IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received 29 July 2022, accepted 6 August 2022, date of publication 10 August 2022, date of current version 16 August 2022.

Digital Object Identifier 10.1109/ACCESS.2022.3197791

RESEARCH ARTICLE

Research on the Scheduling of Mobile Robots in Mixed-Model Assembly Lines Considering Workstation Satisfaction and Energy Consumption

XIAOYUN MA AND XIAOYE ZHOU
School of Management, Shenyang University of Technology, Shenyang 110870, China
Corresponding author: Xiaoyun Ma (332749751@qq.com)

This work was supported in part by the Liaoning Social Science Foundation under Grant L18AGL005, and in part by the Chinese National Natural Science Foundation under Grant 71801160.

ABSTRACT With the intensification of the global energy crisis, the production costs of manufacturing companies have increased significantly. To reduce the production energy consumption and costs in mixed-model assembly lines while improving efficiency and workstation satisfaction, novel line-integrated supermarkets and mobile robots are introduced. Considering the split delivery caused by workstation satisfaction and the mobile robot's energy limitation, a multiobjective mathematical model of mobile robot scheduling in a mixed-model assembly line with a fuzzy time window is presented with the goal of maximizing workstation satisfaction while minimizing energy consumption. On this basis, according to the problem's characteristics, a nondominated sorting genetic algorithm II with variable neighborhood search (VNSGA-II) is developed that constructs the initial solution using a heuristic method, improves crossover operation, and performs neighborhood search using three operators: exchange, insertion, and 2-opt to improve the solution's quality. Finally, two numerical experiments are used to validate the model and algorithm. The results demonstrate that: 1) The scheduling model for mobile robots in a mixed-model assembly line that allows for spilt delivery and uses a normal fuzzy membership function to characterize workstation satisfaction is more in line with production practice. 2) The VNSGA-II algorithm can quickly establish a reasonable scheduling scheme for mobile robots in a mixed-model assembly line, and provide managers with a basis for making scientific decisions. Compared to MOPSO and NSGA-II, workstation satisfaction has improved by 0.91% and 1.12%, respectively, and mobile robots' energy consumption has decreased by 12.53% and 13.66%, respectively.

INDEX TERMS Energy consumption, fuzzy time window, mobile robot, nondominated sorting genetic algorithm II with variable neighborhood search, workstation satisfaction.

I. INTRODUCTION

Under the strain of the energy crisis, manufacturing enterprises face enormous economic and environmental challenges. The industrial sector consumes half of the world's transmitted energy and is responsible for one-third of carbon dioxide emissions, resulting in severe environmental pollution [1]. According to the *World Energy Outlook 2021*, emerging markets and developing economies' emissions will increase by more than 5Gt by 2050, with the largest increases in industry and transportation [2]. As a result, investigating energy-saving mechanisms to reduce energy consumption is critical for lowering energy costs and promoting environmentally friendly manufacturing [3], [4], [5].

Currently, the manufacturing process's energy consumption is being reduced primarily at the machine, product design, and production management levels [6]. Due to the high investment required, small and medium-sized enterprises are unable to design energy-efficient machines at the machine level or develop energy-efficient products at the

The associate editor coordinating the review of this manuscript and approving it for publication was Shaohua Wan.

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product design level. As a result, an increasing number of scholars are studying energy consumption reduction in manufacturing processes at the production management level. Flow shop and job shop are two common types of production lines. The focus of research has shifted to energy-saving production based on these two production lines. The factors influencing production energy consumption and cost efficiency, such as carbon emission policy [7], worker flexibility [8], [9], time-of-use tariffs [1], and machine failure [10], have been incorporated into the study.

As a necessary production component, part feeding consumes a significant amount of energy and incurs high costs. With the rapid advancement of manufacturing intelligence and the widespread use of robots CoBots [11] and CreBots of Sigloch, a German logistics company, an increasing number of manufacturing companies are replacing traditional tow trains and multiple-load carriers [12] with mobile robots to increase part feeding efficiency and reduce energy consumption. Currently, the mobile robot is capable of safe obstacle avoidance, path planning, and other functions. However, the mobile robot's various task orders will receive distinct scheduling schemes, resulting in disparate energy consumption and workstation satisfaction, impacting production efficiency and economic benefits. Reasonable scheduling of mobile robots and reducing energy consumption while improving workstation satisfaction have become a new challenge for enterprises [13], [14].

Thus, considering the split delivery of parts caused by workstation satisfaction and robot energy constraints in actual production, this study develops a multiobjective optimization mathematical model to determine the scheduling scheme for mobile robots in a manner that maximizes workstation satisfaction while minimizing mobile robot energy consumption. Following that, a nondominated sorting genetic algorithm II with variable neighborhood search (VNSGA-II) is proposed, which improves the generation of the initial solution and the crossover operation and tailors three neighborhood search operators, exchange, insertion, and 2-opt according to the problem's characteristics to improve the algorithm's solution quality.

The remainder of the paper is organized as follows. A literature review of the studies on workstation satisfaction and scheduling of mobile robots in the mixed-model assembly line and part feeding time windows is presented in Section 2. A description of the problem and a multiobjective optimization mathematical model are provided in Section 3. Section 4 introduces VNSGA-II in detail. In Section 5, the model and the algorithm are verified through a small case and a group of experiments. Finally, Section 6 concludes the paper and presents some future research directions.

II. LITERATURE REVIEW

A. RESEARCH ON WORKSTATION SATISFACTION

The degree to which a workstation is satisfied with the time it takes for a part to arrive (i.e., workstation satisfaction) can reflect the accuracy of part feeding and service level [15]. As a result, scholars have included workstation satisfaction in their research. Liu *et al.* proposed a dynamic joint distribution strategy to address the issue of parts distribution being inefficient and inaccurate. A mathematical model of part feeding under the constraints of fuzzy time windows was established with the goal of minimizing the cost of single product distribution and maximizing workstation satisfaction [16]. Liu *et al.* established a part feeding model with the shortest distribution route as the optimization goal. They constrained the part feeding time by setting a minimum workstation satisfaction threshold to account for the variety of part types and uncertainty in arrival time [17]. Zhang and Chen considered the variety of part requirements and the uncertainty associated with time in a remanufacturing assembly station when proposing a method for optimizing the part feeding route using a fuzzy time window. The authors thoroughly considered part classification requirements and subsequent assembly costs in remanufacturing warehouses. They developed an optimization model for the route of the part feeding in the presence of a balanced production line. This optimization model was constrained by workstation satisfaction and aimed to reduce distribution costs to a minimum [18]. Yan *et al.* proposed a method for optimizing the distribution route of a complex mechanical assembly shop based on a fuzzy soft time window, considering the part demand time change caused by production beat fluctuation in actual complex mechanical assembly production. The method was based on the ''workstation-centered'' mode of part feeding. It used a fuzzy membership function to characterize the workstation's satisfaction with the part arrival time. On this basis, an optimization model for part feeding routes with a fuzzy soft time window was developed with the constraints of average workstation satisfaction on part arrival time and the objective of minimizing distribution cost [19]. Using the digital workshop as a case study, Zhang *et al.* proposed a multistation mixed distribution scheme with fuzzy appointment times by defining the objective function, including workstation satisfaction, tooling similarity, and the number of distribution vehicles, to achieve the digital workshop's accurate distribution [20].

B. RESEARCH ON SCHEDULING OF MOBILE ROBOT

In recent years, scholars have focused their attention on the scheduling of mobile robots. Nouri *et al.* considered the path planning problem for multiple workshop robots and proposed a neighborhood-based genetic algorithm for optimizing job completion time [21]. Zhou *et al.* studied the kitting distribution problem in an automobile mixed-model assembly line under a robot-operator picking environment and constructed an improved quantum-inspired ant colony optimization algorithm based on an improved quantum rotation gate update mechanism and a nonoptimal individual optimization strategy to optimize the number of labors, robots, and tour period [22]. Shen *et al.* decomposed the logistics task, investigated robot scheduling by considering the cost of the path and the cost of waiting time and verified the effectiveness of intelligent scheduling [23]. Allowing the robot to split and transfer distributed components, Zhou and Xu developed a multistage adaptive search algorithm to schedule the mobile robot to minimize input and energy consumption costs while ensuring efficient and punctual feeding [24]. By introducing a new mutation operator, Tuncer and Yildirim proposed an improved genetic algorithm for solving the global optimization problem of multirobot scheduling in dynamic environments [25]. Panchu *et al.* used a genetic algorithm to solve the minimum task completion time problem of robots [26]. Ren *et al.* used the workshop handling robot as the research object and solved the path optimization problem by considering the time window in the scenario of part feeding and finished product recovery [27]. Li *et al.* analyzed the operation of the ''goods to people'' picking system in the context of e-commerce. They developed a bilevel programming model for robot quantity configuration, robot scheduling, and robot task assignment [28].

