M. Fließner, and A. Scholl, "Sequencing mixed-model assembly lines: survey, classification and model critique," *European Journal of Operational Research*, vol. 192, no. 2, pp. 349–373, 2009.
- [24] M. F. F. Rashid, W. Hutabarat, and A. Tiwari, "A review on assembly sequence planning and assembly line balancing optimisation using soft computing approaches," *The International Journal of Advanced Manufacturing Technology*, vol. 59, no. 1–4, pp. 335–349, 2012.