

Retraction

Retracted: Real-Time Scheduling of Mixed Model Assembly Line with Large Variety and Low Volume Based on Event-Triggered Simulated Annealing (ETSA)

Mathematical Problems in Engineering

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1].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] C. Cai and S. Kan, "Real-Time Scheduling of Mixed Model Assembly Line with Large Variety and Low Volume Based on Event-Triggered Simulated Annealing (ETSA)," *Mathematical Problems in Engineering*, vol. 2021, Article ID 6657506, 8 pages, 2021.

Research Article

Real-Time Scheduling of Mixed Model Assembly Line with Large Variety and Low Volume Based on Event-Triggered Simulated Annealing (ETSA)

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In the contemporary industrial production, multiple resource constraints and uncertainty factors exist widely in the actual job shop. It is particularly important to make a reasonable scheduling scheme in workshop manufacturing. Traditional scheduling research focused on the one-time global optimization of production scheduling before the actual production. The dynamic scheduling problem of the workshop is getting more and more attention. This paper proposed a simulated annealing algorithm to solve the real-time scheduling problem of large variety and low-volume mixed model assembly line. This algorithm obtains three groups of optimal solutions and the optimal scheduling scheme of multiple products, with the shortest product completion time and the lowest cost. Finally, the feasibility and efficiency of the model are proved by the Matlab simulation.

1. Introduction

Mixed model assembly line is a flexible and cost-effective production system [1], but is always difficult for scheduling. The structure and process of productions are similar in the mixed model assembly line. It improves the enterprise's market response ability, meets the diverse demand of products, reduces inventory and production costs, and improves product quality. However, the variety of specifications and models needs better scheduling strategy because there are usually no/less optimizations in the traditional industrial enterprise [2].

Traditional scheduling methods can provide a one-time calculation and optimization. However, during the execution, there are many unpredictable events, such as machine failure, absenteeism of workers, and shortage of materials, which interrupt the original scheduling plan. So, there are strong requirements of real-time scheduling in the mixed assembly line activities [3].

In an assembly line, different products have different procedure and operating time. So scheduling should be

implemented for the continuous product following the rhythm and proportion so that the varieties, production, working hours, and equipment load can achieve a comprehensive balance [4]. To solve the scheduling problem of the hybrid model assembly line, different kinds of optimization algorithms have been proposed. As a pioneer, Kilbridge studied the solution of the hybrid assembly line in 1963 [5, 6]. Yow applied the genetic algorithm, for the first time, to solve production scheduling of the assembly line which overcomes the traditional optimization methods [7]. Dong and Kan proposed an improved particle swarm optimization algorithm to solve multiobjective mixed model assembly line scheduling problems. Their method can be directly applied to discrete space and keep the good performance of PSO [8]. Xing et al. proposed a Knowledge-Based Ant Colony Optimization (KBACO) algorithm for the Flexible Job Shop Scheduling Problem (FJSSP) [9].

To overcome the infeasibility of above methods in real productions, various optimization algorithms have also been studied, such as the fuzzy problem of shop scheduling, fast scheduling problem, multiobjective optimization problem of

assembly line production, and the robust scheduling of working time. Ye et al. proposed an effective optimization method [10] to solve the flexible job shop scheduling problem with fuzzy processing time. Its main idea is applying the learning mechanism and local search operator to the search framework of special double-crossover schemes. A multiobjective adaptive large neighborhood search method (MOALNS) is proposed for distributed re-placement permutation flow shop scheduling by adding the re-entry characteristics [11]. Dai et al. [12] discussed a hybrid local search algorithm to solve various uncertainties in the actual production system, such as machine failures, absenteeism, and order changes.

Most of the scheduling methods or algorithms for hybrid assembly line production are focused on mathematical development and algorithm design. In mathematical modeling, real-time scheduling and fuzzy processing time [13] are combined for the objective functions. In the existing mathematical modeling process of hybrid assembly line production, the cost factor has little direct impact on the structural model, and the economy of the production system has attracted more and more attention. The common objective functions in hybrid assembly line scheduling include the following aspects: reducing raw material consumption, maximizing the cost of workers, and minimizing the total working time. About the algorithm, different algorithms such as simulated annealing algorithm, tabu search algorithm, genetic algorithm, ant colony algorithm, and particle swarm optimization algorithm have been adapted in scheduling. Javadi et al. [14] proposed an improved genetic simulated annealing algorithm which can jump out of the local optimal solution. Cheng et al. [15] proposed a mixed quenching simulated annealing algorithm. An improved simulated annealing method was proposed for the fast scheduling problem of the hybrid assembly line [16].

