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Research Article

Scheduling Scheme Design of Hotel Service Robot: A Heuristic Algorithm to Provide Personalized Scheme

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With the rapid development of machine learning and artificial intelligence, hotel service robots are widely used, but there are many problems to be solved in the scheduling scheme of hotel service robots. In this study, the Pareto optimal definition is used to model the problem, and a nondominated sorting heuristic method including genetic algorithm and differential evolution algorithm is designed to solve this problem. Experimental results show the effectiveness and stability of our algorithm. In addition, compared with the previous methods, the method proposed in this paper can provide a more personalized and reasonable service robot scheduling scheme for hotels. Finally, the hotel can optimize its management and operation and further deepen the degree of hotel intelligence.

1. Introduction

Traditionally, the hotel industry plays an important role in the travel industry, as it is vital to attract tourists and improve customer satisfaction [1]. Unfortunately, the hotel industry has long been plagued by high labor costs, labor shortages, and high employee turnover rates [2–4]. Especially in recent years, with the continuous global labor shortage and rising labor costs, these problems will become more prominent [5]. Obviously, no hotel can do without staff to provide quality service, such as room service, front desk service, and cleaning service. These undoubtedly have a very close impact on the hotel's daily operation and future strategic planning, and to a certain extent, even determine whether the hotel can achieve success [6]. Therefore, under the premise of ensuring the normal operation of the hotel, how to reduce staff costs and retain staff is a problem that any hotel administrator and operator must face. In addition, the COVID-19 pandemic is spreading rapidly around the world, causing major disruptions to the global economic landscape. The pandemic has led to a sharp drop in demand for travel and, as a result, the impact on the hotel industry has been enormous [7]. In response to this unprecedented crisis, hotels have had to design some improvisational innovations to safeguard the health and safety of all parties involved, and in the process to restore the consumer process in the accommodation industry [8].

With advances in artificial intelligence and information technology, robots have been developed for such fields as manufacturing, construction, medical surgery, and defense sectors [9]. Especially in recent years, the integration of robots and the hotel industry is getting closer and closer [10]. More and more hotels are starting to investigate their property more on the adaptation of robots. On the one hand, the reason for the adoption of robots in the hotel industry is to enhance the competitiveness of hotels. In fact, customers are more likely to be interested in hotels where robots are widely used [11]. On the other hand, the adoption of robots in hotels can reduce the cost of employees to some extent and reduce the turnover of employees. Although the initial procurement cost of robots is too high, long-term use of robots can effectively reduce the cost of employee recruitment and training [12]. For instance, Henn-na hotel in Japan achieved a Guinness World Record as the first "robot hotel," and this hotel installs several kinds of robots such as porter robot that delivers luggage to the guest room after customers check in. Finally, robots share the responsibilities of human employees to achieve the goal of increasing attraction and reducing labor costs [13].

The hotel industry increasingly adopts service robots as an alternative to employees. Therefore, this also promotes the research on the operation of service robots in the hotel industry [14]. Although there are a lot of researches on service robots, so far, only limited researches have discussed the mathematical model of the capacity and workload of service robots. Not long ago, according to Lee et al., aiming at the problem of high labor cost and labor shortage in the hotel industry, a mathematical model of service robot number and task quantity based on algorithm is proposed [9]. Except for this study, correlational research of this problem is almost scarce. However, their study had several defects. First, their researches only considered the lowest number of robots purchased by hotels, i.e., the lowest cost service robot operation, but ignores the service level of the robot at the lowest cost. In fact, the service level of the robot is very important, because it has a direct impact on customer satisfaction, and whether the customer is satisfied determines whether the customer carries out word-of-mouth publicity and repeated purchase of the hotel [15, 16]. Second, high service level and low cost are obviously two contradictory goals. In order to maintain an ideal level of service, there is no effective strategy except to increase the investment in service. And control cost is the hotel industry long-term business must [17]. Therefore, how to choose between the two goals is worth serious consideration. The article does not deal with the problem properly. Third, previous articles have separated the number of robots from the specific tasks assigned to them. In fact, the number of robots and the assignment of specific tasks influence each other. Because, when the number of robots is large, the specific tasks assigned by each robot are few. Conversely, the more specific tasks each robot is assigned, the fewer robots there are. Therefore, it is necessary to consider the number of robots and task allocation in combination, rather than in isolation. This consideration turns this article into a multiobjective optimization problem (MOP), where two potentially conflicting goals (satisfaction and cost) should provide a beneficial trade-off based on the characteristics of the hotel (for example, preference for customer satisfaction and cost input). Therefore, this study will explore the optimal capacity and operation design of the hotel robot logistics system to achieve a balance between cost and satisfaction.

2. Literature Review

With the rise of machine learning and artificial intelligence, more and more industries have entered the era of automation and intelligence. It is not new for robots to replace human beings to provide services. Robots are generally considered machines that can perform a series of complex actions [18]. They can accept various environmental information for decision-making according to their own sensors and other sources (i.e., feeling thinking action paradigm) and complete the set purpose, so they can learn from the previous situation [19, 20]. According to the function and nature of robots, robots can be divided into social robots, service robots, and auxiliary robots ([21–23]). In the service industry, Wirtz et al. [24] define a service robot as follows: a service robot is a tool that interacts with users and provides services on the basis of the system's autonomous and adaptive interface.

In the tourism industry, many hotels began to arrange service robots to attract customers and reduce labor costs. Starwood's high-altitude hotels use robot butler Polter to provide amenities to hotel guests [25]. Royal Caribbean's Quantum of the Seas was fitted with a robotic arm to serve as a bartender at the Bionic Bar [26]. Singapore tested a robotic virtual agent Sara (Singapore Automated Response Assistant) to provide information and assistance to visitors [27]. Hilton offers concierge robot "Connie." In addition, the opening of the first robot hotel, Henn-na, analyzed by Osawa et al. [13], the Hanna Hotel (meaning "strange/changing hotel" in Japanese) was built in a resort called Haustenbosch in Nagasaki Prefecture, Japan. The hotel, which opened in July 2015, has 80 robots, including an arm robot for carrying luggage, a porter robot, a female robot and a dinosaur robot in the reception area, a desktop robot for indoor customer service, and a robot cleaner. According to Guinness World Records, this is the first robot hotel. Alibaba's employees at the FlyZoo hotel in Hangzhou are all robots-tmall genie, who can order food from the robot waiter in the FlyZoo restaurant. "Robots will become the ultimate assistant for hotel guests. They hope everything can be found quickly and easily at their fingertips" [28]. Several major hotel brand chains (e.g., Marriott International, Hilton and Hyatt) are using new technology or upgrading existing technology (e.g., cleaning robots and electrostatic sprayers) to enhance hotel disinfection [29], in order to maintain social distance and reduce customer concerns.

On the other hand, industrial layout and academic exploration are accompanied. More and more hotels have arranged service robots, which has also caused a series of discussions on service robots in the academic community. Ivanov and Webster [22] introduce a hotel automatic assistant system based on a series of mobile platforms. The system can interact with guests and service personnel to help them complete different tasks. Pan et al. [30] explore people's reactions to different languages of service robots through a survey. The results show that the language used by the service robot has different attraction to customers in different periods of contact. In addition, Rodriguez-Lizundia et al. [31] believe that adding active greetings to the service robot in the interaction with the service robot can better enhance the user's participation and comfort. For service robots, different cultural backgrounds have different service perception [32]. In the service process, the lovely image of the service robot can alleviate the impact of service failure to a certain extent, so as to improve customer satisfaction [33]. Jia et al. [34], through an experiment, explore the influence of the anthropomorphism degree of service robot on customers. The results show that a medium degree of anthropomorphic robot can significantly improve customer satisfaction and purchase intention. In general, although scholars have a variety of strange researches on human-computer interaction, the vast majority of researches hold positive opinions on the use of service robots.