Scholars have incorporated the concept of energy conservation into their research on mobile robot scheduling. Considering the characteristics of the asymmetric traveling salesman problem, Dang *et al.* chose the part feeding order of a single robot with the goal of minimizing robot energy consumption [29]. Zhou and Fei investigated the problem of the cooperative scheduling of multiple robots. They demonstrated the benefits of cooperative scheduling by utilizing the clustering heuristic and an adaptive large neighborhood search algorithm, with the goal of minimizing the number of robots and lowering energy consumption costs [30]. Bielsen *et al.* investigated the material handling scheduling problem for a single mobile robot in a pervasive manufacturing system with the goal of minimizing handling distance and thus energy consumption [31]. Quan and He used the constraint condition of completing tasks according to the production process as well as the system duration, the maximum consumption of a single robot, and the aggregate consumption of multiple robots to develop a mathematical model of multirobot task allocation and scheduling optimization. The authors solved the problem iteratively using the clone selection algorithm and introduced an affinity function to dynamically change the clonal, mutation, and selection parameters, which increased computational efficiency [32]. Pan *et al.* proposed a flexible material distribution strategy centered on the mobile robot to address the issues of low picking efficiency and high distribution costs associated with traditional pull part feeding in assembly workshops. A model of cooperative distribution scheduling with multiple objectives and multiple robots was proposed with the objectives of minimizing completion time, delay time, load, and energy consumption. The authors proposed a nondominated sorting genetic algorithm II (NSGA-II) and designed the algorithm process, coding method, and genetic operator in conjunction with the model's characteristics [33].

C. RESEARCH ON THE TIME WINDOW OF PART FEEDING

Due to the strict requirements for part feeding times in mixed-model production [34], [35], many scholars use time windows to constrain part feeding times to ensure that parts arrive on time [36]. Ma and Wang used convex fuzzy numbers to represent the fuzzy time window. They constructed a multiobjective mathematical programming model under the condition of fuzzy workstation reservation time to address the part feeding problem under various uncertain factors in the manufacturing process [37]. Considering the just-in-time distribution of auto parts, Wang *et al.* proposed modeling the cyclic and batch distribution of each supplier's parts to maximize vehicle capacity and establish a vehicle scheduling optimization model with a dynamic supply time window [38]. Jiang *et al.* analyzed the complexity and uncertainty inherent in the manufacturing workshop environment and determined the optimal part distribution interval. The authors then constructed an optimization model using the optimal distribution interval as the time window with the goal of minimizing the distribution cost and maximizing the full load rate while meeting the constraints of part demand time, line inventory volume, and distribution route [39]. Lagos *et al.* investigated the simultaneous pickup, delivery, and time window routing problem for vehicles. A particle swarm optimization algorithm was proposed to minimize the total distance of the path while also meeting the delivery and pickup needs of customers [40]. Ramos *et al.* investigated the multipass production, inventory, distribution, and routing problem with time windows (MPIDRPTW) and proposed an accurate graph-based arc flow formulation to solve MPIDRPTW [41]. Zhu and Wu proposed an improved mathematical model for minimizing the total cost of transportation and inventory under a hard time window constraint. This model allowed to split the supplier's collection demand and distribution. However, the hard time window constraint is excessively strict and does not correspond to actual production [42]. Wu *et al.* organically integrated material loading constraints with assembly workshop distribution path planning to address the integrated scheduling problem of part feeding in an electric tool assembly workshop. Using the assembly line's dynamic demand time window information, the authors develop a vehicle routing optimal configuration model that considers soft time window and optimal loading constraints to meet the dual objective of distribution timeliness and cost optimization [43]. To balance the contradictory relationship between cost and meeting customer demand time window (satisfaction), Xu *et al.* developed a joint optimization model for picking and distribution with demand splitting under the constraint of a soft time window to minimize the sum of picking cost, split demand cost, distribution cost, and time penalty cost. However, the impact of vehicles arriving after the time window's upper limit on customer satisfaction is not considered enough [44].

Due to production fluctuations, the relationship between part arrival time and workstation satisfaction cannot be accurately represented by soft and hard time windows. Furthermore, the existing literature is largely focused on optimizing a single objective, such as cost or energy consumption. There are few publications on optimizing both energy consumption and workstation satisfaction with part arrival times. This

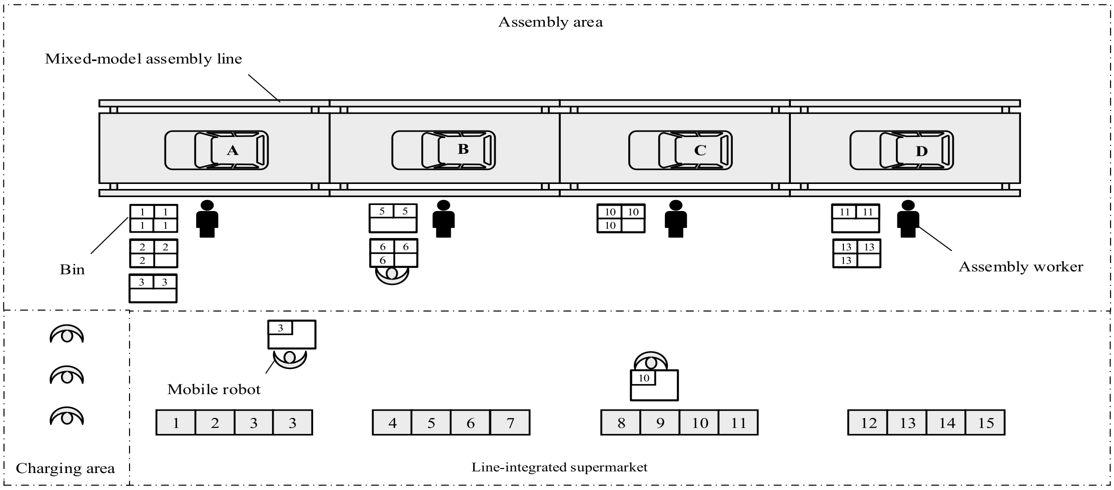

FIGURE 1. **The part feeding system using the line-integrated supermarket and mobile robot.**

paper represents workstation satisfaction using the normal fuzzy membership function of the part arrival time. Considering the split delivery caused by workstation satisfaction and the mobile robot's energy limitation, a multiobjective optimization model for scheduling the mobile robot in the mixed-model assembly line is established under the constraint of the normal fuzzy time window to maximize workstation satisfaction and minimize the mobile robot's energy consumption. Simultaneously, a VNSGA-II is proposed, which employs a heuristic algorithm to generate initial solutions, improves crossover operations, and designs three operators of exchange, insertion, and 2-opt acting on the same chromosome substring and different chromosome substrings to achieve neighborhood search and thus improve the solution's quality.

III. PROBLEM DESCRIPTION AND MATHEMATICAL MODEL

A. PROBLEM DESCRIPTION

Figure 1 shows the part feeding system using the line-integrated supermarket and mobile robot. The supermarket for storing and picking parts is integrated into the mixed-model assembly line [45], [46]. Bins are used to storing the components necessary for assembly, with each bin containing a single type of component. The mobile robot is in charge of the bin's distribution. When a delivery task is assigned, the mobile robot moves to the shelf containing the components to be distributed, selects the components required for assembly, and places them in the corresponding bin. Once all delivery tasks have been completed, the mobile robot returns to the charging area to await the next delivery task.

B. MATHEMATICAL MODEL

1) MODEL ASSUMPTIONS

To effectively describe the research problem, this study makes the following assumptions:

- The parts can meet the needs of the mixed-model assembly line, and out-of-stock is not allowed.
- Each workstation only uses one kind of part, and the delivery task of one workstation is completed by one mobile robot as much as possible. When one mobile robot cannot complete the task, another mobile robot can be assigned to cooperate to complete the delivery task.
- The delivery task of the workstation will not end until all the parts required by the workstation are delivered.
- All mobile robots start from the charging area and return to the charging area after completing the delivery task.

