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RESEARCH ARTICLE

Application of Optimal Scheduling Model Based on Improved Genetic Algorithm in Electric Power Mobile Operation

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ABSTRACT Mobile operation belongs to the innovation of a business model. At present, the management form of mobile operation is still in manual management, and there are many problems in manual management. In order to solve the current situation, an optimized scheduling model for power mobile jobs based on improved genetic algorithm is proposed. The model's objective is to enhance scheduling efficiency and accuracy of power mobile jobs while minimizing automation, scheduling costs, and fault impact. The research conducts simulation experiments to validate the model's efficacy. In the model considering the total task completion time and the cost of idle hours, the algorithm performance of the model is significantly proposed. When the model has completed around 70 iterations, it converges and maintains a fitness value in the range of 600 to 800. In the task assignment of the model, the total task completion time is shortened by 3 hours, the task assignment of each team is more uniform, and the path planning of each team is more reasonable. The research utilizes a genetic algorithm to intelligently schedule human resources, automating the scheduling process and achieving the lowest cost for completing the work.

INDEX TERMS Automation, delay losses, genetic algorithm, overdue loss, power mobile operation, scheduling optimization.

I. INTRODUCTION

The power industry is crucial to society's survival and continuous development, with power services being tightly integrated into daily life. The mobile operation management and scheduling of electric power is an important part of the work of electric power enterprises. Due to the high complexity of work management, manual operations are prone to abnormalities or contradictions. The absence of centralized management and control of the overall situation, as well as rough control or even lack of process monitoring, makes it difficult to adapt to mobile operations [1]. To achieve a continuous and cost-effective power supply, computer optimization has emerged as a necessary method, with intelligent scheduling of grid mobile operations at its core [2], [3]. The objective of this research is to develop a more optimized and intelligent scheduling model for power mobile operation management. The current system faces multiple limitations and problems, resulting in reduced work efficiency, increased costs, and a higher impact of faults on residential electricity consumption. This paper aims to enhance the performance of the mobile job scheduling model by taking into account the tasks and job types, team skills, and completion criteria. A quantitative analysis of operational losses is conducted, examining both time and monetary costs associated with delays. The study examines delay losses from two perspectives. An improved genetic algorithm (GA) is introduced into the model, and a return rule is proposed to ensure that the team can complete the task and return to the base within a certain time window. Parameters in the GA, such as population size, crossover probability, and mutation probability, are adjusted to improve optimization efficiency. By improving the GA, the model increases the fitness value of the population in the mutation operation, thereby improving the

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algorithm's performance. The model can reasonably plan the task route of different teams, realize the fairness and rationality of task distribution, and has the advantages of reasonable task route planning. The innovative aspect of this research pertains to the comprehensive consideration of both the total time needed for task completion and the cost of idle hours. This model balances scheduling efficiency and cost. The optimization model can plan the task path of each team more reasonably and achieve more equitable task allocation. The contribution of the research is mainly reflected in the following aspects: proposing an optimized scheduling model based on improved GA, which improves the fitness value of the population through mutation operation of the GA, thereby obtaining the optimal solution of the model. Compared to traditional manual management methods, this model provides higher efficiency and accuracy in solving mobile job scheduling problems. The effectiveness of the model was verified through simulation experiments, revealing that the improved algorithm exhibited faster convergence in comparison to other models and achieved a more precise optimal solution. At the same time, the model can also reasonably plan the task routes of different teams, making the task allocation more fair and reasonable. The research has improved the efficiency of power mobility operations, resulting in savings for the enterprise while mitigating the impact of faults on residential electricity consumption and ensuring uninterrupted electricity supply. In the field of scheduling job allocation in the domestic power industry, this study fills the research gap and provides useful reference and guidance for the establishment of automated scheduling in the power industry. The research in the field of industrial engineering and operations management aims to improve the efficiency and effectiveness of power mobile job scheduling tasks, promote operational automation in the power industry, and provide a model for intelligent resource dispatch. This reduces manual intervention and the possibility of human error.

II. RELATED WORK

The study proposes a scheduling model utilizing GA. In the hands of scholars at home and abroad, both GA and the scheduling model have been studied in depth. In order to solve the correctness of the schedulability analysis and meet the real-time requirements, researchers such as Yang et al. [4] studied and proposed the IEDF algorithm and combined it with the queuing theoretical model. Through the comparison of simulation experiments, the results show that the waiting time and execution error of the IEDF algorithm are smaller than those of the ordinary queuing algorithm within a sufficient time limit, and it has strong feasibility. Feng and other researchers [5] built a network structure based on the GA, and continuously optimized the parameters to generate a basic model. The model consists of an integrated algorithm that utilizes the initial feature recognition data of individuals. Through relevant biometric recognition experiments, the experimental results show that the model has high prediction accuracy. In order to cope with the losses caused by various disasters, researchers such as Bai et al. [6] proposed an optimal dispatch model for evacuation disaster management. This model is suitable for high population density to help people evacuate quickly. The experiment involved the model automatically planning the evacuation path for disaster evacuees with a humanitarian focus. Nikbakht's team [7] used the GA to optimize the structure of the neural network to find the best solution. The GA optimizes the hidden layer and neuron node of each layer of the structure to achieve the highest accuracy, so that the stress distribution in the structure can be accurately predicted. The results show that the neural network structure optimized by the GA can significantly improve the prediction accuracy of the model. Gholamnejad's team [8] introduced a production scheduling model alternative to integer linear programming, resulting in reduced scheduling complexity during the scheduling cycle. The proposed model reduces the number of workbench scheduling in the production scheduling cycle by 34% in the open-pit mine planning experiment. Mia's team [9] used the GA to optimize the spider web model. Through different encoding methods of the GA, different fitness functions were obtained. It was found that the encoding form of the GA was related to the convergence attribute to some extent. There are also adaptability and group learning behavior between the GA and economic system.