In addition to the above literature, in recent years, customer attitudes towards service robots have gradually become a research hotspot. Generally speaking, the functional dimension of service robot directly determines the customer experience, so this is the most important aspect for customer acceptance [35]. In addition to the functional dimension, Xu et al. [36] verified the leader's attitude towards the use of service robots through the Delphi method. They believe that the emergence of service robots can not only improve the operation of hotels and attract customers but also cause the transformation of human resources and corporate culture. In addition, the higher the expected commercial value of service robot deployment, the higher the acceptance of service robot by future hotel practitioners and students majoring in tourism management [37]. Kim et al. [38] believe that when COVID-19 pandemic is noticeable, consumers have a more positive attitude towards robots equipped with hotels (relative to human powered hotels). Similarly, in the context of the pandemic, Lin and Mattila [39] believe that customers' perceived privacy, the functional advantages of robots, and the appearance of robots have a positive impact on consumers' attitude towards robots. Lee et al. [40] explore the acceptance of service robots by dividing customers into cohesive groups with common characteristics.

Although the research on service robot is in full swing, these studies stay at the theoretical level. In fact, the research on scheduling configuration, appearance design, and acceptance inspection of hotel service robot is equally important. In addition, although there are some studies on capacity planning and operation design, few studies take into account the characteristics of the hotel industry. On the one hand, these studies do not dynamically consider the relationship between capability and planning, but observe the capability and planning of robot in isolation. On the other hand, previous studies ignored a key factor—the relationship between customer satisfaction and cost. Obviously, high service level and low cost are two contradictory goals. In order to maintain the ideal service level, there is no effective strategy except to increase service investment. This consideration transforms this paper into a multiobjective optimization problem (MOP), in which the two potentially conflicting objectives (satisfaction and cost) should make a beneficial trade-off according to the characteristics of the hotel (e.g., preference for customer satisfaction and cost input). Therefore, this study will explore the optimal capacity and operation design of hotel robot logistics system. Finally, a more personalized scheduling scheme is designed for the hotel.

3. Mathematical Modeling

The purpose of this study is to optimize the contradiction between robot service level and cost through heuristic algorithm, and to establish a general algorithm model for the hotel industry to use. Generally speaking, service level and cost are two conflicting factors. In other words, it is difficult to achieve a high level of service in pursuit of low cost, and it is difficult to meet low cost in pursuit of a high level of service. Moreover, robots cannot replace all human work that hotel employees typically handle. Therefore, the service robot in the hotel is mainly engaged in room service, a business that all modern hotels have. In this situation, the hotel operates robots to bring food to the room. In addition, the use of robots can be a good solution to the privacy problems of guests. So, the use of robots can not only bring cost-efficiency advantages to hotels but also better meet the needs of customers for privacy protection. Finally, it significantly increases the competitiveness of the hotel. In this study, the robots can perform one kinds of tasks: more specifically, a single task is to deliver food to a designated room and then return. When the robot is not working, it will stay in the depot. The robot must start from the depot to perform the task and return to the depot at the end of the task. In the following sections, we will introduce the objectives, limitations, and basic assumptions of the hotel robot logistics system model in more detail. The order is processed centrally within a certain period and then dispatched centrally within the next period. Since hotel chefs need time to prepare meals and guests also take time to finish their meal, it is assumed that job occurs only once at each room during an execution cycle. The number of robots required by the hotel and the assignment of tasks will be carried out simultaneously. Robots will then be assigned tasks to minimize costs and maximize service levels. Description of mathematical notations related to the model is as shown in Table 1.

3.1. Assumptions. Because in reality, few hotels have the same structure and number of floors, and other subtle factors are difficult to be similar. In addition, the types of robots, as well as the services provided and how they are served, vary from hotel to hotel. Therefore, in order to help the hotel to provide a suitable algorithm model, for the layout of the hotel and the operation of the robot, we must make some assumptions, so that it can be applied to all hotels.

(1) Only one distribution center is considered. According to the customer's order requirements, the robot will start from the distribution center and return to the distribution center after completing the task

(2) Only consider delivery and not take delivery

(3) All delivery robots are of the same type, with the same rated load capacity and known, and the product delivered is food

(4) The quantity required by each customer is within the rated load range of the vehicle

Table 1: Mathematical notations and descriptions.

Type	Variable	Description
Known parameters	$f, f^{`}$	Index of floor, $f = 1, 2, \cdots, F$, $f^{`} = 1, 2, \cdots, F$
	$r, r^{`}$	Index of guest rooms of f^{th} floor, $r = 1, 2, \cdots, R_f$, $r^{`} = 1, 2, \cdots, R_f$
	K	Index of robot, $k = 1, 2, \cdots, K$
	N	Index of order demand customer node set, $N = i$, $i = 1, 2, 3 \cdots, n$ is the customer node
	F	Index of the objective function
	C_b	The cost per mile of the delivery robot
	D_{ij}	The distance between two nodes (different room distance)
	Q	Maximum load capacity (task capacity) of the delivery robot
	E_i	The earliest time when customer i can accept the delivery service
	L_i	The latest time when customer i can accept the delivery service
	K_{it}	The time when the delivery robot K arrives at customer i
	K_{t0}	The departure time of the distribution robot from the distribution center
	Q_i	Whether the delivery task of the delivery robot meets the time requirement of customer I
	P	All delivery robot service success rate
	q_i	Demand of customer node i
	β	The sensitivity of food to time
	a	The rate at which food goes bad
	C_g	Fixed cost per robot used
	S	Speed of horizontal movement of hotel service robot
Decision variables	${Y^K}_i$	Assign decision variables. If the delivery robot serves customer i, it is recorded as 1, otherwise, it is 0
	${X^k}_{ij}$	Assign decision variables. If the distribution robot drives from the warehouse to the customer i, it is recorded as 1, otherwise, it is 0

(5) Each robot serves more than one room, but each room is only served by one robot

(6) The locations of all customers and distribution centers are known and fixed

(7) If the robot does not deliver within the known time window of all customers, the service will be deemed as failure

(8) The speed of the delivery robot is fixed, that is, it travels at a constant speed

3.2. Objective of the Model. The background of this paper is mainly based on the COVID-19 pandemic, that is, in order to carry out safe hotel room service during the outbreak, the use of robots for contactless hotel room service. Also, to keep things simple, let us assume that the hotel only offers free breakfast from 8 : 00 a.m. to 9 : 00 a.m. (1 hour a day). Guests can order the best time for breakfast delivery the night in advance through the hotel's online self-service system. The robot only needs to deliver food in designated rooms.

Fixed cost of robot can be expressed in equation (1). It represents the cost of a hotel purchasing a service robot, which is usually a one-time cost.

$$C_1 = \sum_{k=1}^{m} \sum_{j=1}^{n} X_{0j}^{k} C_g. \tag{1}$$

Robot transportation cost is as in equation (2). It represents the cost of a hotel operating a service robot, which is usually a recurring cost.

$$C_2 = \sum_{k=1}^{m} \sum_{i=0}^{n} \sum_{j=0}^{n} X_{ij}^{k} d_{ij} c_b. \tag{2}$$

The success rate of robot service is expressed by equation (3) [3]. Each service robot service meeting the requirements of customers is recorded as 1, otherwise, it is recorded as 0. Then, it is accumulated and divided by the total number of tasks, and finally, the success rate of this round of service is obtained.

$$Q_i = \begin{cases} 0, K_{it} < E_i, \\ 1, E_i \leq K_{it} \leq L_i, \\ 0, L_i < K_{it}, \end{cases} \tag{3}$$

$$P = \frac{\sum_{i=1}^{n} Q_i}{\sum_{i=1}^{n}\sum_{k=1}^{m} y_i^k} * 100\%. \quad (4)$$

The cost of food quality loss is as shown in formula (5). If customer i needs Qi's food, and the departure time of the distribution robot from the distribution center is k_{t0} and the time of delivery to customer i is k_{it}, then, it has experienced $(t^k{}_i - t^k{}_0)$ time. At this time, so the quality of food loss is $q^i - q^i a e^{-\beta(t_i^k - t_0^k)}$.