2) ENERGY CONSUMPTION CALCULATION OF THE MOBILE ROBOT

The mobile robot's energy consumption is primarily determined by its driving distance and total weight [47]. Many researchers have developed various energy consumption models to determine the relationship between energy consumption, driving distance, and the total weight of the mobile robot. The specific energy consumption [48] is used in this paper to calculate the mobile robot's energy consumption. Assuming that the energy consumption E of the mobile robot is linear with the driving distance d and the total weight of the mobile robot Ψ, the energy consumption E of the mobile robot can be expressed as:

$$E = \varepsilon d\Psi = \varepsilon d\left(\varphi + \tau\right) \tag{1}$$

where ε is the specific energy consumption of the mobile robot, which represents the total energy consumed by the mobile robot per unit mass and per unit distance, which can be measured by experiments [49], [50]. The total weight of the mobile robot Ψ includes the self-weight of the mobile robot φ and the weight of the loaded part τ.

3) NORMAL FUZZY TIME WINDOW

The fuzzy time window is determined through fuzzy quantification of the effect of the time the part arrives at the workstation on the degree of satisfaction. The fuzzy time window is represented by a fuzzy number [51], defined by the membership function as a normal convex fuzzy set. Compared to triangular and trapezoidal fuzzy numbers, normal fuzzy numbers have a membership degree that is more consistent with workstation satisfaction [52]. Therefore, this paper defines the satisfaction of workstation i as the fuzzy membership function of the time when the part arrives at workstation i. The closer the time T_i when all parts required by workstation i arrive at the workstation is to the expected time, the higher workstation satisfaction. $[ET, LE]$ are the lower and upper limits of the part arrival time that can be accepted by workstation i, respectively. To improve the distribution service level of manufacturing enterprises, set the minimum workstation satisfaction θ and the part arrival time window of workstation i is $\left[et', lt'\right]$, as shown in Figure 2.

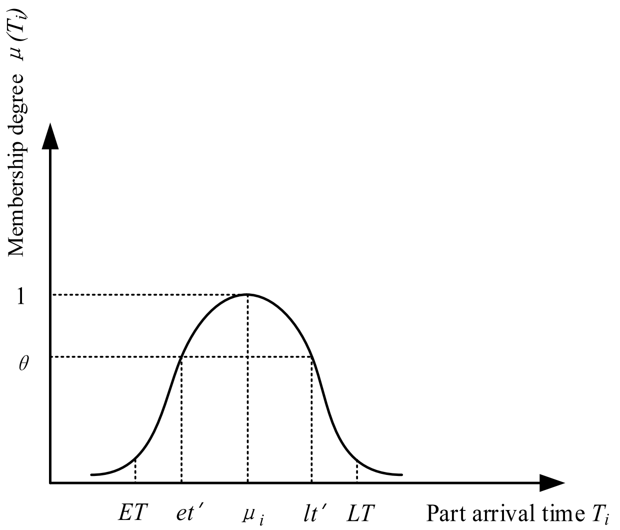

FIGURE 2. Part feeding time window.

Establish a mathematical model of part arrival time satisfaction based on normal fuzzy numbers:

$$\mu\left(T_i\right) = exp\left(-\left(T_i - \mu_i\right)^2 \big/ \sigma_i^2\right) \tag{2}$$

where T_i is the time when all parts required by workstation i arrive at the workstation, $\mu\left(T_i\right)$ is the membership degree of T_i, $\mu\left(T_i\right) \in [0, 1]$. μ_i is the mean of T_i, that is, the expected time for the part to arrive at the workstation, $\mu_i = (ET + LT) \big/ 2$. σ_i is the variance of T_i, $\sigma_i = (LT - ET) \big/ 6$. When $T_i = \mu_i$, the maximum satisfaction is 1. When $T_i \in \left[et', lt'\right]$, $\mu\left(T_i\right) \geq \theta$.

4) MATHEMATICAL MODELING

According to the above description and assumption, the parameters are defined.

$V = A \cup S$, A is the charging area, represented by 0, $S = \{1, 2, \cdots, n\}$ is the set of workstations, $V = \{0, 1, 2, \cdots, n\}$, $i, j \in V$. $L = \{1, 2, \cdots, h\}$ is the set of mobile robots, $w \in L$, other parameters are defined in Table 1.

TABLE 1. Parameters.

Symbol	Definition
Q	maximum energy of mobile robot
d_{ij}	distance from workstation i to workstation j
π	velocity of the mobile robot
p_i	number of parts required for workstation i
γ	picking time of unit parts
u_{iw}	waiting time of mobile robot w at workstation i
ε	specific energy consumption of mobile robot
φ	self-weight of mobile robot

TABLE 2. Variables.

Symbol	Definition
t_{iw}	time when the mobile robot w arrives at the workstation i
q_{iw}	number of parts picked by the mobile robot w at workstation i
x_{ijw}	binary variable:1, if the mobile robot w moves from workstation i to j;0, otherwise
y_{iw}	binary variable: 1, if the parts required for workstation i are distributed by the mobile robot w; 0, otherwise

The following variables are defined in Table 2.
Establish a mathematical model.

$$max\ f_1 = \frac{1}{n}\sum_{i=1}^{n}\mu\left(T_i\right) = \frac{1}{n}\sum_{i=1}^{n} exp\left(-\left(T_i - \mu_i\right)^2 \big/ \sigma_i^2\right) \tag{3}$$

$$\begin{aligned} T_i = max\,\{&(t_{iw} + u_{iw} + q_{iw} \cdot \gamma) \cdot y_{iw}, \\ &(t_{iw'} + u_{iw'} + q_{iw'} \cdot \gamma) \cdot y_{iw'}\}, \\ &\forall i \in S; \quad w, w' \in L;\ w \neq w' \end{aligned} \tag{4}$$

$$min\ f_2 = \sum_{i=1}^{V}\sum_{j=1}^{V}\sum_{w=1}^{h} \varepsilon \cdot d_{ij} \cdot (\varphi + p_i \cdot \xi_i) \cdot x_{ijw} \tag{5}$$

where equations (3) and (5) represent objective functions, and equation (4) expresses T_i in the objective function (3).

Subject to:

$$\mu\left(T_i\right) \geq \theta, \quad \forall i \in S \tag{6}$$

$$t_{jw} = \left(t_{iw} + u_{iw} + q_{iw} \cdot \gamma + \frac{d_{ij}}{\pi}\right) \cdot x_{ijw}, \quad \forall i \in S; \quad j \in V;\ w \in L \tag{7}$$

$$u_{iw} = max\left\{0, et' - t_{iw}\right\}, \quad \forall i \in S; \quad w \in L \tag{8}$$

$$\sum_{w=1}^{h} y_{iw} \geq 1, \quad \forall i \in S \tag{9}$$

$$0 < \sum_{i=1}^{V}\sum_{j=1}^{V} \varepsilon \cdot d_{ij} \cdot (\varphi + p_i \cdot \xi_i) \cdot x_{ijw} \leq Q \quad \forall w \in L \tag{10}$$

$$\sum_{w=1}^{h} q_{iw} \cdot y_{iw} = p_i, \quad \forall i \in S \tag{11}$$

$$\sum_{j=1}^{n} x_{0jw} = 1, \quad \forall w \in L \tag{12}$$

$$\sum_{i=1}^{n} x_{i0w} = 1, \quad \forall w \in L \tag{13}$$

$$\sum_{i=0}^{n} x_{ijw} - \sum_{i=0}^{n} x_{jiw} = 0, \quad \forall j \in S;\ w \in L \tag{14}$$

$$t_{iw} \geq 0, \quad \forall i \in S;\ w \in L \tag{15}$$

$$q_{iw} \geq 0, \quad \forall i \in S;\ w \in L \tag{16}$$

$$x_{ijw} \in \{0, 1\}, \quad \forall i, j \in S;\ w \in L \tag{17}$$

$$y_{iw} \in \{0, 1\}, \quad \forall i \in S;\ w \in L \tag{18}$$

The model's objective functions (3) and (5) represent maximum workstation satisfaction and minimize the mobile robot's total energy consumption, respectively. Due to the equal importance of each workstation, maximum workstation satisfaction is expressed in terms of maximizing average workstation satisfaction [53]. Constraint (6) represents the minimum service level constraint to ensure that the satisfaction of each workstation is not less than θ. Constraint (7) is the time when the mobile robot arrives at workstation j from i. Constraint (8) represents the waiting time. Constraint (9) specifies that each workstation's delivery task is completed by at least one mobile robot. Constraint (10) is the energy constraint that the mobile robot must adhere to complete the delivery task. Constraint (11) specifies that the number of parts delivered by the mobile robot must be sufficient to meet the workstation's requirements. Constraints (12)–(13) indicate that the mobile robot begins and ends its delivery task in the charging area. Constraint (14) represents the workstation's in-out balance. Constraints (15)–(18) denote the variables' domain.