Although different scheduling models and algorithms demonstrate different aspects, there is a lack of methodology consideration of real productions. Especially for the unpredictable events, such as machine failure, absenteeism of workers, and shortage of materials, there should be some strategy or index for the updates of scheduling in real time. In this study, we proposed an event-triggered simulated annealing (ETSA) method to deal with this issue and output the optimized changes of the scheduling plan.

2. General Mathematical Model Considered in This Study

Various objectives have been proposed in finding the optimal MMP sequences [xx,xx]. Here, in this study, we focus on the minimization of work overload.

For the work overload [17],

$$f_1 = \min \sum_{h=1}^H \sum_{w=1}^W T_{hw} \text{cost}_h, \quad (1)$$

where w ($w = 1, \dots, W$) is the index of workstations, h ($h = 1, \dots, H$) is the id of workers, cost_h is the labor cost per unit time, T is the working hours of each worker on workstation.

Material cost is generated in each process. According to the different materials in each stage, the objective function of the total material cost is as follows:

$$f_2 = \min \sum_{w=1}^W \sum_{j=1}^D \sum_{m=1}^M \sum_{r=1}^M S1_{jmr} \text{cost}_{wmr}, \quad (2)$$

where w ($w = 1, \dots, W$) says workstation numbers, m ($m = 1, \dots, M$) says product variety numbers, J ($j = 2, \dots, D$) says products in a sequence of position, cost_{wmr} is the adjustment costs per unit time when the type of production is converted from m to r in workstation- w , and $S1_{jmr}$ is a symbol function. When the position j and $j + 1$ stand for type m and r , the value is 1; otherwise, 0.

A basic requirement of the efficient production system is continuous and stable supply of parts. For the successful operation of the system, the constant demand rate is required. The objective function is as follows:

$$f_3 = \min \sum_{j=1}^D \sum_{m=1}^M \left(\left| \frac{\sum_{l=1}^j S_{ml}}{j} - \frac{d_m}{D} \right| \right). \quad (3)$$

In a Minimum Part Set, MPS is a vector that represents the sequence of a product, such as $(d_1, \dots, d_M) = (D_1/H, \dots, D_M/H)$, M is the number of product varieties, D_m ($m = 1, \dots, M$) is the demand for products m , and H is the greatest common divisor of D_1, D_2, \dots, D_M . For any $j \in [1, D]$, the deviation is described as

$$\Delta = \left| \frac{\sum_{l=1}^j S_{ml}}{j} - \frac{d_m}{D} \right|, \quad (4)$$

which should be as little as possible.

2.1. Multiobjective Decision Model of the Mixed Assembly Line. As the cost of parts, workers, and materials is calculated, the total cost of processing each product can be calculated. Use the price of each product to get the total profit of the enterprise, and the total profit objective function is as follows:

$$P_{\text{price}} = \sum_{p=1}^P \text{price} * N, \quad (5)$$

$$\min f_4 = P_{\text{price}} - \min(f_1 + f_2).$$

The mathematical model of mixed model assembly line production problems are as follows:

$$\min f = w_1 f_3 + w_2 f_4, \quad (6)$$

where p ($p = 1, \dots, P$) says the number of products, N says the total number of products, price says the unit price of each product, P_{price} says total sales of all products. $\min(f_1 + f_2)$ says Minimize total product cost. w_1 and w_2 says Weights of objective function.

In the objective function (7), when other costs remain unchanged, it is only necessary to adjust the allocation of workers on the job to save time, thereby improving the profits of enterprises. However, a trade-off should be made according to the number of parts required. The unit price of

each product is $1 * P$ matrix, and the quantity of each product is $N (1 * P$ matrix.

3. Event Triggered Simulated Annealing (ETSA)

3.1. Classical Simulated Annealing Algorithm. The simulated annealing (SA) algorithm, introduced by Kirkpatrick et al. [18], is a local search procedure capable of escaping from the local optimum to solve combinatorial optimization problems. To start the procedure, SA draws an initial solution to generate the neighborhood solution. If the neighborhood solution is better than the incumbent solution, the former is automatically accepted and replaces the latter; otherwise, the incumbent solution is used. The whole process is repeated until no significant improvement in the neighborhood solution is found or the prespecified conditions are met. SA uses this repetitive improvement approach, but in particular it enables a search algorithm to escape from a local optimum.

Considering the use of the simulated annealing algorithm to solve the mixed assembly line problem, the simulated annealing algorithm starts with a higher initial temperature T , sets the temperature parameter drop value a , and calculates the energy difference ΔE . If the energy difference $\Delta E < 0$, the new solution is accepted. Otherwise, the objective function solution space of the global optimal solution is randomly found by combining the hopping probability characteristic $\exp(-\Delta E/kT)$ (where K is a constant), that is to say, it is accepted with a certain probability. A bad solution may jump out of the probability of the local optimal solution and eventually approach the global optimal solution.