Therefore, the loss of food quality in the whole process can be expressed as

$$C_3 = \sum_{k=1}^{m}\sum_{i=0}^{n} y_i^k \left(q^i - q^i a e^{-\beta\left(t_i^k - t_0^k\right)}\right). \quad (5)$$

Equation (7) represents the objective function in this paper, that is, to pursue the least number of robots (or the lowest cost). It is mainly composed of fixed purchase cost and driving cost. According to the requirements of this article, the optimal objective function of cost is min $f1 = C1 + C2$, as follows:

$$\mathrm{Min} F_1 = \sum_{k=1}^{m}\sum_{j=1}^{n} X_{0j}^k C_g + \sum_{k=1}^{m}\sum_{i=0}^{n}\sum_{j=0}^{n} X_{ij}^k d_{ij} c_b. \quad (6)$$

In addition to pursuing the lowest cost hotel robot operating system, the service level is also worthy of serious consideration. Formula (7) indicates whether the time spent by the robot performing the task is less than the standard of service satisfaction. It is mainly composed of service success rate and food quality loss. According to the requirements of this article, the optimal objective function of satisfaction is $\mathrm{Min} F_2 = \lambda_1(1-P) + \lambda_2 C_3$ (where λ is the weight coefficient), as follows:

$$\mathrm{Min} F_2 = \lambda_1\left(1 - \frac{\sum_{k=1}^{m} Q_k}{\sum_{i=1}^{n} y_i^k} * 100\%\right) + \lambda_2 \sum_{k=1}^{m}\sum_{i=0}^{n} y_i^k \left(q^i - q^i a e^{-\beta\left(t_i^k - t_0^k\right)}\right). \quad (7)$$

3.3. Model Constraints. In this part, the constraints of the robot operation model will be introduced in more detail. In the process of robot operation, the robot will perform a task repeatedly in the same task or more than one robot. Therefore, in order to ensure that the hotel robot operation model does not appear conflict tasks, as well as invalid tasks. At the same time, the paper achieves the initial goal of achieving low cost and high service level of multiobjective optimization of the robot operation model. The following limitations must be made:

$$\sum_{i=1}^{n} q_i y_i^k \le Q, (k = 1, 2, \cdots, m), \quad (8)$$

$$\sum_{j=1}^{n}\sum_{k=1}^{m} Y_i^k \le m, i = 0, \quad (9)$$

$$\sum_{k=1}^{m} y_i^k = 1, (i = 1, 2, \cdots, n), \quad (10)$$

$$\sum_{i=0}^{n} X_{ij}^k = y_i^k, (j = 1, 2, \cdots, n\,; k = 1, 2, \cdots, m), \quad (11)$$

$$\sum_{j=0}^{n} X_{ij}^k = y_i^k, (i = 1, 2, \cdots, n\,; k = 1, 2, \cdots, m), \quad (12)$$

$$\sum_{i=0}^{n} X_{ih}^k = \sum_{j=0}^{n} X_{hj}^k, (h = 1, 2, \cdots, n\,; k = 1, 2, \cdots, n), \quad (13)$$

$$\sum_{i=0}^{n} X_{0i}^k = \sum_{j=0}^{n} X_{j0}^k, (k = 1, 2, \cdots, n), \quad (14)$$

$$\sum_{i=1}^{n}\sum_{k=1}^{m} y_i^k = n, (i = 1, 2, \cdots, n). \quad (15)$$

Equation (8) indicates that in the distribution process, the actual demand of customers is within the range of the maximum distribution volume of the robot. Equation (9) indicates that the number of robots actually providing services does not exceed all robots. Equations (10), (11), and (12) indicate that each customer has and only has one service. Equations (13) and (14) indicate that the robot starts from the distribution center, completes the task, and returns to the distribution center. Equation (15) indicates that each customer is served.

4. Solution Algorithm

As mentioned above, the robot scheduling problem proposed in this study has greater complexity and challenge. It is similar to PVRPTW in the field of logistics, which has been proved to be "NP-hard" [41]. On this basis, this study also needs to achieve a balance between robot cost and robot service quality. Obviously, these are two conflicting goals. In order to achieve the purpose of this study, we use Pareto frontier to deal with multiple objectives, which is widely regarded as an effective means to solve the problem of multiobjective planning [42]. In addition, in order to optimize the number of robots and order allocation and sorting at the same time, we innovatively combine genetic algorithm with differential algorithm. Therefore, according to the characteristics of the current research problems, we innovatively designed NSEPSDE, which involves genetic algorithm (GA) and Ensemble of mutation strategies and parameters in DE (EPSDE). In our research, we use GA to optimize the number of robots and EPSDE to evolve the distribution route of robots. The overall NSEPSDE framework is illustrated in Figure 1, which comprises initialization, hybrid evolution, and Pareto sort.

4.1. Step 1: Initialization. In view of the problems solved in this study and the characteristics of the hotel industry, we set the execution cycle time of the robot to 1 hour. In order to achieve the simultaneous allocation of the number of robots and robot tasks, therefore, we designed a two segment

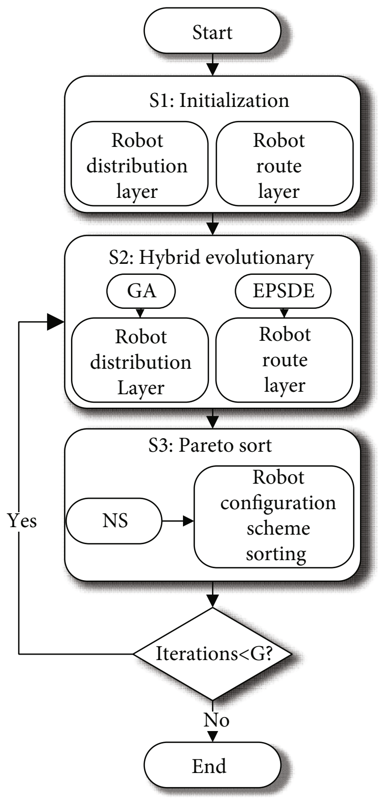

Figure 1: The methodological framework.

chromosome to encode. The left segment of chromosome represents the number of robots and subsequent insertion position, which is encoded by integer. More specifically, we randomly generate a set of any number of natural numbers from 0 to $N-1$ (representing the total order quantity of a day minus 1). The right segment of chromosome is used to represent the sorting of distribution routes, which is encoded by real numbers, from 0 to 1. Then, the numbers represented by the real numbers of the left segment of the chromosome are inserted into the corresponding positions of the right segment of the chromosome in turn.