IV. VNSGA-II

Scholars have used a variety of multiobjective evolutionary algorithms to obtain the Pareto optimal solution set for the multiobjective optimization problem [54], [55], [56]. NSGA-II is the most widely used evolutionary algorithm. In comparison to the nondominated sorting genetic algorithm (NSGA), NSGA-II incorporates an elite strategy, a hierarchical fast nondominated sorting method, and a crowding degree comparison operator, which expands the sampling space, reduces the algorithm's complexity, and eliminates the need to formulate shared parameters manually [57]. To further improve the NSGA-II algorithm's solution quality and consider the characteristics of mobile robot scheduling problems in a mixed-model assembly line, the VNSGA-II algorithm is designed. Its flow is depicted in Figure 3.

A. CODING

Natural number coding is more concise, intuitive, and readable than 0-1 coding. As a result, this paper employs a natural number sequence as the chromosome coding format. Figure 4 illustrates the chromosome coding, with 0 denoting the charging area of the mobile robot, 1-6 denoting the workstation, and three mobile robots provide delivery services for six workstations. Specifically, the mobile robot w_1 starts from charging area 0, provides delivery services for workstations 2, 4, and 5, and then returns to the charging area, forming delivery route 1, that is, chromosome substring 1. Mobile robot w_2 starts from charging area 0, provides delivery services for workstations 3 and 4, and then returns to the charging area to form delivery route 2, and so on. A mobile robot scheduling scheme is formed until all the distribution tasks have been completed.

The advantages of this chromosome coding are as follows:

- Each chromosome can clearly indicate the station and its sequence of delivery by the mobile robot.
- The arrival time of parts can be calculated according to constraint (7), and whether the workstation satisfaction constraint is satisfied can be judged according to constraint (5).
- The number of parts delivered by each mobile robot can be easily calculated, so as to judge whether the energy consumption constraint of the mobile robot is exceeded according to constraint (10).

B. INITIAL SOLUTION GENERATION

A better initial solution can speed up the algorithm's search for a solution. As a result, this paper employs a heuristic algorithm to arrive at the initial solution. The following are the specific steps:

Step 1: Generate a set *all_station* of all workstations with delivery requirements and a set *need_station* of part demand quantity of each workstation.

Step 2: Insert 0 at the head of the delivery route δ_k.

Step 3: Generate a workstation set $allow_k$. Put the workstations starting from the station at the end of the delivery route δ_k and meeting the workstation satisfaction and energy consumption into the set $allow_k$.

Step 4: Randomly select a workstation i from $allow_k$, put workstation i at the end of the delivery route δ_k, and calculate whether the delivery quantity meets the requirements of workstation i under the constraints of workstation satisfaction and energy consumption of the mobile robot. If the demand is met, delete the workstation i in *all_station* and update the *need_station*, otherwise, split the quantity of parts required by workstation i, calculate the unmet requirements and update *need_station*.

Step 5: Repeat Step3-4 until $allow_k$ is empty, insert 0 at the end of δ_k, and the delivery route (i.e., chromosome substring) is generated.

Step 6: Repeat Step2-5 until *all_station* is empty, connect all delivery routes end to end, one of the two adjacent 0 is deleted, and the initial solution is generated.

C. GENETIC OPERATION

1) CROSSOVER OPERATION

Due to the structural characteristics of the solution to the scheduling problem for the mobile robot in the mixed-model

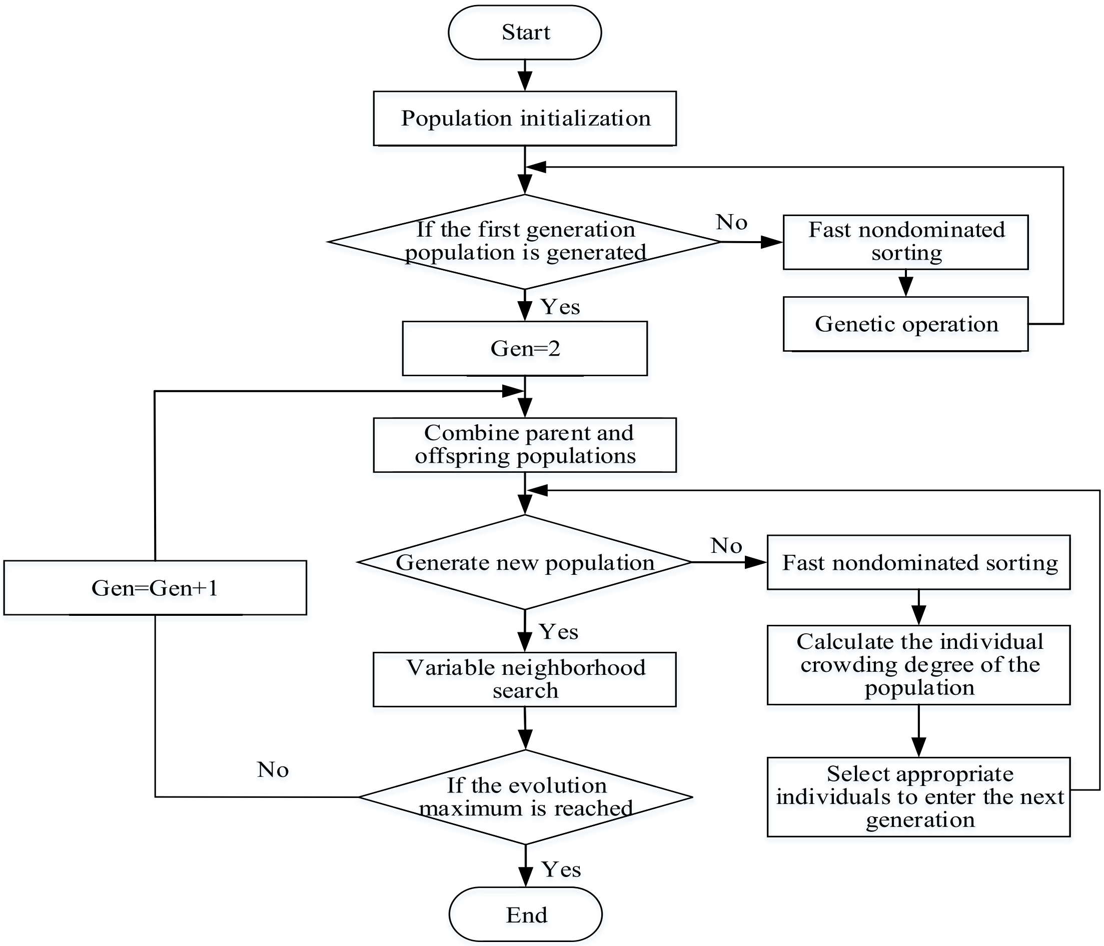

FIGURE 3. Flow of the VNSGA-II.

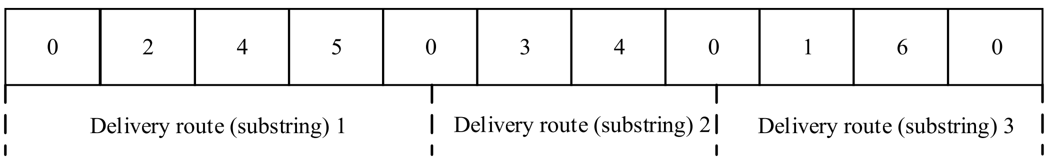

FIGURE 4. Chromosome coding.

assembly line, if the traditional crossover method is used, the chromosome's excellent substrings will be destroyed. When the two parent chromosomes are identical, the conventional operation is impossible. As a result, the conventional crossover operation is enhanced. To protect the existing excellent substring, the crossover process places the substring to be exchanged at the head of the offspring chromosome rather than directly copying it to the exchange position. The following are the steps involved in the crossover operation:

Step 1: Calculate the number of substrings L_1 and L_2 of two parent individuals F_1 and F_2 conforming to the crossover probability of Pc, and randomly generate two natural numbers rn_1 and rn_2 in $[1, L_1]$ and $[1, L_2]$ respectively to locate the excellent substrings ft_1 and ft_2, as shown in Figure 5 (a).