The simulated annealing algorithm is widely used to solve NP complete problems [19], but its parameters are difficult to control. Its main problems are as follows:

3.1.1. Initial Value Setting of Temperature T . The initial setting of temperature T is one of the important factors affecting the global search performance of the simulated annealing algorithm. If the initial temperature is higher, the possibility of finding the global optimal solution is higher, but it takes a lot of computing time. On the contrary, low initial temperature can save computing time, but it will affect global search performance. In practical applications, it is usually necessary to adjust the initial temperature several times according to the experimental results.

3.1.2. Annealing Speed. The global search performance of the simulated annealing algorithm is also closely related to the annealing speed. In general, a "full" search (annealing) at the same temperature is necessary, but it takes computation time. In practical application, reasonable annealing equilibrium conditions should be set according to the properties and characteristics of specific problems.

3.1.3. Temperature Management. The temperature management problem is also one of the difficult problems to be solved by the simulated annealing algorithm. In practical

applications, due to the practical feasibility of computational complexity, the cooling method shown in the following is often adopted:

$$T(t + 1) = k \times T(t). \quad (7)$$

In the formula, k is a positive constant slightly less than 1.00, and t is the degree of cooling.

In order to solve the problem of premature convergence of the simulated annealing algorithm, a higher temperature is set at the beginning of the algorithm [20]. In order to achieve a better optimization effect, the cooling speed is maintained at 0.99 or 0.98. Random probability is added to expand the search space to reach the global optimum.

The flow chart of the simulated annealing algorithm is shown in the figure. The flow chart of the simulated annealing algorithm is shown in Figure 1.

In the application of the simulated annealing algorithm, the cooling rate is an important factor affecting the performance of the simulated annealing algorithm. The solution of the simulated annealing algorithm is independent of the initial value and has asymptotic convergence. The temperature needs to be gradually reduced to find the minimum value. In the process of parameter optimization, random adjustment is made according to the gradient change direction of the objective function to avoid entering the local minimum and to ensure the global convergence of the method. It can also make the function have different initial temperatures and cooling values, or a larger search space, to improve the probability of finding the global optimum.

3.2. Pseudocode. Algorithm 1

$J(y)$: Value of evaluation function in state y

$Y(i)$: Represents the current status

$Y(i + 1)$: Represents a new state

r : Used to control cooling rate

T : The temperature of the system, which should initially be in a high temperature state

T_{\min} : The lower limit of temperature. If T reaches T_{\min} , stop searching.

4. A Case Study on the Mixed Model Assembly Line Production Problem

4.1. Problems to Be Solved and Constraints. In this case, the company's product line has the characteristics of multiple varieties and small batches, including reactor assembly, slicing, winding, vertical wire harness packaging, upper and lower core assembly, welding base, inductance testing, pre-drying, oil immersion, cleaning, oven, beneficiation, testing, packaging, and storage.

The company divides the workers into different groups, and the staff of each station is not fixed. Some workers can work on multiple workstations, and we find that assembly line species conversion requires necessary personnel and tools adjustment. Adjustment costs arising from the