In order to show our encoding and decoding methods more clearly, specific examples will be introduced later. The overall coding form is shown in Figure 2. In order to facilitate everyone's understanding, our experiment omits the kitchen and warehouse, and each route code only contains the number of robots and order information. In this case, the cycle time is set to 1 hour. Specifically, the left segment of chromosome represents the number of robots, insertion positions, and order sequencing. The right segment of chromosome indicates the information of hotel service order. Obviously, as we mentioned earlier, three robots are required for service in this time period, which are, respectively, inserted into the designated position of the right section. Then, we need to decode it first and take the distribution route decoding as an example, as shown in Figure 3. Eight guest orders need to be allocated this time. Customer order chromosome: 0.03-0.35-0.6-0.2-0.8-0.86-0.72-0.94. The above numbers are in the order of 1-3-4-2-6-7-5-8, representing the guests with the corresponding

3	6	0.11	0.29	0.55	0.18	0.76	0.86	0.63	0.92

Figure 2: An example of route coding.

scheduled time in the self-service system from small to large. Then, the assumed guest ID (room number) can be decoded as 202-304-302-201-502-308-210-207. Combined with the previous context, the hotel needs a total of three robots in this service cycle. More importantly, the transportation route of each robot can be described as follows: robot 1 : 202-304-302; robot 2: 201-502-308; robot 3 : 210-207.

4.2. Step 2: Hybrid Evolutionary. The goal of evolution at this stage is to evaluate the feasible solutions provided by the algorithm and realize a better route with higher utility. As mentioned earlier, the solution is encoded as a two segment chromosome, and the chromosome segment on the left represents the number of robots and subsequent insertion positions, which is a discrete decision variable. The right segment of chromosome represents the sorting of allocation route, which is encoded by real number, which is a continuous decision variable. Genetic algorithm is widely used in discrete optimization problems [43], and differential evolution algorithm is especially suitable for continuous optimization problems [44]. In addition to this study, in this study, the discussion on optimizing solutions with discrete and continuous decision variables is negligible. Therefore, this study adopts the strategy of hybrid evolution to optimize the robot allocation layer and robot route layer, respectively. GA is used for robot allocation layer, and EPSDE is used for machine routing layer. More specific details are as follows:

(1) Evolution based on a GA

GA originates from in silico studies performed on biological systems. It is a random global search and optimization method developed to mimic the mechanism of biological evolution in nature, drawing on Darwin's theory of evolution and Mendelian inheritance. Its nature is an efficient, parallel, global search that automatically acquires and accumulates knowledge about the search space during search and adaptively controls the search process to achieve optimal solutions. In this paper, we utilize GA for crossover and mutation of the left segment of the chromosome to enable evolution with respect to the number of robots and the position of insertion. Its implementation is shown in Figure 4.

After going through the above steps, the initial solution got evolved to produce superior offspring towards the goal we set. At the same time, gene conflict detection was set up in our experiments with the aim of preventing the occurrence of repetitive numbers among a group of chromosomes during the crossover, which obviously caused us to optimize errors in the number of robots and insertion positions. On the other hand, GA's mutation operation is simply a transformation for a certain order of solution internal numbers, and its use does not play an evolutionary role in our research problem, so we do not consider mutation operation.

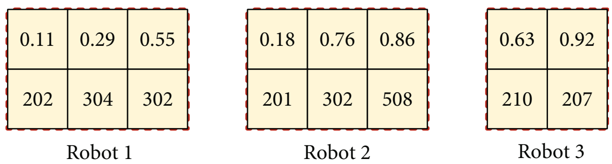

Figure 3: An example of the delivery route decoding.

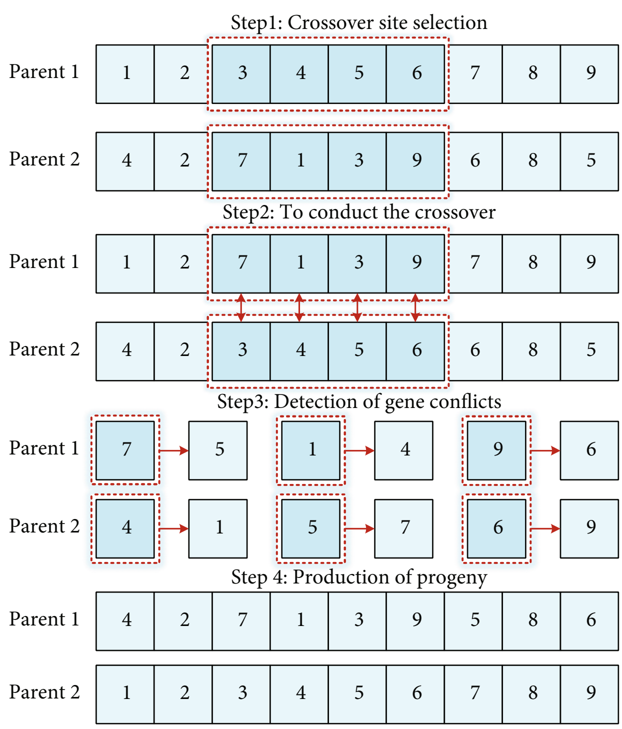

Figure 4: GA crossover process.

(2) Evolution based on a EPSDE

Differential evolution algorithm is an optimization algorithm based on population theory. Compared with the evolutionary algorithm, this algorithm retains the global search strategy based on population and adopts real number coding, simple mutation operation based on difference and "one to one" competitive survival strategy, so it reduces the complexity of operation. On the other hand, the unique memory ability of differential evolution algorithm enables it to dynamically track the current search situation and adjust the search strategy, so it has strong convergence ability and robustness and does not need to use the characteristic information of the problem. In general, the evolution of DE has three key parameters: difference vector amplification factor (F), crossover control parameter (CR), and population size (NP); and five mutation strategies: DE/rand/1, DE/best/1, DE/rand-to-best/1, DE/best/2, and DE/rand/2. EPSDE realizes the self-adaptation of parameter and mutation strategy, mainly by setting F and CR in mutation strategy and parameter of De, respectively, as a selection pool. Members of the initial population will allocate their corresponding parameters and mutation strategy from the pool and retain

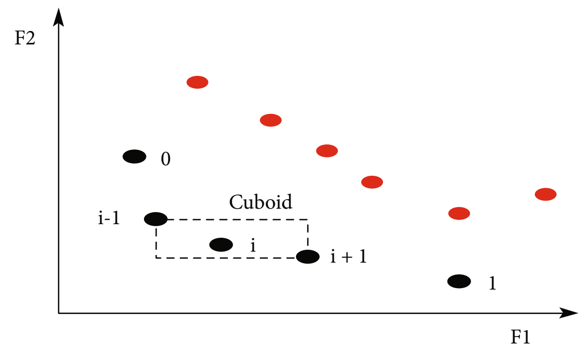

Figure 5: Congestion calculation.

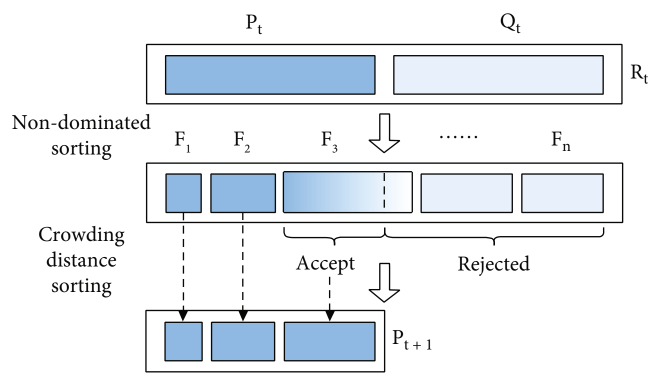

Figure 6: Elite retention policy.

the better strategies and parameters in the evolution process. Therefore, the influence of parameter setting and mutation strategy selection on the evolution effect is weakened to a certain extent, and the optimization ability and stability of the algorithm are enhanced. Therefore, our study uses JDE to process the coding in order to optimize customer order ordering. Details are as follows.

Before we begin to introduce the specific process, let us define something.

Solution: according to the dimension D of the problem, we use a D-dimensional vector to represent it as a solution. It should be noted that each dimension should have its own upper and lower bounds (this study is set to 0-1).

Population: we package a fixed number of solutions to form a population (NP).