Rosita and Jaco [10] used the GA and CNN algorithm to optimize the computer detection algorithm in the process of spam detection. Researchers used real data to verify the performance. Through comparison of various performance indicators, such as accuracy, accuracy, F1 value and mean square error, they found that the detection model optimized by the GA has better performance. Han and other researchers [11] adapted the GA to optimize the BPNN model to obtain the GA-BP model. The model was used to set the relevant parameters of the product design scheme. After training, the model predicted the products. Upon training, the model was found to have a high prediction accuracy with an error rate within 3.5% as compared to the real results. In order to solve the workshop scheduling problem, Shi and other scholars [12] built a fuzzy FJSP non static scheduling model about the delivery date. The results of their simulation experiments indicated that this model resolved the issues of minimum energy consumption and consumer attitudes in workshop scheduling. In the context of the IPv6 environment, Ni's team [13] integrated the GA and ant colony algorithms to optimize the router. They evaluated the path smoothness in the search path, implemented a reward mechanism for the smooth path, and a penalty mechanism for the non-smooth path. The final model experiment results in solving the optimal solution showed that the algorithm has the performance to effectively solve the network quality problem, thus improving the quality of service to users. Liu and other researchers [14] proposed a GA-based dynamic scheduling model for track lead vehicles. The model can balance the relationship between the distributed system and the central information system, and provide accurate and timely information for RGV. The experimental verification resulted in the model demonstrating increased optimization efficiency and successfully achieving real-time dynamic programming.

Yin et al. [15] developed a new blockchain-based framework for addressing the issue of optimal scheduling of interconnected micro-grids. They have used this framework to provide a completely reliable, economical, and secure hybrid proton exchange membrane-blockchain structure for supplying residential loads. They also considered a socioeconomic framework that not only minimizes the total operating costs of micro-grids, but also enhances social factors by optimizing switching to benefit users. Considering the complexity and non-linearity of the problem, an effective modified crow search algorithm is used to find the optimal operating point of the micro-grid. The quality and capability of the proposed model are studied using a real residential interconnected micro-grid. The results show that the optimal switching can reduce the total operating cost. Average unsupplied electricity decreased from 1.4115 kWh/customer.yr to 1.352 kWh/customer.yr. Duan et al. [16] proposed an improved directed Acyclic graph (DAG) approach to enhance the security of data transactions within smart cities. The approach incorporates a security layer into the blockchain, effectively preventing cyber hackers from accessing system information. An effective energy management plan is also developed. For this purpose, Intelligent Priority Selection (IPS) based on advanced mathematical operators is provided to optimally allocate Metro-owned charging stations (MCS). In addition, untrace transformation (UT) is used to deal with the uncertainty of the system parameters. The results show that the proposed IPS can reduce the CPU time of the method by more than 75% compared to other well-known meta-heuristic methods in the field. Mohamed et al. [17] proposed a compatible optimization algorithm based on the θ-Firefly Optimization algorithm (θ-FOA) to minimize ship costs and uncharged load requirements. The θ-FOA is a polar meta-heuristic algorithm inspired by the mutual attraction and search nature of fireflies. In this paper, a new three-stage modification method is proposed to improve the searching ability of the algorithm and avoid premature convergence of ADMM agents. Satisfactory performance of the proposed method has been tested in the ship power system test. Mohamed et al. [18] proposed an improved line flow optimal power flow that combines the dynamic hot wire ratings in SCUC with TS. This approach can effectively decrease operating expenses, decrease switching times, and extend the lifespan of power switches. In such a power flow, the system loss is modeled by a linear formula. In addition, a linear approximation of the heat loss caused by the power flow through the line is presented. The Benders decomposition method is applied to solve the proposed model. The performance of the proposed framework has been evaluated on 6-bus and 118-bus IEEE test systems. Chen et al. [19] focused on the energy-constrained scheduling problem of workflow in heterogeneous multi-processor embedded systems. Firstly, the workflow and energy consumption of the processor are modeled, and the energy constraint scheduling problem is expressed as an optimization problem. The goal is to shorten the scheduling length of the workflow as much as possible. Then, with an improved per-allocation energy strategy, they proposed a new scheduling algorithm based on the energy difference coefficient to produce an approximately optimal allocation of processors, frequencies, and startup times for each task. This is all while ensuring that data dependence and energy constraints are met. Finally, the reliability and effectiveness of the proposed method are verified by experiments on random generation and real workflow. Chen et al. [20] designed a reinforcement learning algorithm based on global and local attention for cooperative behavior control of UAVs. The authors first analyze the collision avoidance, motion state update, and task execution constraints of multiple UAVs using the motion and coordination model. Subsequently, the multi-constraint decision problem for cooperative behavior control is abstracted. Then, inspired by the higher focus on important parts of data in the human learning, a multi-agent reinforcement learning algorithm with global and local attention mechanisms is designed. This is to collaboratively control the behavior of the drone and achieve coordination. Simulation experiments are carried out in the multi-agent particle environment provided by Open AI to verify the effectiveness and efficiency of the proposed method. Compared with the baseline, this method has significant advantages in terms of average reward, training time, and coordination effect.

To sum up, through this process of addressing targeted challenges, the models' prediction accuracy and execution are enhanced, intelligent controls are established, and work difficulty is decreased. These findings showcase the versatility of the GA in diverse fields. These include scheduling analysis, individual identification, disaster management, neural network optimization, production scheduling, economic system modeling, and preventive maintenance, among others. However, there are still some shortcomings in their research. When the GA is faced with complex scheduling problems, its operation efficiency is low, and the adaptability and scalability of the model need to be further studied. In the face of identification problems, more data and parameters are needed to improve robustness. Therefore, when studying the mobile scheduling problem of electric power operation, the paper firstly uses the GA to realize intelligent scheduling of mobile operation, and then adds information such as restriction conditions and data parameters to solve the shortcomings of the algorithm. This paper tries to intellectualize the mobile job scheduling in the power industry to achieve the purpose of computer intelligent scheduling, ensuring prompt and accurate responses to power outages, and controlling dispatching costs. The research innovation involves the implementation of an enhanced GA to address the scheduling issue of power mobile operations. Additionally, an intelligent scheduling model that relies on present-day mobile device terminals or information communication technology is established to gather data pertaining to personnel, equipment and other aspects of power on-site operations. This model utilizes the GA for scheduling and achieves automated management of power grid mobile operations.