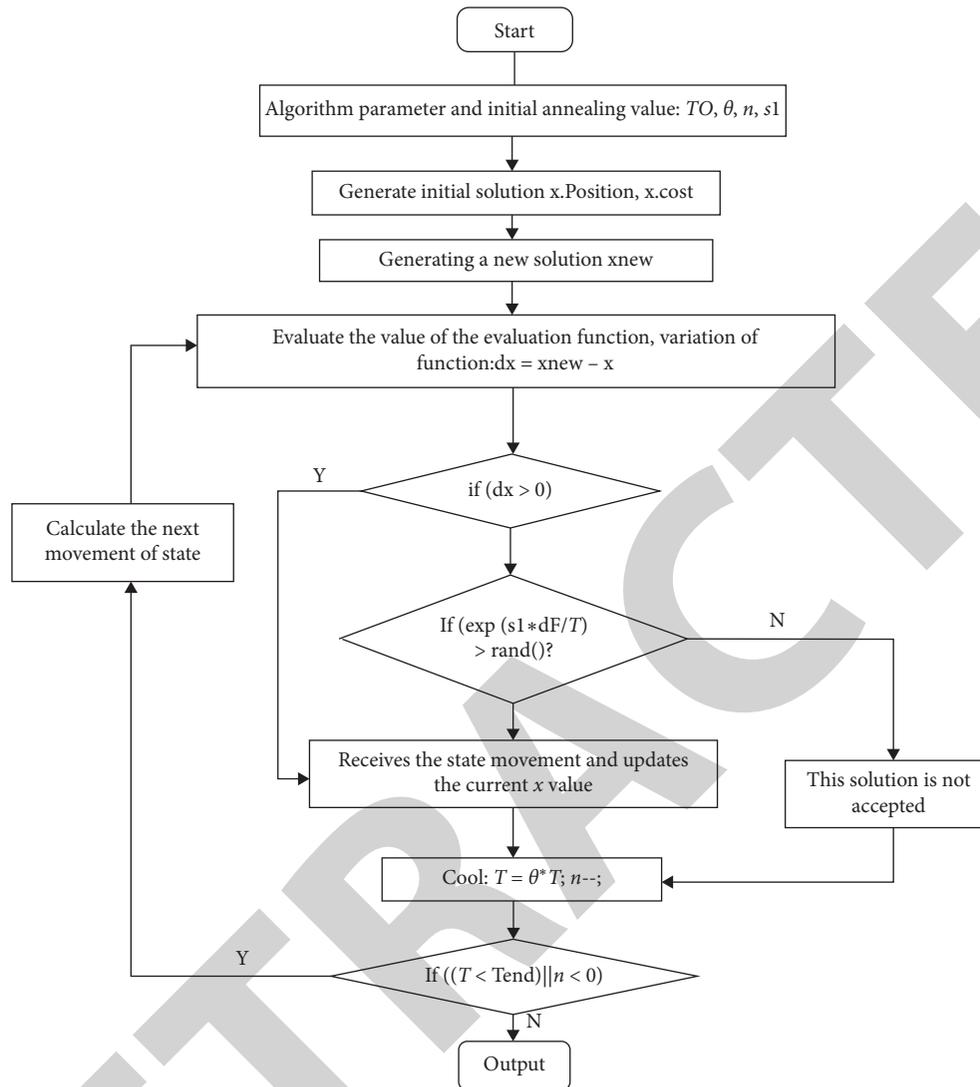


FIGURE 1: Simulated annealing algorithm flow chart.