Step 2: Delete the substrings ft_1,ft_2 and all 0 codes in the parental individuals F_1 and F_2, and retain one of the remaining repeated codes to generate chromosome fragments F_1' and F_2', as shown in Figure 5(b).

Step 3: Calculate the number of the i-th nonzero code contained in ft_1 in F_1', denoted as Num_i. If $Num_i = 0$, it means that the demand of the workstation can be met after this delivery, then delete the code of the workstation from F_2' and complete the missing code. If $Num_i \neq 0$, complete the missing code. The newly generated chromosome segment is denoted as F_1''. The code in ft_2 is the same operation, as shown in Figure 5 (c).

Step 4: Under the constraints of workstation satisfaction and energy consumption of the mobile robot, the workstations

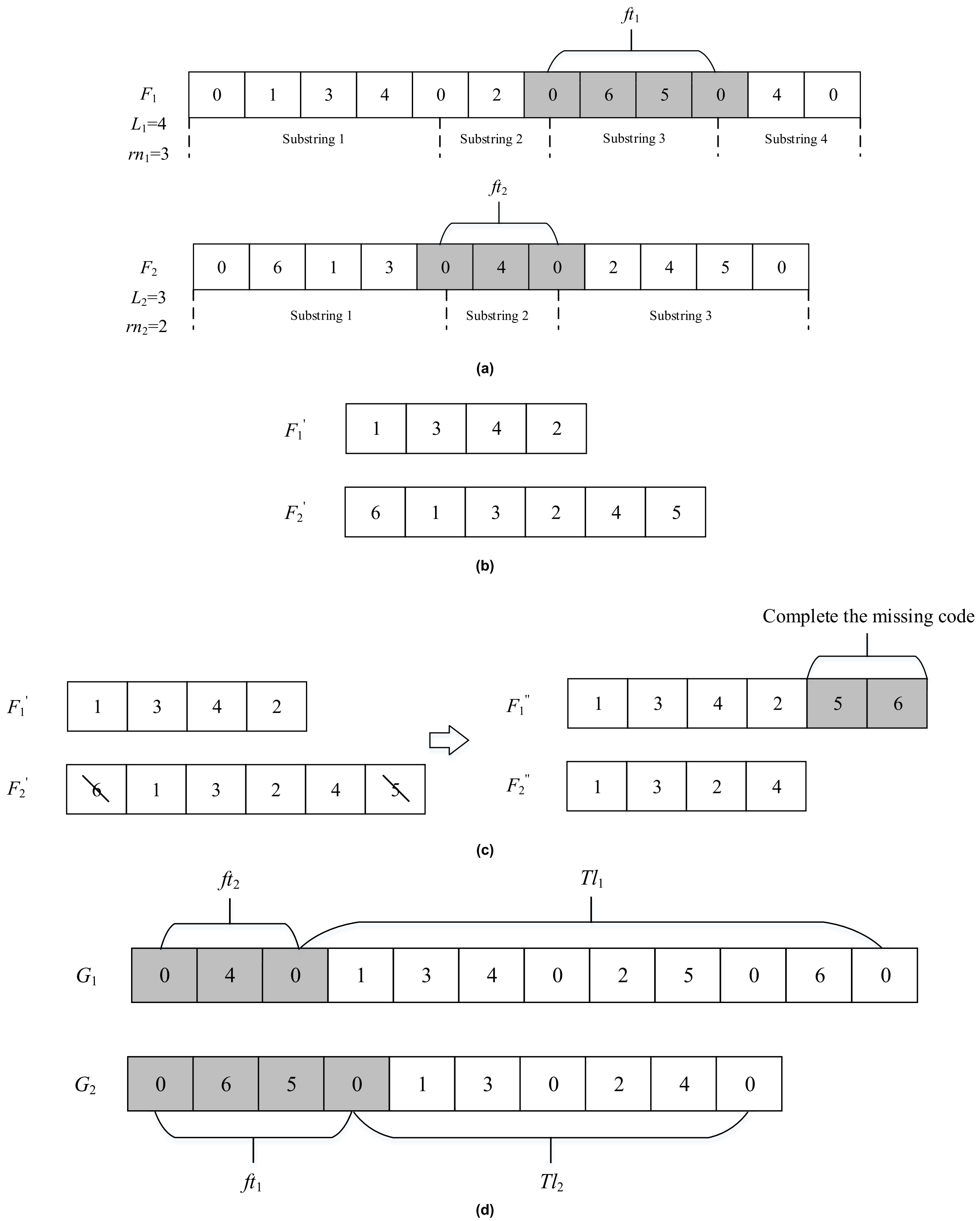

FIGURE 5. **Crossover operation.**

in F_1'' and F_2'' are reassigned to the mobile robot to generate new substrings Tl_1 and Tl_2. Insert Tl_1 and Tl_2 into ft_2 and ft_1, respectively, to form offspring individuals G_1 and G_2, as shown in Figure 5 (d).

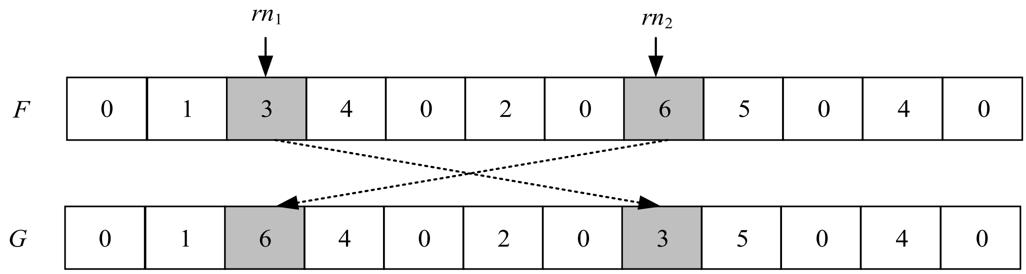

FIGURE 6. Mutation operator.

2) MUTATION OPERATOR

Calculate the number of nonzero codes *Num* in the parent individual F that conforms to the mutation probability Pb. Two different natural numbers rn_1 and rn_2 are randomly generated from $[1, Num]$, and the codes of rn_1 and rn_2 are exchanged to generate a new offspring individual G. The mutation operation is shown in Figure 6.

3) ELITE RETENTION STRATEGIES

According to NSGA-II's mechanism, the championship method is used to select chromosomes based on sorting results and the degree of crowding. The parent and offspring populations are combined following the selection of the offspring population. A certain number of individuals are selected to form the new generation of offspring populations based on the degree of fast nondominated sorting and crowding.

D. VARIABLE NEIGHBORHOOD SEARCH

Since it is common for the genetic algorithm to fall into a local optimal solution, the variable neighborhood search strategy is used to solve this problem. Specifically, a local optimal solution is obtained by searching the solution space beginning in the smallest neighborhood. Then, the next local optimal solution is obtained by starting the search from the smallest neighborhood again after systematically altering the neighborhood's structure based on the previous local optimal solution. The flow of variable neighborhood search algorithm is shown in Figure 7.

Three operators are used for variable neighborhood search, depending on the characteristics of the problem: exchange, insertion, and 2-opt [58]. At the same time, the three operators are considered to operate on the same substring and distinct substrings of the chromosome.

Define 1: Feasible exchange. Randomly select two different codes on the same or different substrings of the chromosome for exchange. The exchange is feasible if the newly generated solution is feasible following the exchange. The exchange procedure is depicted in Figure 8.

Define 2: Feasible insertion. Randomly select a code in the chromosome. A new solution is still feasible if the code is deleted from its current location and then inserted into the same or a different substring. This type of insertion is referred to as feasible insertion. Figure 9 illustrates the insertion operation.