(a) *Initialization*. The value of each dimension in each solution is initialized to the random value in the upper and lower limits of the dimension. The formula is

$$X_{i,j,o} = \mathrm{Min}_j + \mathrm{rand}_{i,j}[0,1] \cdot \left(\mathrm{Max}_j - Min_j\right), \qquad (16)$$

where i is the solution serial number, j is the dimension serial number, and 0 is the generation.

(b) *Mutation Strategy and Parameter Adaptive Setting*. EPSDE sets mutation strategy and Cr and F in

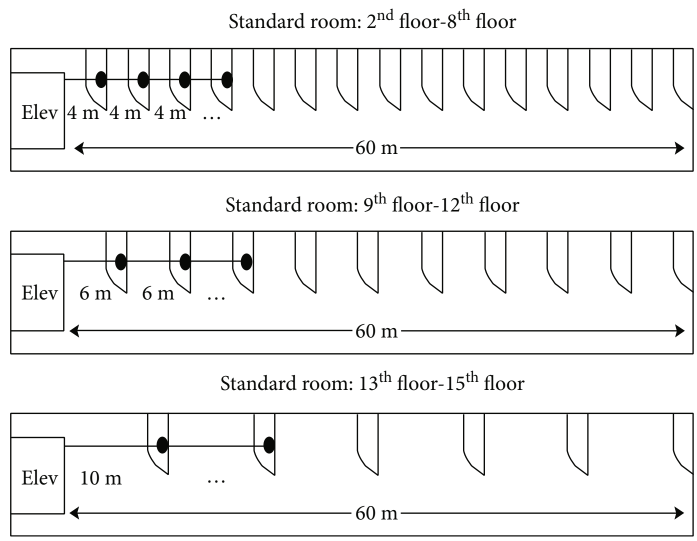

Figure 7: A floor plan of three guest room types.

parameters as strategy pool and parameter pool, respectively. In order to realize the adaptation of mutation strategy and parameters, each polarization member randomly assigns a mutation strategy from the strategy pool and randomly selects relevant parameter values from the corresponding parameter pool. Among them, the value of Cr in the parameter pool is in the range of 0.1-0.9, and the step is 0.1. The value of F in the parameter pool is in the range of 0.4-0.9, and the step is 0.1. There are five main mutation strategies in the mutation pool

DE/rand/1: $V_{\mathrm{i},G} = x_{r_1^i,G} + F \cdot (x_{r_2^i,G} - x_{r_3^i,G})$.

DE/best/1: $V_{\mathrm{i},G} = x_{\mathrm{best},G} + F \cdot (x_{r_1^i,G} - x_{r_2^i,G})$.

DE/rand-to-best/1: $V_{\mathrm{i},G} = x_{i,G} + K \cdot (x_{\mathrm{best},G} - x_{i,G}) + F \cdot (x_{r_1^i,G} - x_{r_2^i,G})$.

DE/best/2: $V_{\mathrm{i},G} = x_{\mathrm{best},G} + F \cdot (x_{r_1^i,G} - x_{r_2^i,G}) + F \cdot (x_{r_3^i,G} - x_{r_4^i,G})$.

DE/rand/2: $V_{\mathrm{i},G} = x_{r_1^i,G} + F \cdot (x_{r_2^i,G} - x_{r_3^i,G}) + F \cdot (x_{r_4^i,G} - x_{r_5^i,G})$.

Next, members of the initial population are randomly assigned mutation strategies and parameters from their respective pools. Group members (target vectors) use specified strategies and parameters to generate offspring (trial vectors). If the evaluation of the trial vector is better than the target vector, the trial vector will replace the target vector to generate a new trial vector, and the strategy and parameter combination can be retained. Instead, replace the strategy and parameters of the target vector. Finally, the adaptive updating of parameters and mutation strategy is realized.

(c) *Mutation*. Mutation is the process of producing a mutation vector under the joint action of target vector and F. In EPSDE, the mutation strategy and the value of F are randomly assigned to each solution in the population according to the parameter pool and strategy pool mentioned above. Therefore, each target vector $X_{\mathrm{i},G}$ in the population generates its own mutation vector $V_{i,G}$ according to the assigned mutation strategy and F value.

(d) *Crossover*. The goal of crossover is to select a vector from the target vector $X_{\mathrm{i},G}$ and mutation vector $V_{i,G}$ as the training vector $U_{i,G}$ through the parameter CR. There are two reorganization methods, but they are inseparable from the parameter Cr, which is the basis for whether the dimension variable is updated. In EPSDE, Cr value is randomly selected from the parameter pool, and only one reorganization method is adopted. The specific formula is as follows:

$$U_{\mathrm{i},G} = \left\{ U_{i,G}^1, U_{i,G}^2, \cdots, U_{i,G}^D \right\},$$
$$U_{i,G}^j = \begin{cases} V_{i,G}^j, \text{if } \left(\mathrm{rand}_j[0,1] \le \mathrm{CR}\right) \text{ or } (j = j_{\mathrm{rand}}) \\ X_{i,G}^j, \quad \text{otherwise} \end{cases} j = 1, 2, \cdots, D, \tag{17}$$
$$j_{\mathrm{rand}} = [\mathrm{rand}\ (0, 1).D].$$

Finally, each target vector is updated to prepare for the next choice.

(e) *Selection*. In both DE and EPSDE, the selection is performed by a greedy algorithm, which aims to select a better solution according to the fitness value of the solution and save it into the next generation. In EPSDE, the best individual $X_{\mathrm{best},G}$ in each generation G is selected and updated. The specific formula is as follows:

$$X_{i,G+1} = \begin{cases} U_{i,G}, \text{if } f(U_{i,G}) < f(X_{i,G}), \\ X_{i,G}, \text{otherwise}, \end{cases}$$
$$X_{\mathrm{best},G} = \begin{cases} U_{i,G}, \text{if } f(U_{i,G}) < f(X_{\mathrm{best},G}), \\ X_{i,G}, \text{otherwise}. \end{cases} \tag{18}$$

Table 2: Order information.

Order	Room number	Warehouse distance	The lift time	Service time	Early time	Late time
1	206	34	60	180	20	30
2	210	50	60	180	0	10
3	304	30	70	180	40	50
4	402	26	80	180	50	60
5	408	50	80	180	20	30
6	503	34	90	180	0	10
7	506	46	90	180	0	10
8	601	30	100	180	30	40
9	603	38	100	180	40	50
10	609	62	100	180	50	60
11	704	46	110	180	50	60
12	705	50	110	180	10	20
13	710	70	110	180	10	20
14	802	42	120	180	30	40
15	809	70	120	180	20	30
16	904	58	130	180	40	50
17	907	73	130	180	0	10
18	1001	47	140	180	20	30
19	1102	56	150	180	40	50
20	1105	71	150	180	20	30
21	1109	91	160	180	50	60
22	1201	55	170	180	10	20
23	1204	70	170	180	20	30
24	1208	90	170	180	30	40
25	1303	78	180	180	0	10
26	1305	94	180	180	30	40
27	1401	66	190	180	20	30
28	1402	74	190	180	50	60
29	1503	86	200	180	10	20
30	1505	102	200	180	40	50

Table 3: Algorithm parameters.

Parameter	C_b	C_g	a	β	S	G	Q	P	Pc
Value	\$10000	\$10	0.6	0.2	1 m/s	100	100	30	0.9

Through the above five steps, we have also completed the evolution of the right segment of chromosome, which provides an excellent solution set for our follow-up work through difference and parameter adaptation. Obviously, EPSDE is applicable to continuous variables, while our order information is discrete. Therefore, we will adopt equality transformation to convert continuous variables into order sorting through size sorting, so as to facilitate the following work.