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while(T > T_min)
{
  dE = J(Y(i+1)) - J(Y(i));
  if (dE <= 0) // Expresses that if the solution is better after moving, it always accepts moving.
  Y(i+1) = Y(i); // Accept the movement from Y(i) to Y(i+1)
  else
  {
    if (exp(dE/T) > random(0, 1))
    Y(i+1) = Y(i); // Accept the movement from Y(i) to Y(i+1)
  }
  T = r * T; // cooling annealing, 0 < r < 1. The larger the r, the slower the cooling is; the smaller the r, the faster the cooling is.
  i++;
}
  
```

ALGORITHM 1: Algorithm of ETSA.

manufacturing sequence of products should be considered first. Secondly, uncertainties will lead to the establishment of the objective function of the minimum labor cost in order to reduce the waste of personnel scheduling [21], save production time, and arrange suitable workers to production at the appropriate sites. Successful operation of the system requires that the demand rate of parts remains unchanged.

The hybrid assembly line has the problem of multivariety and multiprocessing operation. According to the model established in the second part and the actual situation of the hybrid assembly line [22], the constraint conditions of the hybrid assembly line problem are as follows:

- (1) Each machine can process only one product at a time
- (2) Each machine can process different processes
- (3) The same workpiece must be processed according to its process sequence
- (4) For the first phase, all jobs are available at $t=0$
- (5) There is no precedence between the operations of different jobs, but there is precedence between the operations of a job
- (6) For the same operation, the processing time of different unrelated parallel machines in the production phase is different

4.2. Optimized Processing by Simulated Annealing Algorithms. Taking the company's hybrid assembly line as an example, it is assumed that product category $P=5$, number of products $M=10$, process $H=5$ for each product, station quantity $W=5$, and material quantity $K=5$ for each product. Assuming that the workers is enough, In the case of understanding the material cost, labor cost and product profit, it is necessary to find the optimal combination to minimize the cost and maximize the profit of the enterprise. When there are a large number of products in the hybrid assembly line, the traditional production method is difficult to obtain the optimal sequence and cannot consider multiple objective functions at the same time. The algorithm proposed in this paper can quickly provide the optimal solution for the objective function.

Considering that the mixed product of each step of the production line machining position is fixed, we have developed a product processing order of the steps on different machines, and, combined with the processing time of each process on different machines, constituted a multiobjective optimization problem, which requires reasonable production arrangements so that a large variety and low volume products can be completed in the shortest possible time and improve the enterprise. The process time represents the processing time of each process, and the machine number has sorted the jobs.

4.3. Real-Time Scheduling. Scheduling stability is usually not a problem in static and deterministic scheduling environments because the scheduling environment does not need to

be updated. However, in the real-time scheduling environment, stability and robustness are important performance indicators [21].

In the case of machine failure or absenteeism, the process of rearranging due to delayed processing can be time-consuming. In this study, a real-time scheduling method was developed to deal with any time delay in a process. In addition, there are two main parameters affecting the reactive power dispatching process. The first parameter is the time of job delay, while the second parameter is the number of jobs to be delayed [23]. With this real-time scheduling method, if the remaining jobs are not rearranged, the jobs will be rearranged only after this moment.

As described in Section 3.2, the time and process constraint matrix in the absence of uncertain factors is shown in Table 1. It is assumed that machine $m=3$ is delayed, the delay time is $K=15$, and the delay time is $T=20$. Therefore, the products on the third machine after 15 minutes of product processing need to be rescheduled. Each group of scheduling problems contains different processes. The processes before 15 minutes are completed according to the original schedule, where P represents the work to be processed on the machine.