III. OPERATION AND OPTIMIZATION ANALYSIS OF ELECTRIC POWER MOBILE JOB SCHEDULING MODEL

A. OPERATION AND OPTIMIZATION OF THE ELECTRIC MOBILITY OPERATION MODEL

The power mobile job scheduling model is to obtain or schedule the information of power field personnel, equipment and tasks through mobile devices under the condition of information integration. The GA can automate the established manual scheduling model and realize intelligent scheduling, thereby improving the efficiency of power mobile operation, saving operation costs and reducing losses. Scheduling of electric mobility jobs needs to consider many aspects [21], [22], [23], [24]. The first is the task and task type. The second is the team members and the team type. The third is the work standard. At the same time, without considering the traffic delay, there will be two losses in the scheduling operation. One is the overdue loss. The overdue loss is the loss caused by the team's lack of ability to complete the task within the specified time period. The second is the delay loss. The delay loss is due to the lack of personnel, resulting in the inability to finish the dispatch station within the projected time-frame, leading to loss. The delay loss of the task is expressed as L_{td}. The overdue loss of the task is expressed as L_{ot}, and the calculation formulas of the two losses are shown in Formula (1).

$$\begin{cases} L_{td}(i,j) = \begin{cases} B_h(i)(T_p(i,j) - T_e(i)) \\ L_h(i)(T_p(i,j) - T_e(i)) \end{cases} \\ L_{ot}(i,j) = \begin{cases} B_h(i)(T_{std}(i,j) - T_r(i)) \\ L_h(i)(T_{std}(i,j) - T_r(i)) \end{cases} \end{cases} \tag{1}$$

In Formula (1), $T_e(i)$ represents the expected start hour of the $T_r(i)$ task. It represents the time required to complete the task. $T_p(i,j)$ represents the start time of the scheduling plan. $T_{std}(i,j)$ represents the standard time for the team to complete $T_d(i,j)$ the task. The time is also the scheduled start time of the next task $T_p(i^{+1},j)$ for representation. Then there is Formula (2).

$$T_d(i,j) = T_p(i^{+1},j) = T_d(i^{-1},j) + T_{std}(i^{-1},j) \tag{2}$$

In the scheduling, there are several influential factors affecting space movement. The traffic time often only affects the delay loss of the task, and has no effect on the overdue loss of the task. Assuming that the traffic time is calculated in minutes, the task start time is calculated in hours, and the delay exceeds 20 minutes, it is calculated as an integer hour, and the delay time is expressed as d_T, then the expression of d_T is shown in Formula (3).

$$d_T(i,j,i^{-1}) = int(f_2(j,(x(i^{-1}),y(i^{-1})),(x(i),y(i))) + 20)/60 \tag{3}$$

In Formula (3), f_2 represents the traffic time. According to the national legal working hours, it is assumed that the working hours of electric mobile operations are from 8:00 am to 5:00 pm, including 1 hour of rest time in between. When scheduling tasks are continuously scheduled, the time to return to the enterprise after the last task is completed is 5:00 pm. Therefore, the relevant task return rules are established: at any time, starting from the enterprise, when making work arrangements for the next 5 days, if there is a suitable and allowable return time window, the team or personnel can return to the enterprise. If this does not occur, a forced return is possible on the fifth day. The prerequisite for all allowed return time windows is that the scheduled task is fully completed. Forcing a return may cause task interruption and segmentation. Therefore, the next time a task is scheduled, the segmented task segment must be completed first. The flowchart of the return rule is shown in Figure 1.

There are three cases where the return rules are interpreted in terms of mathematical expressions. One is satisfied $m \leq K_j$, then the return formula on the first day is shown in Formula (4).

$$\Delta_{LT} \geq \left| \sum_{k=1}^{m} (T_{k-1,k} + T_{std}(j,k)) + T_{m,r} - 8 \right| \tag{4}$$

In Formula (4), Δ_{LT} represents the width of the return time window of the scheduling team, and the value is 1 hour. In the second case, according to the analogy, the return rule formula is obtained as shown in Formula (5).

$$\Delta_{LT} \geq \left| \sum_{k=1}^{m} (T_{k-1,k} + T_{std}(j,k)) + T_{m,r} - 8q \right| \tag{5}$$

In Formula (5), q represents the number of days. The third case is that when the q value is [1] and [4], the termination time of the task is not satisfied, then an appropriate task is selected on the 5th day, and the termination time of the task is shown in Formula (6).

$$T_{stp}(k) + T_{k,r} = 40 \tag{6}$$

In the case where all the tasks are determined, the scheduling work measurement index can also be based on the total time of all the teams to complete the tasks as a standard. In a scenario with a long distance, the cost of selecting a relatively close team to do the job may exceed the cost of scheduling the team in a timely manner, due to the increased delay loss and overdue loss. In this case, the scheduling work does not expect the total time for the task to be completed to be extended, so $T_{\max}$ a constraint is introduced in the scheduling work, which $T_{\max}$ represents the total time for the task to be completed. Let the final completion time of a certain task be T_{he}. When the tasks are performed in sequence, the standard time of the task is represented by t_{ij}, and the starting time of the sequence task is T_{hB} represented by. The specific calculation is shown in Figure 2.