Define 3: Feasible 2-opt. Randomly select two nonadjacent codes in the same substring or different substrings of the chromosome, then flip the codes between the two codes. If the new solution is feasible, the 2-opt operation is called feasible 2-opt, and the 2-opt operation is shown in Figure 10.

During variable neighborhood search, it should be noted that due to the change in the distribution workstations' order, it is necessary to determine whether the generated solution is feasible. When determining the feasibility of a solution, it is necessary to consider the constraints of workstation satisfaction, the energy consumption of mobile robots, and workstation demand concurrently.

V. NUMERICAL EXPERIMENTS

The current experimental studies distinguish two experiments: Experiment 1, which verifies the feasibility of the VNSGA-II, and Experiment 2, which verifies the algorithm's performance across six different problem scales.

A. EXPERIMENT 1: THE FEASIBILITY OF THE VNSGA-II

A mixed-model assembly line in an automobile plant's assembly shop has ten workstations. Each workstation is labeled $1, 2, \ldots, 10$, and the mobile robot's charging area is labeled 0, the mobile robot's velocity is 30m/min, and the picking time for unit parts is 0.15min. Table 3 shows the distance between the mobile robot's charging area and each workstation.

The number of parts demanded for each workstation, the weight of unit parts, and the demand time window are shown in Table 4.

Regarding the parameters that significantly affect the algorithm's performance, this study employs the control variable method to determine the parameter's value through multiple test experiments. Initial population size $N = 200$; maximum evolution times $Gen = 100$; exchange probability $Pc = 0.7$; mutation probability $Pb = 0.05$.

The algorithms in this paper were encoded in MATLAB R2016a and executed on a personal computer with Intel(R) Core (TM) i3-1115G4 CPU 3.00GHz and 8GB RAM. When θ is 0.8, the scheduling scheme corresponding to several

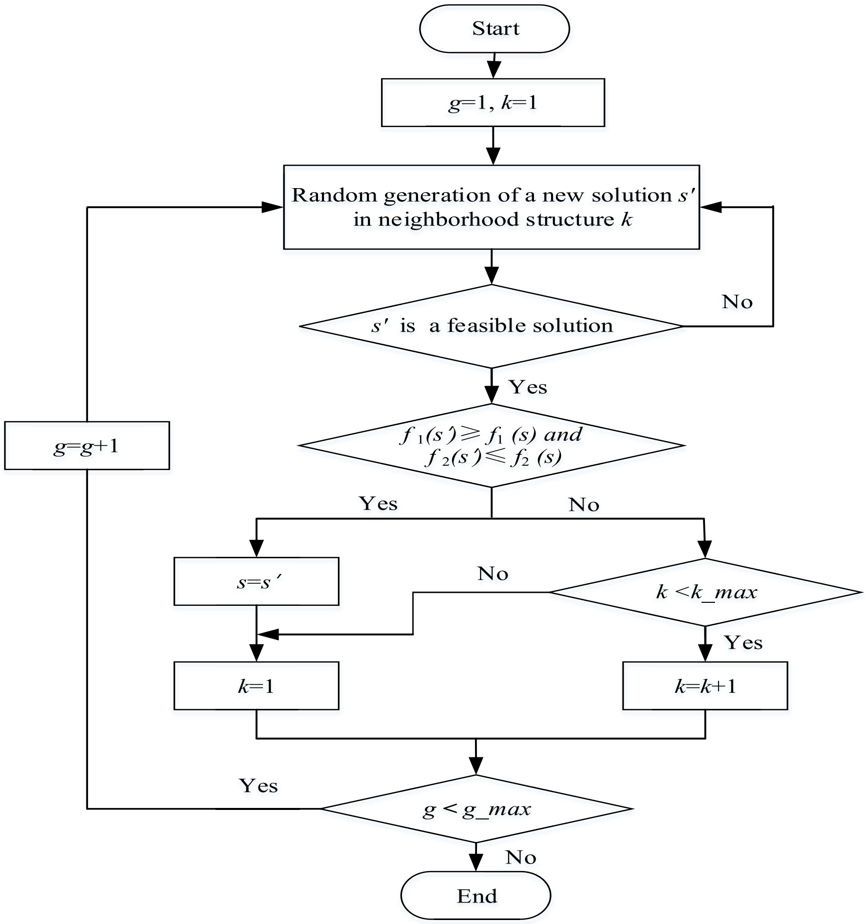

FIGURE 7. The flow of variable neighborhood search algorithm.

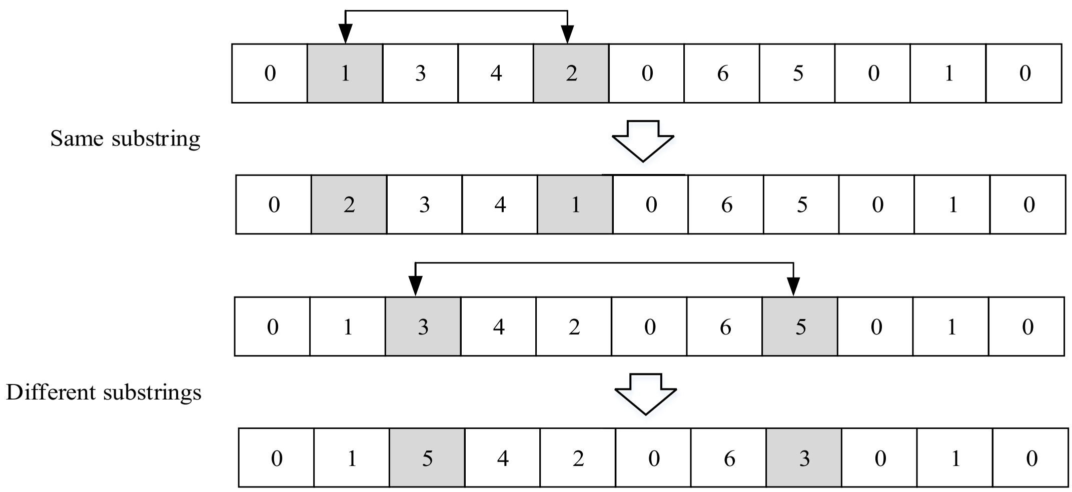

FIGURE 8. Exchange operation.

representative points on the Pareto optimal frontier is shown in Table 5.

As shown in Table 5, as workstation satisfaction increases, the energy consumption required to complete the delivery task increases as well. In actual production, the enterprise's manager can locate a satisfactory solution on the Pareto optimal frontier based on various preference values. Table 6 details the time of part arrival at the workstation of the above three schemes.

According to Tables 5 and 6, an increase in workstation satisfaction results in increased energy consumption. However, the satisfaction of the three schemes is greater than

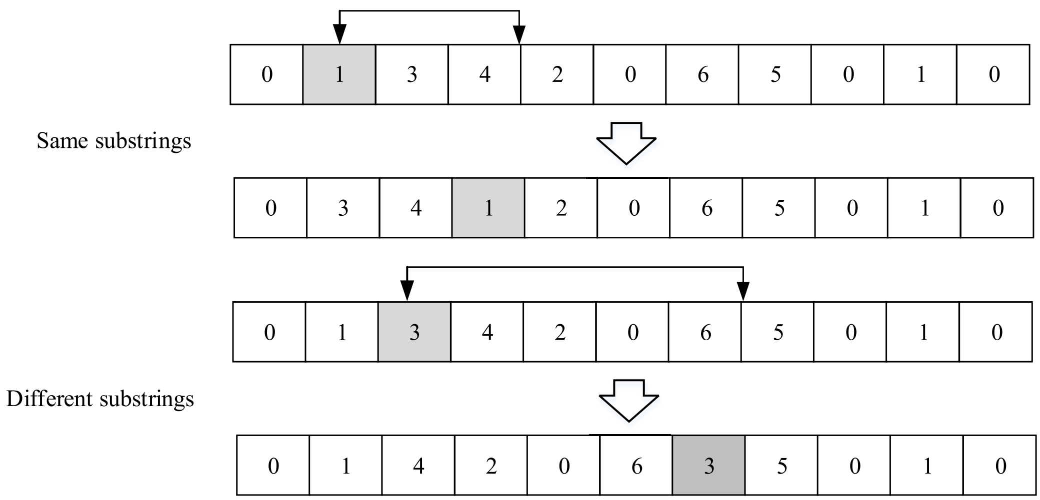

FIGURE 9. Insertion operation.