5. Results' Analysis

The improved simulated annealing algorithm was adopted for optimization, and the constraint matrix in Tables 1 and 2 in Section 3 was simulated on MATLAB. Figure 2 shows the Gantt chart of static assembly line scheduling. Figure 3 shows the Gantt chart of the rescheduling.

The optimal solution for static scheduling is considered in Figure 2, that is, the optimal solution for the makespan is $C_{max}=49$. The results of production scheduling are shown in Table 2. Table 2 illustrates the results of product scheduling and calculates the the makespan required for each product on the mixed pipeline, where $\{x, y, z\}$, X and Y denote the start and end time of process processing and Z denotes the process. The results are the same as those of the Gantt chart. Suppose that machine 3 fails in 15 minutes, it takes 20 minutes to delay, resulting in a new scheduling scheme, as shown in Figure 3, and the optimal solution is 56. The sequence and time interval of processing in the first 15 minutes remain unchanged. After 15 minutes, the makespan of each machine is rescheduled. The results show that the makespan of each machine is 56, 56, 45, 43, and 51. In addition, we found that M1, M2, M3, M4, and M5 machine tools on the same machine have a long working interval and are in the state of waiting for processing. Therefore, it will cause waste of resources. The mathematical model described in Section 2 is then implemented to determine the cost of the processed product and the actual profit. The related cost and profit data of the production scheduling are calculated, as shown in Table 3.

Figure 4 shows the results of 500 consecutive iterations, in which the red line is the result of real-time scheduling and the blue line is the result of static scheduling. At the beginning, the initial value of real-time scheduling is higher than that of static scheduling, which is related to the increase

TABLE 1: Scheduling data.

Job	Process time					Machine number				
	P1	P2	P3	P4	P5	M1	M2	M3	M4	M5
1	1	3	6	7	6	3	1	2	4	5
2	8	5	10	10	4	2	3	5	1	4
3	5	4	9	1	7	3	4	1	2	5
4	5	5	5	3	8	2	1	3	4	5
5	9	3	5	3	1	3	2	5	1	4

TABLE 2: Timing and resource constraints for rescheduling.

Constraints	Machine 3	Job 1	Job 2	Job 3	Job 4	Job 5
Time requested	—	1	5	5	5	9
Delay time	20	21	25	25	25	29
Process requested	P_{1-5}	P_1	P_2	P_3	P_4	P_5

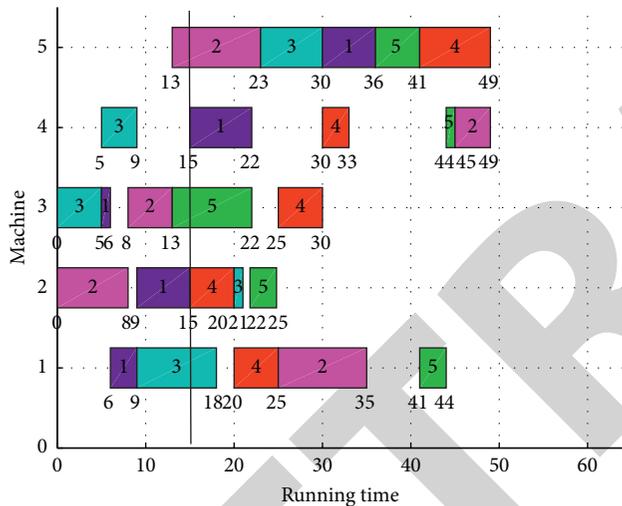


FIGURE 2: The Gantt chart of the production scheduling.

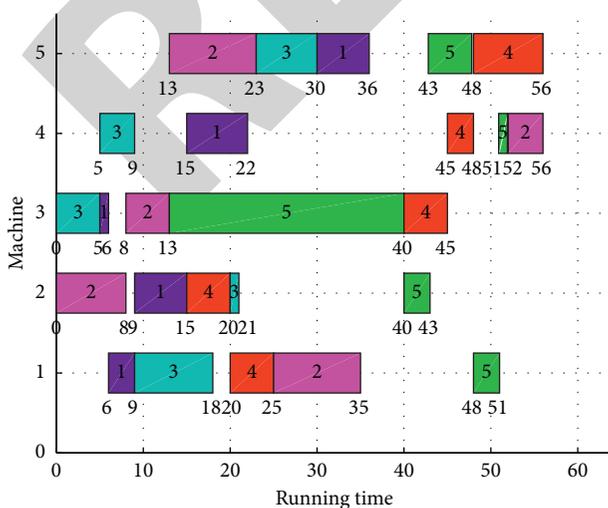


FIGURE 3: The Gantt chart of the rescheduling.

of time. The two results basically find the optimal solution within 50 times, and the trend of the curve is the same because the mode of scheduling is unchanged, but increases in time. In addition, the points on each line are the scheduling process at that time. The curve shows the annealing process of the optimization algorithm, and the solutions of each cooling process are obtained by continuous iteration. Because the realization of the simulated annealing algorithm depends on the choice of parameters, different optimal solutions appear in our scheduling process. The probability of finding the optimal solution by counting different results is shown in Table 4. Running 20 records the results and calculates the probability of finding the optimal solution. Among them, as can be seen from Table 4, the optimal result of static scheduling is 49, and the probability of occurrence is higher, but the value of the optimal solution 56 appears in real-time scheduling. In real-time scheduling, the result of rescheduling depends on the result of the first time, which leads to the diversity of rescheduling results.

5.1. Variable Hybrid Assembly Line Size. In order to explore the reliability and validity of the improved simulated annealing algorithm in multivariety and small-batch applications, we propose a scheduling scheme between different quantities of products and machines, using 4×4 , 5×5 , and 6×6 small-scale scheduling and 10×10 . The results of static scheduling, real-time scheduling, and non-optimal scheduling are compared by the simulated annealing algorithm. The statistical curves are shown in Figure 4.