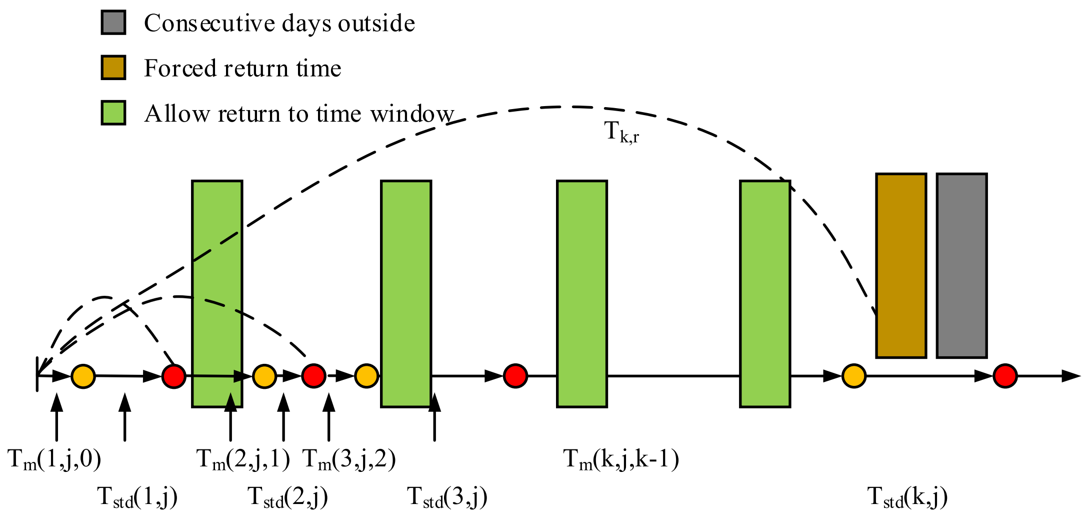

FIGURE 1. Specific flow chart of return rules.

In the team, in order to avoid the idle situation of the team, certain measures are taken to restrict the availability of the team. The penalty amount per idle hour of the team is shown in Formula (7).

$$P_{wg}(j) = W_{gh}^2(j) \tag{7}$$

In Formula (7), $P_{wg}(j)$ represents the penalty amount for the idle hour of the team unit. $W_{gh}(j)$ represents the hourly wage of the team. The research optimizes the scheduling model and obtains the objective minimization formula, such as Formula (8).

$$\begin{aligned}\min G = &\sum_{i=1}^{n}(L_{td}(i,j',x(j^{'-1}),y(j^{'-1})))+L_{ot}(i,j'))\\&+\sum_{i=1}^{n}f_3(i,j',x(j^{'-1}),y(j^{'-1})),(x(i),y(i)))\\&+c_1T_{\max}+c_2\sum_{j=1}^{l}(T_{dl}(j')P_{wg}(j'))\end{aligned} \tag{8}$$

In Formula (8), the c_1 dimension is 10,000 yuan per hour, c_2 represents dimensionless, and the values are 10,000 yuan/h and 100 respectively. $T_{\max}$ represents the time when the last task is completed. f_3 represents the cost incurred by the shift of the team, which f_2 is similar to. Formula (9) can be obtained.

$$\begin{aligned}&f_3(j',(x(i^{-1})),(x(i),y(i)))\\&\quad=\gamma(j')\beta_2\cdot\sqrt{(x(i)-x(i^{-1}))^2+(y(i)-y(i^{-1}))^2}\end{aligned} \tag{9}$$

In Formula (9), γ represents the driving cost coefficient of the team or the comprehensive cost coefficient of the team's personnel and machines. β_2 represents the correction coefficient of the path cost, that is, the straight-line distance and the optimal path between different positions are corrected, and the distance is converted into a cost.

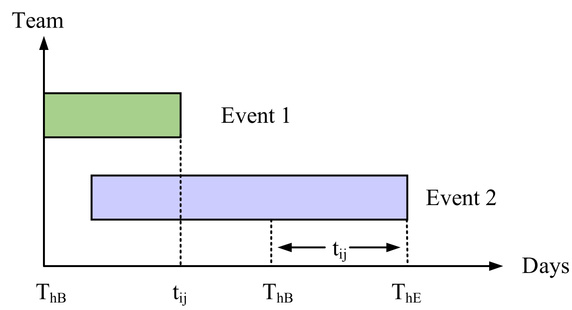

FIGURE 2. Calculation flow chart of total task completion time.

B. ELECTRIC MOBILE OPERATION MODEL BASED ON GA

The GA originates from the survival of the fittest and elimination of the fittest in the natural law idea, and is obtained by applying its idea to the optimization process of the model [25], [26]. The GA has a high advantage in the process of finding the optimal solution. The algorithm does not need to make clear rules, but can find the optimal solution by adjusting the parameters through its own adaptability. When dealing with a large number of data, the GA has a high probability of obtaining the optimal solution despite the unclear objective function. However, the GA is prone to fall into local optimal solution. To overcome this problem, multi-layer coding GA is used in this study. Such coding mechanism can provide more complex gene expression forms and increase the diversity of search space. Additionally, specific crossover and mutation techniques are implemented to preserve the genetic diversity of the population. The application of motion trajectory and return rules also proves to be beneficial in escaping local optimization. By optimizing task scheduling under specific constraints, the population is guided to concentrate in more advantageous regions, thus helping to escape from the local optimal region [27], [28], [29], [30].