4.3. Step 3: Pareto Sort. In our research, our goal is to achieve the lowest robot cost and the highest robot service satisfaction. Obviously, these are two conflicting goals. On the one hand, the cost of robot people is positively correlated with the satisfaction of robot service, so it is difficult to achieve a satisfactory result at the same time; on the other hand, multiobjective results are difficult to compare, because some solutions may have very high satisfaction and high cost, which brings great challenges to our comparison and consideration of different results. In order to solve this challenge, we introduce fast nondominated sorting, which sorts different results and finally saves the better solution in each evolution, which makes the whole algorithm search in the right direction and strengthens the efficiency and accuracy of the algorithm. The specific steps are as follows:

Table 4: The initial plan.

Strategy	Cost	Satisfaction	Allocate
No multiple strategies	67890	24%	No. 1 robot: 12-30-1-13-6-8 No. 2 robot: 28-4-7-12-22-20 No. 3 robot: 11-15-5-18-24-2 No. 4 robot: 19-21-29-9-14-3 No. 5 robot: 10-23-17-28-16-19

Table 5: Sample statistics.

	Mean	N	Std. deviation	Std. error mean
NSJDE	2.235638	30	1.599777	0.292077
NSEPSDE	1.581146	30	0.909894	0.166123
NSGA- II	2.355621	30	1.702574	0.310846
NSCODE	1.843396	30	0.980286	0.178975

(1) Fast nondominated sorting

Among the algorithms in multiobjective, the comparison of multiobjective has always been a difficult problem, so we need a better method to compare the results of multiobjective. In this study, fast nondominated sorting is introduced to solve this problem. Two parameters need to be set for fast non dominated sorting: NP represents the number of dominant individuals P in all individuals in the population, and SP represents the set of individuals dominated by individual P in the population. The steps of nondominated sorting of population individuals are as follows:

(a) Find the individual of nondominated solution in the population, that is, the individual with $\mathrm{NP} = 0$, and put the nondominated individual into the set $F1$

(b) For each individual in $F1$, find the individual set SP dominated by each individual in the set, subtract 1 from NP for individual P in SP, so that $\mathrm{NP} = \mathrm{NP} - 1$, if NP size is 0, this individual is stored in set H

(c) Set $F1$ is defined as the first layer non dominated set, and the same nondominated sequence prank is marked for each individual in $F1$

(d) For the individuals in set h, follow steps 1, 2, and 3 above until all individuals are layered

Through the above steps of fast nondominated sorting, the solutions of each robot distribution route and the number of robots can be divided into different Pareto frontiers, that is, different levels. The representative solutions on the same frontiers are equally good. Second, the solutions with small frontiers are better than those with large frontiers. In this step 1, we clearly understand the situation of each solution so that we can carry out the next work.

(2) Congestion ranking

For the comparison of solutions on the same Pareto front, it is obvious that the fast nondominated sorting fails, because it considers multiple target values at the same level. Therefore, we introduce the crowding distance to judge the quality of the solution on the same Pareto front. The average distance between two points on both sides of the point is calculated according to each objective function, which is used as the estimation of the perimeter of the box with the nearest neighbor as the vertex (as the congestion coefficient). As shown in the following Figure 5, the congestion coefficient calculated for solution i can be understood as a rectangle surrounded by dotted lines in the figure (for two-objective optimization). To calculate the congestion coefficient, we need to sort each objective function. The solutions at both ends of the head and tail are defined as infinity. The larger the congestion coefficient, the easier it is to be selected in the selection stage of genetic algorithm, which enhances the diversity of the same frontier.

By calculating the crowding distance, we can not only know which Pareto front surface the solution of robot distribution route and robot number is located but also know the crowding distance of the solution in the same Pareto front surface. In this way, we have a comprehensive grasp of the advantages and disadvantages of each solution.

(3) Elite retention policy

After fast nondominated sorting and congestion calculation, each solution has its own Pareto frontier and congestion distance. Therefore, the principle of elite retention strategy is how to select a better solution from the parent and offspring to enter the next evolution according to the Pareto front and crowding distance of the solution. The selection method can be shown in Figure 6. The specific steps are as follows:

(a) Create an initial parent population P_t uses crossover and mutation operations to generate offspring populations Q_t

(b) For P_t and Q_t as a whole, R_t performs nondominated sorting and constructs nondominated solution sets of all different levels $F1, F2, F3 \cdots$

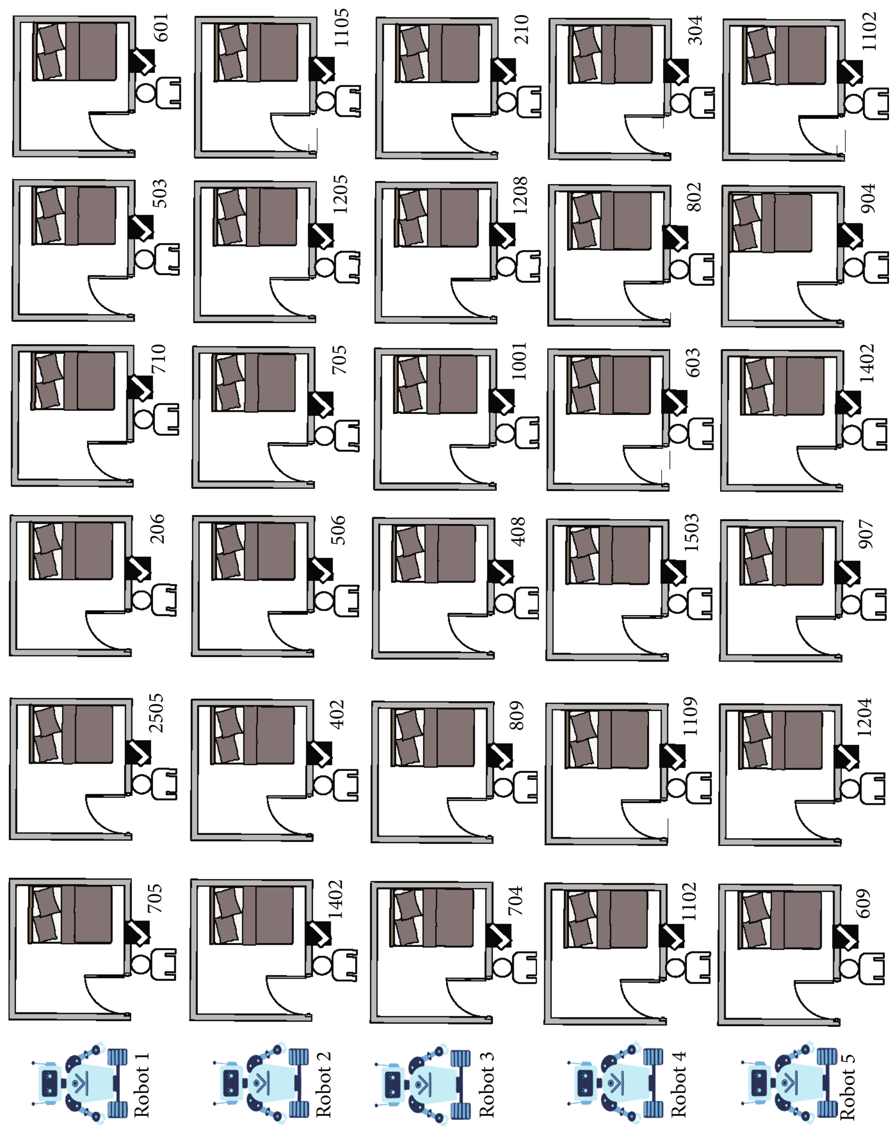

Figure 8: Distribution example.