It can be seen from Figure 5 that, on the one hand, the relationship between makespan and mixed pipelines of different scales is positively correlated. The optimized makespan increases slowly with the increase of the scale, while the unoptimized makespan doubles with the increase of the scale. On the other hand, the utilization efficiency of the machine before optimization is obviously improved, and the makespan of different scales is obviously improved. Making span increases significantly when the scale is not optimized from 6×6 to 10×10 . The possible reason is that the processing time of the machine is irregular, and the processing time of some processes may be longer than before. In addition, the larger the scale of real-time scheduling and static scheduling curves, the smaller the difference of optimization results is because with the increase of product types, the possibilities of arrangement and combination among them increase. Increasing the processing time of a certain stage alone will reduce the impact on the optimization results.

Just as the above analysis, in the actual production scheduling of enterprises, there are often unexpected events such as unexpected inserts, withdrawals, and unexpected events in the workshop. In this case, real-time scheduling is of great significance. Real-time scheduling is essentially a kind of rescheduling. Rearrangement must take into account orders produced to half, so we use the computer system for the workshop status. Real-time updating and regular archiving so that even if the computer system or program fails,

TABLE 3: Scheduling results and makespan.

Job	Machine					Makespan <i>T</i>
	M1	M2	M3	M4	M5	
1	{1, 4, 2}	{10, 19, 3}	{19, 24, 1}	{24, 34, 4}	{35, 38, 5}	36
2	{0, 8, 4}	{8, 14, 1}	{14, 19, 2}	{19, 20, 5}	{22, 25, 3}	38
3	{0, 1, 3}	{1, 6, 4}	{8, 13, 1}	{13, 22, 2}	{24, 29, 5}	30
4	{6, 10, 2}	{14, 21, 1}	{29, 32, 3}	{34, 38, 4}	{38, 39, 5}	49
5	{13, 23, 4}	{23, 30, 2}	{30, 35, 1}	{35, 41, 5}	{41, 49, 3}	45

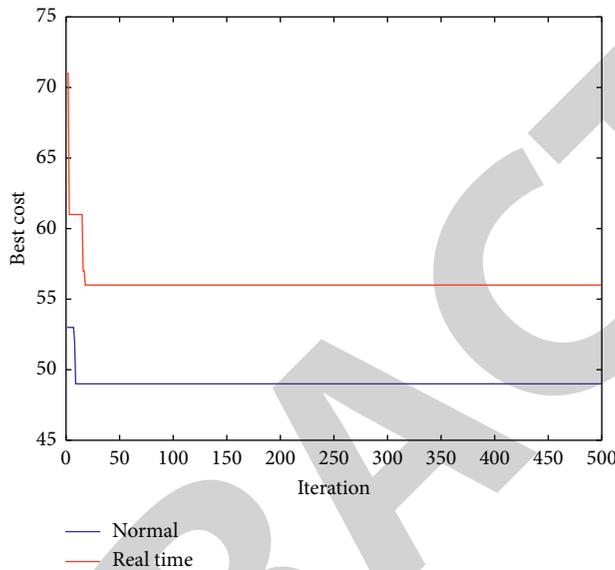


FIGURE 4: Cooling schedule.

TABLE 4: Comparison of simulation running.

Comparison of algorithms	Average evolution generation	Output	
		The optimal solution of the objective function	Probability statistics (%)
No optimization	—	133.0	100
Static scheduling	500	50.0	15
		49.0	85
		69.0	20
Real-time scheduling	500	68.0	5
		64.0	10
		63.0	25
		62.0	30
		56.0	10

the scheduling plan can be rearranged in time to achieve the dynamic scheduling of the workshop and optimize the subsequent production. Figure 3 is the rearrangement after machine failure. Comparing the two Gantt charts, we can see that, after machine 3 failure, the processing time of all kinds of products on machine 3 has changed, and the scheduling plan has been redesigned. We can also look forward to the next step: according to the maintainability of the machine to make a certain prediction of machine failure, if a machine is

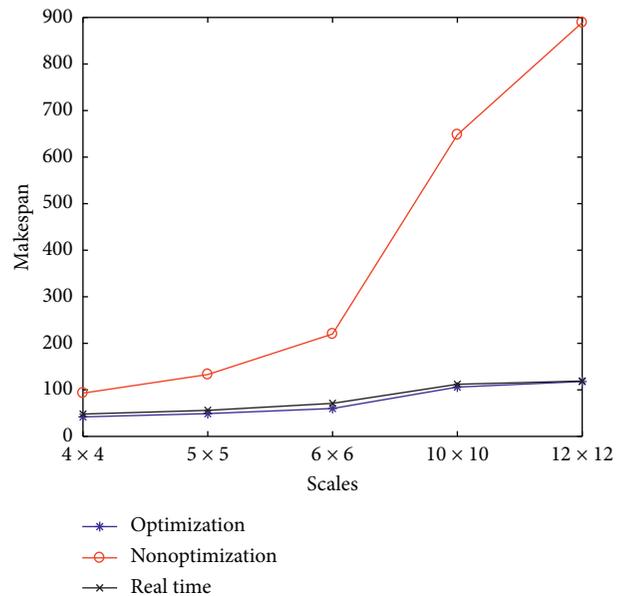


FIGURE 5: Multiscales for the makespan.

predicted to be in trouble, then our program should also give a backup response plan so that the workshop production site can switch the better schedule in time.

6. Discussions and Conclusions

Based on the dynamic, complex, multiconstraint, and multiobjective characteristics of job-shop scheduling in multivariety and small-batch production enterprises, this paper proposes a dynamic job-shop scheduling model based on the simulated annealing algorithm, which can meet the characteristics of multivariety and small-batch production in enterprises. Save the cost of the enterprise, and improve the profit of the enterprise. Numerical examples and simulation results of the hybrid model assembly line show that the proposed simulated annealing algorithm can maintain the excellent performance of the basic genetic algorithm and is an efficient optimization algorithm with better search performance.

To sum up, we must discuss the limitations of this study and the content of future research. Firstly, the actual data of production scheduling is limited. More evaluation of hybrid assembly lines is needed in plant applications by specifying the given parameters. Secondly, uncertain events such as machine failure, number of new jobs, and cancellation of existing jobs should be considered in energy-aware flexible job shop scheduling problems. We plan to add an energy-saving dynamic scheduling model in the future.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

References