The flowchart for the GA is presented in Figure 3. Initially, the algorithm generates random solutions that can address the

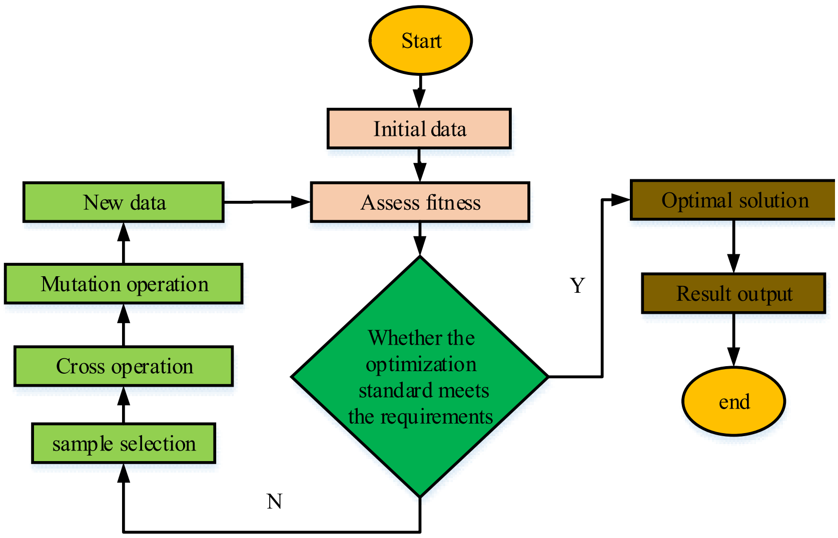

FIGURE 3. Chart of GA.

target problem [31]. The algorithm imitates the way of biological reproduction, and selects, cross breeds, and mutates the samples to obtain a new sample set. This sample set combines the advantages of the parent sample to get more adaptable children to solve the problem, and finally obtains the optimal solution through repeated genetic reproduction. By adjusting the parameters, the model can prevent the possibility of falling into local optimums and boost operational efficiency.

As the first step of the GA, coloring problem coding plays a very important role [32], [33], [34]. There are many coding forms in the GA, and the research adopts binary coding form. The two-level coding system can process several characteristic chromosomes simultaneously with high accuracy. After chromosome coding, the fitness value of each chromosome is calculated by fitness function [35], [36], [37]. The designed fitness function needs to avoid some necessary problems, such as the large differences in the early evolution of individuals that affect the search ability, and the small differences in the late evolution of individuals, which cause the decline of algorithm performance. Therefore, the specific expression of the function is shown in Formula (10).

$$Fit\ (f\ (x)) = 1/(1 + c + f(x)) \tag{10}$$

In Formula (10), $Fit\ (f\ (x))$ represents fitness function. c represents the threshold valuation of $f(x)$. Formula (10) is used to solve the minimum value problem. The solution to the maximum problem is shown in Formula (11).

$$Fit\ (f\ (x)) = 1/(1 + c - f(s)) \tag{11}$$

During the genetic operation process, a new sample set is formed from the chromosome samples with large final fitness, and the quality of chromosome individuals will directly affect the results of the algorithm. This makes the sampling more random. The roulette wheel selection method can be utilized for sampling, with the probability formula is shown in Formula (12).

$$p_k = f(x_k)/F = f(x_k)/\sum_{k=1}^{n} f(x_k) \tag{12}$$

In Formula (12), p_k represents the possibility of the sample being selected in roulette. $f(x_k)$ represents the fitness value of any individual x_k. After the sample is selected according to Formula (12), the parent is obtained, so that the parent can perform the cross operation. The cross operation includes multi-point cross and one point cross. Figure 4 shows the schematic diagram of multi-point cross operation.

It randomly selects two or more points on the chromosome. And it takes two points as an example, in Figure 4, the chromosome is divided into three parts: front, middle and back. The middle part and the back part are exchanged to generate new offspring chromosomes. This series of processes is a cross-transformation. In Figure 4, the fitness values of the parent genes before the exchange are $(2^9 + 2^8 + 2^6 + 2^4 + 2^3 + 2^1)^2 = 858^2$ and $(2^{11} + 2^8 + 2^5 + 2^2 + 2^0)^2 = 2341^2$ respectively. The fitness values of the offspring obtained after the exchange of genes at positions 5-12 between the parents are $(2^9 + 2^8 + 2^5 + 2^2 + 2^0)^2 = 805^2$ and $(2^{11} + 2^8 + 2^6 + 2^4 + 2^3 + 2^2)^2 = 2396^2$. It can be seen from the results that children will produce new individuals superior to their parents. The mutation operation is to mutate the chromosome gene, for example, the "0" in the chromosome code becomes "1", so as to increase the fitness of the chromosome. The mutation operator is introduced into the GA to make the training process of the algorithm more mature and further optimize the GA effect. Therefore, the parameters for the GA include population size, crossover probability and mutation probability. The population size is based on the actual target problem, with a value range of 10−200, a crossing probability of 0.4 − 0.99, and a variation probability of 0.0001 − 0.1.

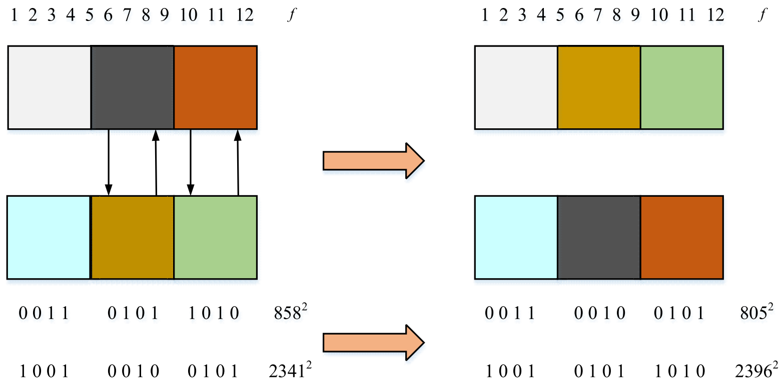

FIGURE 4. Example of multipoint crossing.