(c) Add P_{t+1} as a whole in the order of leading edge, that is, $F1$, $F2$, and so on; until F_i is added to P_{t+1}, the total number exceeds N

(d) For the individuals in F_i, the congestion degree is calculated, and the optimal individuals are selected to join, so that the total number of new parent P_{t+1} is N

In order to solve our problem, the purpose of Pareto ranking is to make the solution with better robot distribution path and number of robots enter the next generation. Through the above three steps, the fast nondominated training helps us divide the solutions into levels (i.e., different Pareto frontiers), the crowding distance helps us compare the advantages and disadvantages of solutions at the same level, and the elite retention strategy helps us select these solutions with Pareto frontiers and crowding distance. Therefore, the algorithm can eliminate the bad solutions of robot distribution route and number of robots, make the whole population evolve towards our goal, and finally get a set of Pareto optimal solutions, that is, a set of solutions with high satisfaction and low cost.

5. Performance Evaluation and Discussion

5.1. Experimental Scene. The focus of this study is to design a more satisfactory robot distribution scheme for customers' ordering service in the highly complex random environment of the hotel, and the two objectives of robot cost and customer satisfaction should be considered. Therefore, when we choose the experimental scene, we take into account the rationality and generality of the experimental scene. For the above reasons, the scene of this experiment is modified based on the scene of X et al. The specific structure and layout have not been changed, but some room distances and floors have been modified. These modifications are to ensure

Table 6: The NSEPSDE plan.

Strategy	Cost	Satisfaction	Allocate
High-high	87890	100%	No. 1 robot: 8-26-13 No. 2 robot: 24-3-4-5 No. 3 robot: 10-19-7-1 No. 4 robot: 22-23-25-2-29 No. 5 robot: 21-27-18-14-20 No. 6 robot: 17-28-16-11-15-6-9 No. 7 robot: 30-12
Middle-middle	57890	66.8%	No. 1 robot: 15-9-28-29-25-13-6 No. 2 robot: 22-12-11-5-27-17 No. 3 robot: 26-1-24-19-14-16-20-30-18-23 No. 4 robot: 10-8-2-4-3-21-7
Low-low	37890	33.8%	No. 1 robot: 8-13-27-21-4-11-7 No. 2 robot: 23-6-24-28-17-22-30-1-5-18-26-20-29-15-9-2-16-12-25-3-10-19-14

Table 7: Only optimize allocation.

Strategy	Cost	Satisfaction	Allocate
High-high	167890	50%	No. 1 robot: 13-1 No. 2 robot: 4-5 No. 3 robot: 19-7 No. 4 robot: 29-2 No. 5 robot: 6-9 No. 6 robot: 11-15 No. 7 robot: 30-12 No. 8 robot: 22-23 No. 9 robot: 8-26 No. 10 robot: 24-3 No. 11 robot: 17-18 No. 12 robot: 25-27 No. 13 robot: 10-14 No. 14 robot: 16-20 No. 15 robot: 21-28
Middle-middle	107890	30%	No. 1 robot: 25-27 No. 2 robot: 11-15-16-20 No. 3 robot: 7-19-21 No. 4 robot: 30-2-12 No. 5 robot: 8-10-13-22 No. 6 robot: 29-14-1 No. 7 robot: 4-17-5 No. 8 robot: 18-3-24-9 No. 9 robot: 23-6-26-28
Low-low	47890	23%	No. 1 robot: 24-15-27-2-16-12-25-3-10-19-23 No. 2 robot: 14-6-29-28-17-7-30-1-5-18-8-20 No. 3 robot: 20-13-9-21-4-11-22

that our experiment is both reasonable and universal. Because most of the hotel layout and structure are familiar, but the room spacing and the number of floors are quite different. In the experimental scenario we designed, a hotel with 15 floors and 163 rooms was invented, and the hypothetical data were tested to verify the effectiveness of the algorithm. Generally speaking, the first floor of the hotel is basically a lobby, front desk, and kitchen. We will not introduce it in detail here. Then, our hotel rooms are divided into three types: standard rooms and king rooms from the second floor to the eighth floor, luxury rooms from the ninth floor to the twelfth floor, and suites from the thirteenth floor to the fifteenth floor. As the room size varies according to the room type, each floor can have 15 standard rooms and king rooms, while each floor can have 10 luxury rooms and 6 suites. Although the elevator can be located in many different locations in the real world, in this example, it is assumed that the elevator is located at the left end of the hotel. We show it in Figure 7.

Through the layout of the hotel, we can clearly calculate the distance from each room to the kitchen. There is no doubt that this will help us carry out our next work. After the distance from each room to the kitchen is calculated, we import the data into the algorithm. According to our calculation, we randomly simulated 30 customer orders, and the specific information is shown in Table 2.

5.2. Parameter Setting. In our research, in order to achieve the contradictory goal of low robot cost and high customer satisfaction, we need to set some parameters. On the one hand, the setting of parameters should fit the specific situation of the hotel industry; on the other hand, the setting of parameters should be more in line with the purpose of our research. On the basis of these two principles, we set the parameters, as shown in Table 3.

For C_b, it represents the cost of purchasing a service robot. This value is the result of considering several hotel service robots. The running cost of each hotel service robot is represented by C_g. Since our research is carried out in summer, according to the temperature characteristics of Chengdu, we set the deterioration speed a of food to 0.3 and the sensitivity β of food to time to 0.3. For the moving speed s of hotel service robot, we set it as 1 m/s, and our research does not consider obstacles or other emergencies, resulting in speed changes. Because it is difficult to predict and model. In our algorithm, we will produce 100 initial solutions Q (i.e., 100 groups of distribution schemes) and then set the number of iterations G to 100. For the length P of the solution, we set it to 30, because this study is carried out on the basis of 30 distribution orders. For the crossover probability PC in the algorithm, we set it to 0.9.

5.3. Performance Evaluation. This section aims to evaluate the superiority and applicability of our proposed method by comparing with several other methods. In mops comparison, several algorithms are widely used as baseline. They include genetic algorithm based on nondominated sorting (NSGA-II), particle swarm optimization (M-PSO), ant colony algorithm (M-ACO), and DEA algorithm (M-DE). In our research, we will use NSGA-II, our improved NSCODE and NSJDE as benchmarks to test the superiority and applicability of our algorithm. In addition, for the single objective optimization problem, we can evaluate the quality of the solution by the value of the objective function, that is, the smaller (or larger) the value, the better the solution [45]. However, our study considered two objectives, namely, cost and satisfaction. Therefore, we cannot simply evaluate the value of the objective function to judge the quality of the algorithm. At present, inverted generational distance (IGD) is widely used to evaluate the performance of different methods used in mops [46]. IGD mainly evaluates the convergence performance and distribution performance of the algorithm by calculating the sum of the minimum distance between each point (individual) on the real Pareto front (PFTure) and the individual set obtained by the algorithm. The smaller the value, the better the comprehensive performance of the algorithm, including convergence and distribution performance. In our experiment, we run NAEPSDE, NSJDE, NSCODE, and NSGA-II for 30 times and then calculate the IGD value of each method according to the following formula.

$$\mathrm{IGD}\left(\mathrm{PF}^{*}, \mathrm{PF}_{\mathrm{Ture}}\right)=\frac{\sum_{\mathrm{PR}\hat{\mathrm{I}}\mathrm{PF}^{*}} d\left(\mathrm{PR}, \mathrm{PF}_{\mathrm{Ture}}\right)}{\left|\mathrm{PF}^{*}\right|}. \tag{19}$$

The reason why each method needs 30 repeated experiments is that it can reduce the random error as much as possible and ensure the superiority and applicability of the method. In Table 4, we give the IGD mean, standard deviation, and standard error of the four methods. Adoption of Table 5, we can clearly see that the average value of nsepsde30 times IgD is significantly lower than that of other methods, and the values of standard deviation and variance also meet the statistical requirements. Therefore, this shows that our improved algorithm EPSDE is effective for solving the scheduling problem of hotel service robot. At the same time, our method also has good adaptability to multiobjective problems and can achieve a good balance between hotel cost and customer satisfaction. To sum up, our method is competitive compared with several mainstream algorithms to solve VRP problems.