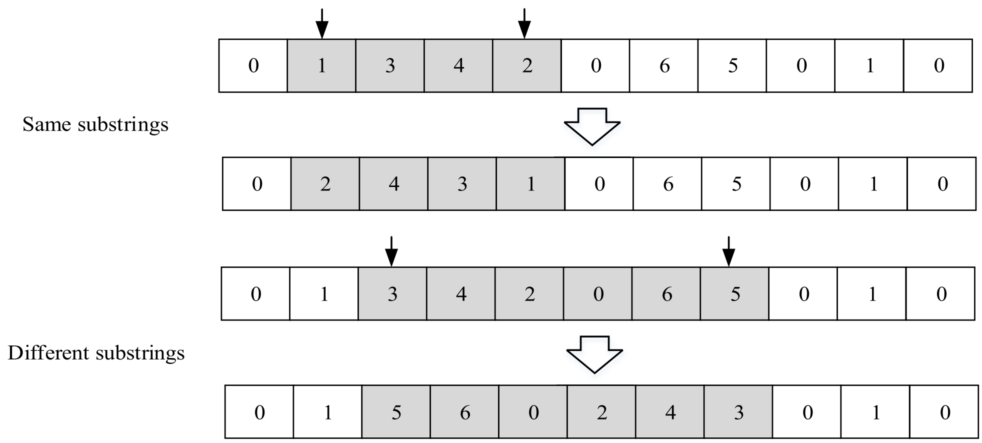

FIGURE 10. 2-opt operation.

TABLE 3. Distance between the charging area and each workstation.

	0	1	2	3	4	5	6	7	8	9	10
0	0	36	41	45	50	55	59	64	68	74	77
1	36	0	5	9	14	19	23	28	32	38	41
2	41	5	0	4	8	13	18	22	27	32	35
3	45	9	4	0	5	10	14	19	23	29	32
4	50	14	8	5	0	5	10	14	19	24	27
5	55	19	13	10	5	0	5	9	14	19	22
6	59	23	18	14	10	5	0	4	9	14	17
7	64	28	22	19	14	9	4	0	5	10	13
8	68	32	27	23	19	14	9	5	0	5	8
9	74	38	32	29	24	19	14	10	5	0	3
10	77	41	35	32	27	22	17	13	8	3	0

TABLE 4. Experiment data.

	Demand	The weight of unit parts	Demand time window
1	50	0.36	[4,25]
2	35	0.43	[4,30]
3	25	0.15	[5,24]
4	62	0.56	[2,35]
5	25	0.21	[6,21]
6	43	0.18	[7,42]
7	50	0.023	[4,54]
8	40	0.47	[10,32]
9	76	0.27	[5,33]
10	61	0.008	[4,54]

87 percent, and the time of part arrival at the workstation meets the time constraint when θ is 0.8, demonstrating the algorithm's feasibility.

B. EXPERIMENT 2: RELATIVE PERFORMANCE OF THE VNSGA-II

To further validate the algorithm's performance, the VNSGA-II proposed in this paper is compared and analyzed

TABLE 5. The scheduling results.

	Workstation satisfaction	Energy consumption
Scheme 1	87.53%	305.44
Scheme 2	89.04%	360.60
Scheme 3	90.80%	488.73

TABLE 6. Time of parts arrival at the workstation.

	θ =0.8		Part arrival time		
	Lower limit of arrival time	Upper limit of arrival time	Scheme 1	Scheme 2	Scheme 3
1	12.85	16.15	12.85	12.85	12.85
2	14.95	19.05	18.37	18.28	18.28
3	13.00	16.00	13.00	13.00	13.00
4	15.90	21.10	20.21	21.04	20.96
5	14.06	15.94	14.06	14.06	14.06
6	22.32	27.68	23.72	25.33	23.72
7	25.06	32.94	31.36	28.18	31.36
8	19.27	22.73	20.52	20.52	20.52
9	16.80	21.20	16.80	16.80	21.15
10	25.06	32.94	29.95	31.09	29.95

with the classical NSGA-II algorithm and multiobjective particle swarm optimization algorithm (MOPSO). The NSGA-II algorithm [59], [60] is often used to solve the multiobjective workshop scheduling problem. As a multiobjective optimization algorithm based on the Pareto optimal solution, it serves as a common benchmark for performance comparison of multiobjective optimization algorithms. The MOPSO algorithm has also been applied to various optimization fields, such as production workshop scheduling [61], and has the characteristics of simplicity and versatility. Based on the size of the problem, six groups of samples are set as test objects, and each group is run 20 times. The differences in the three algorithms in solving quality and operation time are compared. The experimental results are presented in Table 7.

Table 7 demonstrates that the results obtained with VNSGA-II are superior to the other two algorithms. When the problem is small-sized (Samples 1-3), the results of the three algorithms have little difference, the workstation satisfaction is more than 85 percent, and the energy consumption is controlled within 5000. As the problem's scale grows, the number of workstations requiring part delivery increases, as does the number of mobile robots used and the number of parts distributed, all of which contribute to a rapid increase in energy consumption. Because the VNSGA-II employs a heuristic algorithm to generate a high-quality initial solution and a variable neighborhood search strategy to broaden the search range of the solution space, the VNSGA-II's quality is enhanced. Compared to MOPSP and NSGA-II, the

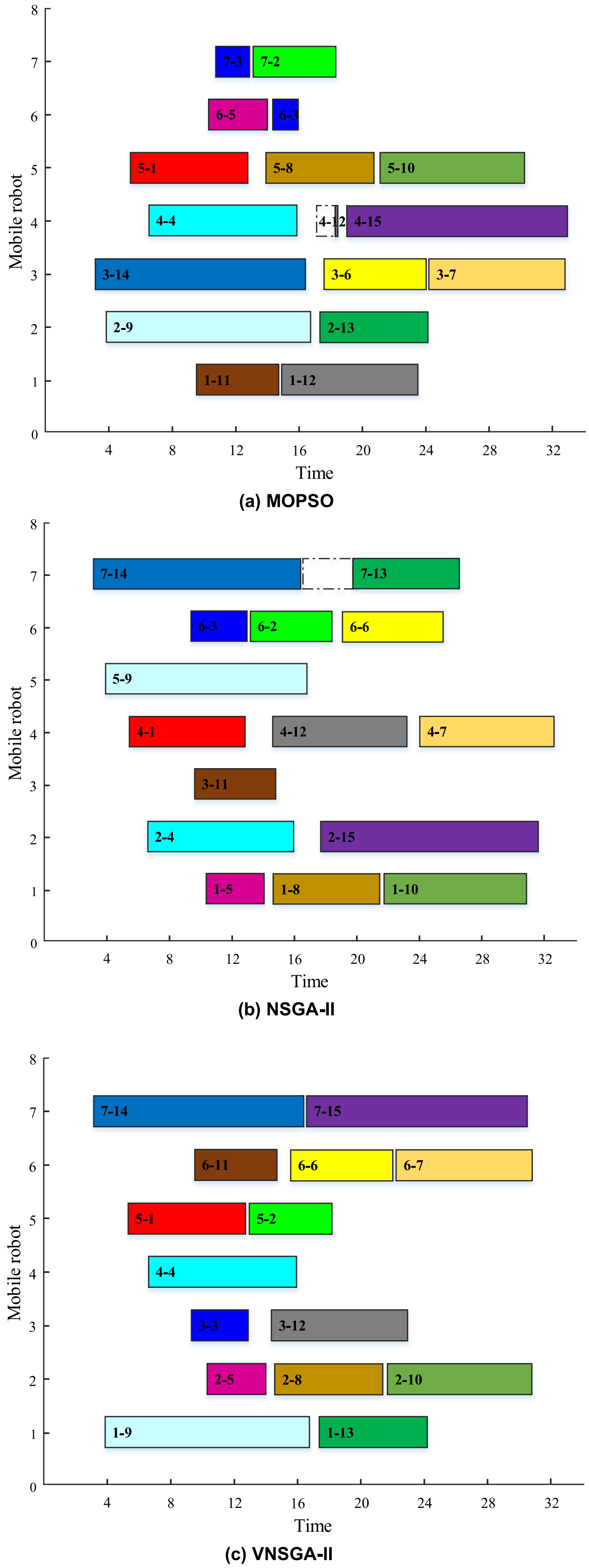

FIGURE 11. Scheduling scheme.

workstation satisfaction of VNSGA-II is increased by 0.91% and 1.12%, while the energy consumption is reduced by 12.53% and 13.66%, respectively.