According to the characteristics of power mobile operation, in order to help the model improve the optimization efficiency and the optimization effect, it is studied to improve the scheduling model in the form of multi-layer coding GA. It sets the number of tasks for scheduling jobs as n, then the number of chromosomes is $2n$, to identify the chromosomes $\Theta(k)$. The tasks corresponding to each team of the factor are shown in Formula (13).

$$\Theta(k) = \{T_{od}(k), M_{od}(k)\} \tag{13}$$

In Formula (13), it $T_{od}(k)$ represents the task serial number. $M_{od}(k)$ it represents the team serial number. The task sequence subset can be obtained by mapping the chromosomes with the task sequence of each team $T_{od\_s}(j)$, and its expression is shown in Formula (14).

$$\Theta(k) = \left\{k; \left[T_{od\_s}(j), j = 1, 2, \cdots, l\right]\right\} \tag{14}$$

The fitness value of chromosomes is designed as Formula (15).

$$F_{fitness}(\Theta(k)) = \min G(T_{od}(k), M_{od}(k)) \tag{15}$$

Through the combination of Formula (8) and Formula (15), the motion trajectory of any group of chromosome monosomy can be obtained, and the calculation formula is as Formula (16).

$$F_{fitness}(\Theta(k)) = c_1 T_{\max} + \sum_{j=1}^{l} G_j(T_{od\_s}(j), P_{od}(j)) \tag{16}$$

Formula (16), $P_{od}(j)$ represents the spatial movement trajectory of the team based on the task sequence, and this formula needs to satisfy the return rule. According to the basic Formula (12), the individual selection probability of the scheduling task is obtained, and its expression is shown in Formula (17).

$$\pi(\Theta(k)) = \frac{F_{fitness}(\Theta(k))}{\sum_{k=1}^{K} F_{fitness}(\Theta(k))} \tag{17}$$

Formula (17) $\pi(\Theta(k))$ represents the probability of a chromosome being selected. K represents the number of generated chromosomes. New chromosomes of a population can be obtained by crossover operations, thus facilitating the evolution of the population. The specific way of the crossover operation is shown in Figure 3. After the population is mutated, new individuals are also be generated. The mutation operator randomly selects the individuals to be mutated, and exchanges the task number represented by the mutation position in the individual with the corresponding team number. In the above content, the research clarified several constraints, including working time constraints $T_{\max}$, team busyness constraints $P_{wg}(j)$, personnel and team capacity constraints $T_{std}(i, j)$, traffic and movement time constraints f_2, overdue loss and delay loss constraints L_{td}, L_{ot}, team return time constraints Δ_{LT}. $T_{\max}$ The aim is to ensure that work is carried out within specified working hours, in compliance with Labour regulations and corporate policies, and that working time is used efficiently. This helps to plan rational work schedules and prevent overwork or additional costs caused by working overtime. $P_{wg}(j)$ is to maximize the use of team and personnel resources, reduce the waste of working hours and ensure the efficiency of work. By avoiding excessive idle time in teams, productivity can be increased and unnecessary expenditure of human capital can be reduced. $T_{std}(i, j)$ The purpose is to ensure that the assignment of tasks matches the skills and qualifications of the team or person. This ensures that the job is completed to predetermined standards, while improving job satisfaction and safety. The purpose of the f_2 is to accurately plan the order of tasks, ensuring an appropriate buffer time to deal with unpredictable traffic issues, while also preventing scheduling from being so tight that it cannot actually be achieved. L_{td} and L_{ot} are intended to prevent additional costs caused by mission delays. Scheduling should take into account both efficiency and time management in order to minimize financial losses from non-compliance with deadlines. Δ_{LT} is to ensure that the team is able to return to the enterprise or starting point at the end of the set working hours, which helps to manage the team work-life balance.

IV. APPLICATION EFFECT OF OPTIMAL SCHEDULING MODEL BASED ON GA IN POWER MOBILE OPERATION

A. MODEL VALIDATION RESULTS WITHOUT CONSIDERING THE TOTAL TASK COMPLETION TIME AND IDLE HOURS

After the model construction and analysis, the important parameters in the model are clarified, and the relevant parameters are now assigned to verify the feasibility of the algorithm model. The team work ability is divided into three levels, with level 3 being the weakest and level 1 being the strongest. The coefficients for travel time at each level are 1.6, 1.4, and 1.2, respectively. The travel cost coefficients are set to 1.0, 1.5, and 2.0, respectively. In order to simplify the calculation, the path cost correction coefficients between teams are all equal. The number of teams is 5 and the number of tasks is 12. The time allotted by each team for each task is displayed in the PT matrix, while the standard working times for each task are shown in the STD matrix. If the value in the PT matrix is greater than the corresponding value in the STD matrix, it will be overdue. The initial state before the team starts the task is represented by the Inis matrix. After the task is completed, the average hourly delay loss and overdue loss of the team are represented by the OLS matrix. According to the established GA, its algorithm effect is directly related to its parameter settings. Therefore, by increasing the experimental training samples, the parameter size of the optimal performance of the algorithm is analyzed. Figure 5 showcases the details.

It can be seen from Figure 5 of the scheduling optimization model of the GA in the power mobile operation, there is a large gap between the sample number of 50 and 100, while the gap between the number of samples of 100 and 200 is relatively small. Therefore, the initial population number of the model is set to 100. In different sample numbers, the training error of the algorithm is relatively stable after 700 iterations, so the maximum genetic iteration number of the algorithm is 700. The cross probability will have different effects on the model. The performance of the model is determined by incrementally increasing this probability. The results are shown in Table 1.

It can be seen from Table 1 that, considering the algorithm error and running time, it is most appropriate to set the cross probability to about 0.6. The size of the mutation probability value has a great impact on the model. Although the probability value is too large to increase the probability of new individuals, it also has the possibility of destroying the good structure of the model. The low probability presents drawbacks for individuals, and affects the operation efficiency of the algorithm. In addition, the number of individual samples and model iterations is small in the research, so the mutation probability value is 0.3. The main purpose of the model is to reduce the delay loss and overdue loss in the scheduling process, so as to reduce various costs. Therefore, each matrix is used for simulation verification. Figure 6 shows the efficiency results of the GA without considering the total task completion time and idle time.