- [1] M.-C. Hsiao, "Scheduling of hybrid types of machines with two-machine flowshop as the first type and a single machine as the second type," *IOP Conference Series: Materials Science and Engineering*, vol. 311, pp. 826–837, 2017.
- [2] B. Joseph, M. Ezey, and E. I. Dar, "Mixed model assembly line design in a make-to-order environment," *Computer & Industrial Engineering*, vol. 41, pp. 405–421, 2002.
- [3] Y. Y. Leu, "Genetic algorithm for assembly line balancing," *International Journal of Production Economics*, vol. 41, no. 3, pp. 343–354, 1999.
- [4] J. H. Chul and Y. Kim, "A genetic algorithm for multiple objective sequencing problems in mixed model assembly lines," *Computers and Research*, vol. 25, no. 7, pp. 675–690, 1998.
- [5] J. Miltenburg, "A theoretical basis for scheduling mixed-model production lines," *Management Science*, vol. 35, no. 2, pp. 192–207, 1989.
- [6] A. R. Rahimi-Vahed, M. Rabbani, R. Tavakkoli-Moghaddam, S. A. Torabi, and F. Jolai, "A multi-objective scatter search for a mixed-model assembly line sequencing problem," *Advanced Engineering Informatics*, vol. 21, no. 1, pp. 85–99, 2007.
- [7] Y. L. Yow and L. A. Matheson, "Sequencing mixed model assembly lines with genetic algorithms," *Computers & Industry Engineering*, vol. 30, no. 4, pp. 1027–1036, 1996.
- [8] Q. Dong and S. Kan, "Mixed model assembly line production of the modified discrete particle swarm optimization," *Computer Engineering and Applications*, vol. 45, no. 12, pp. 218–221, 2009.
- [9] L.-N. Xing, Y.-W. Chen, P. Wang, Q.-S. Zhao, and J. Xiong, "A knowledge-based ant colony optimization for flexible job shop scheduling problems," *Applied Soft Computing*, vol. 10, no. 3, pp. 888–896, 2010.
- [10] X. Ye, L. Wang, S.-Y. Wang, and M. Liu, "An effective teaching-learning-based optimization algorithm for the flexible job-shops scheduling problem with fuzzy processing time," *Neuro Computing*, vol. 148, pp. 260–268, 2015.
- [11] A. P. Rifai, H.-T. Nguyen, and S. Z. M. Dawal, "Multi-objective adaptive large neighborhood search for distributed reentrant permutation flow shop scheduling," *Applied Soft Computing*, vol. 40, pp. 42–57, 2016.
- [12] M. Dai, D. Tang, A. Giret, M. A. Salido, and W. D. Li, "Energy-efficient scheduling for a flexible flow shop using an improved genetic-simulated annealing algorithm," *Robotics and Computer-Integrated Manufacturing*, vol. 29, no. 5, pp. 418–429, 2013.
- [13] M. Ham, Y. H. Lee, and S. H. Kim, "Real-time scheduling of multi-stage flexible job shop floor," *International Journal of Production Research*, vol. 49, no. 12, pp. 3715–3730, 2011.
- [14] B. Javadi, A. Rahimi-Vahed, M. Rabbani, and M. Dangchi, "Solving a multi-objective mixed-model assembly line sequencing problem by a fuzzy goal programming approach," *The International Journal of Advanced Manufacturing Technology*, vol. 39, no. 9-10, pp. 975–982, 2008.
- [15] S.-C. Cheng, D.-F. Shiau, Y.-M. Huang, and Y.-T. Lin, "Dynamic hard-real-time scheduling using genetic algorithm for multiprocessor task with resource and timing constraints," *Expert Systems with Applications*, vol. 36, no. 1, pp. 852–860, 2009.
- [16] A. Roshani and D. Giglio, "Simulated annealing algorithms for the multi-manned assembly line balancing problem: minimising cycle time," *International Journal of Production Research*, vol. 55, no. 10, pp. 2731–2751, 2017.
- [17] T. Kellegöz, "Assembly line balancing problems with multi-manned stations: a new mathematical formulation and Gantt based heuristic method," *Annals of Operations Research*, vol. 253, no. 1, pp. 377–404, 2017.
- [18] S. Kirkpatrick Jr., C. D. Gelatt, and M. P. Vecchi, "Optimization by simulated annealing," *Science*, vol. 220, no. 11, pp. 650–671, 1983.
- [19] A. Roshani, A. Roshani, A. Roshani, M. Salehi, and A. Esfandyari, "A simulated annealing algorithm for multi-manned assembly line balancing problem," *Journal of Manufacturing Systems*, vol. 32, no. 1, pp. 238–247, 2013.
- [20] E. Aarts and J. Korst, *Simulated Annealing and Boltzmann Machines*, Wiley, New York, NY, USA, 1988.
- [21] Y. Zhang, J. Wang, and Y. Liu, "Game theory based real-time multi-objective flexible job shop scheduling considering environmental impact," *Journal of Cleaner Production*, vol. 167, pp. 665–679, 2017.
- [22] J. T. Lin and C.-M. Chen, "Simulation optimization approach for hybrid flow shop scheduling problem in semiconductor back-end manufacturing," *Simulation Modelling Practice and Theory*, vol. 51, pp. 100–114, 2015.