5.4. Discussion. In Section 5.3, the results clearly show that our proposed method achieves a better balance between hotel operation cost and customer satisfaction than the existing algorithms and shows excellent performance in optimization. Therefore, under the background of repeated COVID-19 pandemic, a more diversified distribution scheme and a more reasonable distribution scheme can be designed by comprehensively considering the number of robots and task allocation, supplemented by Pareto optimal non dominated sorting.

(1) Provide personalized distribution scheme

Our method provides hotel managers with a more personalized distribution scheme choice, and the general distribution method of the hotel is shown in Figure 8. In real life, hotels can be divided into many types according to the purpose of hotel management and the groups they face, such as full-service hotels, limited-service hotels, suite hotels with food and beverage, and suite hotels without food and beverage [16]. Obviously, different types of hotels have different business strategies [47]. Its focus on customer satisfaction and hotel operating costs is different. Therefore, a single hotel service robot scheme cannot fully meet the needs of these hotels. The improved model based on fast nondominated theory can just meet the requirements of providing managers with a variety of nondominated solution sets. To some extent, these nondominated solutions have the same effect except that they focus on customer satisfaction and hotel operating cost, that is, the total utility of hotel selection: "high-high, medium medium-medium, low-low" strategy is the same in the same environment. Therefore, the specific selection of these schemes should be considered according to the situation of the hotel.

As shown in Tables 4 and 6, Table 4 is a scheduling scheme designed for the hotel by using the method of Lee et al. [9]. It is obvious that on the one hand, it does not consider customer satisfaction and ignores the key hotel industry feature of customers' requirements for robot delivery time. In addition, it cannot put forward personalized scheduling schemes for different hotel types. Compared with our Table 6, we designed three scheduling schemes with no difference in utility based on Pareto optimal solution and nondominated ranking according to different satisfaction and cost, that is: "high-high, medium- medium, low-low." Different hotel managers can choose their own scheduling scheme according to their hotel type and business strategy, rather than adopting the only scheme. Therefore, to some extent, our method will provide more diversified scheduling strategies for hotels and better meet the needs of hotel managers.

(2) Provide reasonable distribution scheme

When designing scheduling schemes for hotel service robots, few studies consider the number and task allocation of hotel robots as a whole. Obviously, the number of hotel robots is closely related to task allocation. On the one hand, the more the number of hotel robots, the simpler the task allocation, and the amount of tasks assigned to each robot will be reduced; on the other hand, the more reasonable the task allocation is, the number of hotel robots may be reduced to avoid unnecessary redundancy. Therefore, our scheme design makes up for this defect, considers the number of robots and task allocation, and puts forward a more reasonable hotel service robot scheduling scheme.

As shown in Tables 6 and 7, Table 7 is the scheduling scheme obtained by limiting our method, that is, only optimize the task allocation of robots while keeping the number of robots unchanged to verify whether it is necessary to consider the number of robots and task allocation as a whole. Through comparison, we can clearly see that considering the number of robots and task allocation, it has significantly improved both in hotel operation cost and customer satisfaction. Therefore, our research provides a more reasonable way to solve this problem, that is, a more reasonable scheduling scheme is adopted.

(3) Optimized the operation and management of the hotel

Based on discussion (1) and discussion (2), we propose discussion (3), that is, our method can also optimize hotel operation and management. On the one hand, under the background of repeated COVID-19 pandemic, the global hotel industry has been severely impacted, and the need to strengthen hotel management and operation is particularly urgent. On the other hand, according to the Wall Street Journal [48], Henn-na fired 243 robots after they failed to meet the expectations of hotel managers. Obviously, it is not enough for hotels to improve customer attraction, reduce operating costs, and reduce management burden only by arranging robots. The hotel also needs a reasonable scheduling scheme to cooperate with the operation and management of hotel managers, so as to help the hotel gain an advantage in the increasingly fierce competition.

Therefore, our research breaks through the previous limitations (most studies focus on what kind of service robot the hotel should use) and puts forward from a more comprehensive perspective that it is not enough for the hotel to only consider what kind of service robot to use, but also consider the scheduling and configuration of service robot people. Our research results can be used to optimize the resource allocation of hotels. Reasonable and personalized scheduling scheme will help hotel managers optimize their decision-making of using hotel service robot to some extent.

6. Conclusions and Future Research

As the COVID-19 pandemic is becoming more and more intense and the trend of normal development, the global economic development has been faced with unprecedented challenges. Many services have stagnated, or even gone into reverse. In the service sector, the hotel sector has been particularly affected by the outbreak. This is because the epidemic has intensified tourists' resistance to human-intensive places and human-contact behaviors, and people are more and more inclined to reduce the number of trips and unnecessary human contact, resulting in a sharp decline in hotel occupancy compared with preepidemic levels [49, 50]. And the hospitality industry has long been plagued by its own three major problems: high labor costs, labor shortages, and high employee turnover [2, 3, 4]. All these problems are the current any hotel must face. For these reasons, development of robotics and AI technology led robots to enter hospitality industries; many jobs in the hotel industry are gradually being replaced by robots, such as front desk service, cleaning service, handling service, and service (meal delivery); and more automated services will be adopted in the future [51].

Therefore, according to the Pareto optimal processing of multiple objectives (cost and satisfaction), we designed NSEPSDE, including genetic algorithm and EPSDE, to provide a scheduling scheme for the rational use of service robots for today's hotel industry. Through the example analysis, it is proved that this method is superior to the existing algorithms. Compared with other methods, this model provides a more reasonable and diversified scheduling scheme for the hotel industry. Our NSEPSDE may attract considerable interest from hotel practitioners because of the current difficulties faced by the hotel-epidemic and labor force. In addition, this research is of great significance to the methodology and practice of hotel robot scheduling scheme. In this method, we propose an effective personalized scheduling scheme for hotel service robot. This method considers multiple objectives based on Pareto optimality. The solution is encoded by two asymmetric chromosomes, and the discrete variables and continuous variables are optimized by combining the improved GA and EPSDE. Finally, the elimination and selection strategy of nondominated sorting is adopted, and a hybrid evolutionary structure is designed to improve the evolutionary efficiency.

In practice, this study uses the latest machine learning and artificial intelligence technology to provide personalized service robot scheduling scheme for hotel managers, which will greatly reduce the cost of hotel operation, improve customers' accommodation experience, and finally achieve the purpose of improving customer satisfaction and loyalty, so as to bring better business performance to the hotel [52]. At present, the hotel industry is facing unprecedented difficulties. Therefore, the scheduling scheme provided by our research institute will help hotels make better use of hotel service robots, so as to gain an advantage in the fierce competition. On the other hand, this study also helps the hotel industry to quickly deploy hotel service robots, let the wave of artificial intelligence sweep the hotel industry, and help the hotel change to intelligence.

Future research can consider the design of personalized scheduling scheme in uncertain environment and the selection of loading capacity of hotel service robot. When many hotels implement distribution services, the midway is not the same. It is plain sailing, and many uncertain problems may occur. For example, the service robot needs to wait when encountering obstacles, or the customer does not pick up the meal at the appointed time, etc. These uncertain environments will certainly have an impact on the scheduling system. In the future, we can take these uncertain problems into account and put forward the scheduling scheme of hotel service robot. Finally, it is valuable and promising to design a highly robust scheduling scheme to deal with the uncertainty of the environment.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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