Figure 6 showcases that the optimal fitness function value displays a clear convergence trend before the number of iterations reaches 70. This suggests that the GA rapidly discovered the optimal solution during the initial iterations. The emergence of convergence trends may be due to the introduction of mutation operations in the population by improved GA, thereby increasing the fitness value of the population. After more than 70 iterations, the convergence trend of the optimal fitness function value entered a relatively slow state. This may mean that further iterations did not significantly improve the optimal fitness function value. This situation may be due to the fact that the GA has already approached the global optimal solution in later iterations, resulting in relatively small optimization effects of the algorithm. When the number of iterations reaches 120, the optimal fitness function value tends to a stable value. This indicates that the GA has approached the optimal solution, and additional iterations do not yield significant improvements. This stable state may indicate that the algorithm has found a scheduling solution that can provide better results in the current situation. The Gantt chart of team scheduling is automatically generated according to the calculation results of the model algorithm, as shown in Figure 7.

The Scheduling Gantt chart displays the job-related content in the coordinate chart in the form of diagrams, so as to reflect the work progress. Aiming at the scheduling problem of electric mobility operations, the research divides the task frame of the Gantt chart into three parts, the first part is the task number. The second part is the travel time. The third part is the work completion time. According to Figure 7, it can be observed that the layout distribution of each class and group is messy and uneven. This can mean that tasks are not evenly distributed in terms of time, with some groups taking on more tasks and others taking on less. This uneven distribution of tasks can result in some groups being overburdened while others may be in a relatively idle state. In order to minimize the cost incurred during the task, most of the tasks were assigned to the first four groups. This implies that the study took into account the rank and efficiency of the teams and minimized the cost by assigning more tasks to the more efficient teams. The fifth group had a lower rank and was not given as many tasks. This may be due to the relatively low efficiency of the fifth group or the small size of the group, which can therefore only undertake fewer tasks. The distribution of tasks shows that the task distribution among the groups is not balanced. The level and efficiency of the groups are taken into account when deciding on the distribution of tasks. This distribution may require further analysis to determine the rationality of the task allocation and optimize the space. At the same time, a careful assessment of the ranks and capabilities of the teams can contribute to a more balanced and efficient distribution of work. Figure 8 is a plan diagram of the team scheduling path automatically generated according to the calculation result.

In Figure 8, taking task 1 as an example, its task information expression is "C4, 2, T1". The letter C4 stands for the

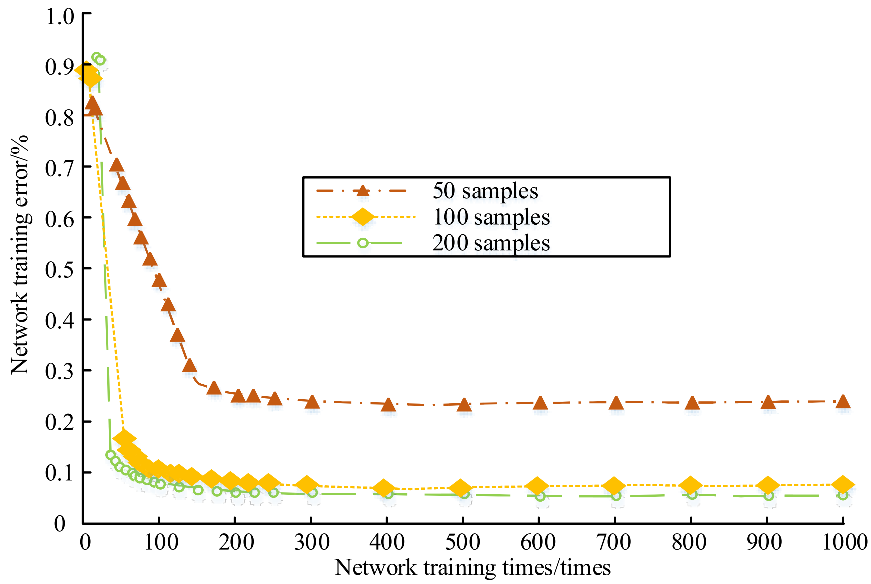

FIGURE 5. Graph of training time and training error.

task's job team, the number 2 represents the task's execution order within the team, and T1 denotes the task number. From the analysis of the optimization results in Figure 8, the task route planning of each group is relatively complicated, and the driving route is unreasonable. Through the simulation experiment results, in general, the path scheduling time of this method is about 2 minutes and 20 seconds. The delay loss value is 432,000, indicating that there is an overdue phenomenon in the scheduling task. The overdue loss value is 136,000, indicating that the overall planning. There is an overdue phenomenon. The total time required to complete the task was 17 hours, with a driving cost of 26,500 yuan and a total cost of 594,500 yuan. Therefore, without considering the total task completion time and idle time, this model takes a long time for algorithm scheduling, and each loss value is also high, which needs to be improved urgently.

B. CONSIDERING THE TOTAL TASK COMPLETION TIME AND THE MODEL VALIDATION RESULTS UNDER THE CONDITION OF IDLE HOURS

The total task completion time and idle hourly wages are introduced into the fitness function, and the expression form of model optimization is Formula (8). In the model, the total time for task completion and idle hours are of lesser magnitude when compared to other parameters. The parameter in Formula (8) is c_1 set to 5 and the c_2 parameter is set to 200, which enhances the optimization effect of the model. It is determined taking into account the total time to complete the task. After determining the total task completion time according to Figure 2, it compares it with the team's completion time and uses Formula (7) to assign the corresponding penalty to the idle hours of the three-level teams. It sums up the idle wages of all teams to get the optimization idle hourly wages.