TABLE 7. Experimental results.

	Number of stations	MOPSO		NSGA-II		VNSGA-II	
		Workstation satisfaction	Energy consumption	Workstation satisfaction	Energy consumption	Workstation satisfaction	Energy consumption
1	15	88.63%	1118.27	88.51%	1122.94	88.75%	1106.65
2	30	88.04%	3008.33	88.16%	3013.85	88.44%	2807.48
3	45	86.17%	4853.16	85.61%	4989.02	86.48%	4554.09
4	60	84.83%	8054.93	84.75%	8146.30	85.85%	6723.21
5	75	84.23%	11957.58	84.38%	11837.53	85.49%	9266.18
6	90	83.76%	14385.60	83.18%	15063.25	85.36%	11181.53

TABLE 8. Algorithm evaluation metrics.

	Number of stations	A: MOPSO B: VNSGA-II		A: NSGA-II B: VNSGA-II		IGD		
		C (A, B)	C (B, A)	C (A, B)	C (B, A)	MOPSO	NSGA-II	VNSGA-II
1	15	0.2970	0.4684	0.1762	0.8557	0.0357	0.0247	0.0144
2	30	0.1577	0.6857	0.0184	0.7527	0.0265	0.0275	0.0126
3	45	0.0796	0.6429	0.1266	0.8261	0.0357	0.0387	0.0218
4	60	0.3547	0.5835	0.0827	0.8468	0.0184	0.0359	0.0106
5	75	0.2854	0.4523	0.1047	0.7973	0.0259	0.0572	0.0164
6	90	0.1389	0.6419	0.0105	0.9122	0.0458	0.0584	0.0238

In addition, the quality of the Pareto optimal solutions obtained by the three algorithms is quantitatively compared using two performance evaluation metrics: C-metric and inverted generational distance (IGD).

1) C-METRIC

$$C\left(A,B\right)=\frac{\left|\left\{b\in B\mid\exists a\in A:a\ dominates\ b\right\}\right|}{\left|B\right|}\tag{19}$$

where A and B are two different Pareto optimal solution sets, $|B|$ represents the number of optimal solutions in solution set B, and $C\left(A,B\right)$ represents the proportion of solutions in B dominated by at least one solution in A to the number of solutions in B.

2) IGD

$$IGD\left(P,P^{*}\right)=\frac{\sum_{x\in P^{*}}min_{y\epsilon P}dis\left(x,y\right)}{\left|P^{*}\right|}\tag{20}$$

where P^{*} represents the true Pareto optimal solution set and $|P^{*}|$ is the number of solutions. In this paper, all algorithms are executed multiple times to obtain the solution set, which is then compared using nondominated sorting. The ultimate optimal solution is represented as $|P^{*}|$. P is the optimal solution set obtained by an algorithm, $dis\left(x,y\right)$ represents the Euclidean distance between any two solutions x and y. The smaller the IGD value, the better the performance of the algorithm.

Based on the above examples, optimization algorithms, and algorithm performance evaluation metrics, the performance evaluation results of MOPSO, NSGA-II, and VNSGA-II algorithms are shown in Table 8.

As shown in Table 8, VNSGA-II has the largest C-metric and the smallest IGD in all calculation examples. This indicates that VNSGA-II has the best performance in both performance evaluation metrics when compared to the other two algorithms. These prove the diversity and convergence of VNSGA-II.

The scheduling schemes for the MOPSO, NSGA-II, and VNSGA-II for the first sample are depicted in Figures 11 (a), (b), and (c). As illustrated in the figure, the time required to complete all delivery tasks is approximately the same, and all take less than 32min. However, it is clear from Figure 11 (a) that the fourth mobile robot reaches workstation 12 at 17.09min after completing the delivery task for workstation 4. After picking up the parts required by workstation 12, the workstation's part demand time has not yet been met. As indicated by the dotted line in Figure 11 (a), the waiting time of 1.24min is generated. This waiting time is also shown in Figure 11(b), where the seventh mobile robot generates the waiting time of 3.09 min at workstation 13. The delivery tasks assigned to seven mobile robots in Figure 11 (c) are reasonably distributed, the time intervals are short, and there is no downtime. As a result, VNSGA-II is capable of scheduling the mobile robots and arranging the distribution route in such a way that it meets the demand and satisfaction of each workstation's part, demonstrating the algorithm's effectiveness.

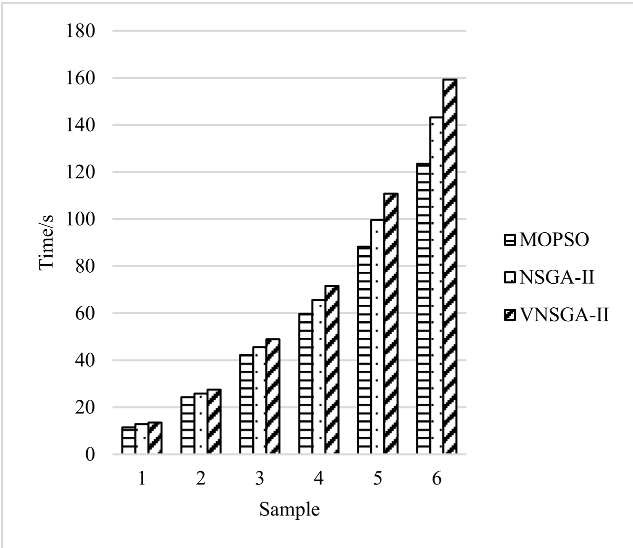

FIGURE 12. **Comparison of running time.**

The algorithm running time is depicted in Figure 12. Due to the addition of the heuristic algorithm and variable neighborhood search strategy to the VNSGA-II, the running time of VNSGA-II is longer than the other two algorithms. When the problem is small-sized, the running times of the three algorithms are similar, and both are lower than 50s. When the size of the problem increases, the running time of the VNSGA-II is increased significantly. However, the average running time of the six groups of samples only increases by 13.63s and 6.49s, respectively, which is within the acceptable range.

VI. CONCLUSION

To address the scheduling problem of mobile robots in a mixed-model assembly line, a multiobjective scheduling mathematical model for mobile robots in a mixed-model assembly line under the constraint of the normal fuzzy time window is established, and the VNSGA-II algorithm is designed. The scheduling model considers split delivery of workstations and sets the maximum workstation satisfaction and minimum energy consumption as optimization objectives. The VNSGA-II designed according to the characteristics of the problem can generate multiple Pareto nondominated solutions. Enterprise managers can make decisions based on their preference for workstation satisfaction and the energy consumption of mobile robots.

The following are the paper's major conclusions: (1) The scheduling model proposed in this paper not only considers the actual situation of parts splitting caused by part arrival time and mobile robot energy constraints, but also uses the normal fuzzy membership function to characterize the workstation's satisfaction with the arrival time of the parts, making the research on the scheduling of mobile robots in mixed-model assembly line closer to the production practice. (2) Numerical experiments validate the feasibility and effectiveness of VNSGA-II. The results indicate that VNSGA-II can rapidly obtain multiple high-quality mobile robot scheduling schemes, increasing workstation satisfaction, reducing the mobile robot's energy consumption, and assisting enterprise managers in making decisions. The algorithm proposed in this article is shown to be an efficient algorithm for solving the scheduling problem for mobile robots in a mixed-model assembly line.

This paper assumes that the quantity of parts required for all workstations is known, and the researchers can refine the optimization model further by considering uncertain demand. Additionally, the researchers can design other genetic operations or novel metaheuristic algorithms to address the scheduling problem for mobile robots in a mixed-model assembly line.

ACKNOWLEDGMENT

The authors would like to thank anonymous reviewers for their thoughtful comments and suggestions.

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XIAOYUN MA received the M.Sc. degree in management from the Shenyang University of Technology, where she is currently pursuing the Ph.D. degree with the School of Management. Her research interests include production logistics and intelligent logistics.

XIAOYE ZHOU received the Ph.D. degree from the Shenyang Institute of Automation, Chinese Academy of Sciences. She is currently a Professor with the School of Management, Shenyang University of Technology. Her research interests include production logistics and intelligent logistics.