TABLE 1. Algorithm and simulation time corresponding to different cross probability.

Crossover probability	Algorithm error	Simulation time (seconds)
0.4042	0.0450	0.2681
0.4890	0.0398	0.2672
0.5659	0.0817	0.1735
0.6407	0.0376	0.2818
0.7356	0.0756	0.1579
0.8104	0.0842	0.1726
0.9052	0.0283	0.6530
0.9900	0.0401	0.8204

When the model algorithm introduces the parameters of total task completion time and idle hours, its algorithm efficiency is shown in Figure 9.

From Figure 9, the optimal fitness value significantly converged within the first 70 iterations of the model. This indicates that the GA quickly finds the optimal solution in the initial stage, and the value of the objective function is significantly improved. This convergence indicates that at the beginning of the iteration, the GA adjusts the individual composition of the population to gradually optimize the performance of the fitness value. After more than 70 iterations, the optimal fitness function entered a stable region and remained within the stable value range. This suggests that the GA has approached a global optimal solution, and there is no significant room for further improvement in the subsequent iteration process. The model may have found a scheduling scheme that achieves a good level of fitness. The average fitness of the population is between 600 and 800, which indicates that the fitness of the whole population has been improved in the value of the objective function and is at a high level. This may be due to the fact that the evolutionary

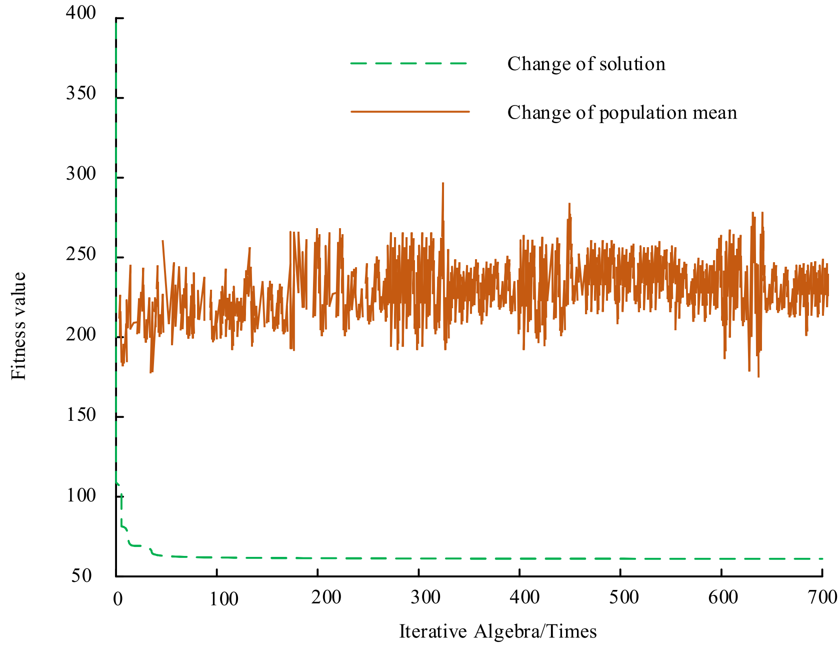

FIGURE 6. The algorithm efficiency of GA does not consider the total task completion time and idle hours.

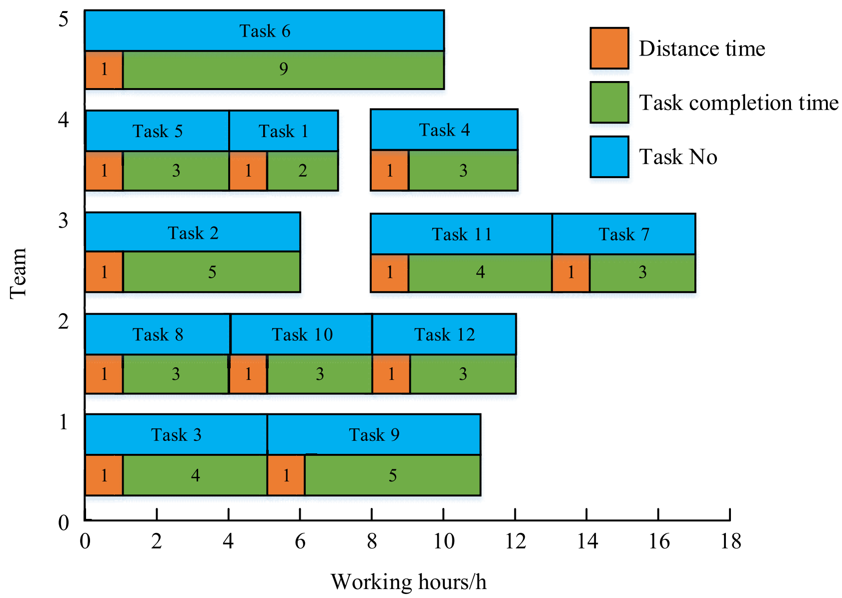

FIGURE 7. Automatically generated Gantt chart for team scheduling.

algorithm optimizes the population through the operation of selection, crossover, and mutation, so that the population as a whole is closer to the optimization goal. Figure 10 is a task scheduling Gantt chart generated after considering the total time of task completion.

As you can see from Figure 10, the task distribution is fairly average. This means that in this scheduling model, tasks are distributed relatively evenly among different workers or shift groups. This evenness may contribute to the efficiency and fairness of the scheduling process. By properly distributing tasks, the number of workers/teams can be reduced that are overloaded or under-loaded, thereby improving overall work efficiency. In this model, the scheduling order of tasks is optimized to meet specific requirements. For example, some urgent tasks may be prioritized, or tasks may be ordered based on other priorities or constraints. The satisfaction of scheduling priorities may help to improve the quality and efficiency of the overall scheduling scheme. This scheduling

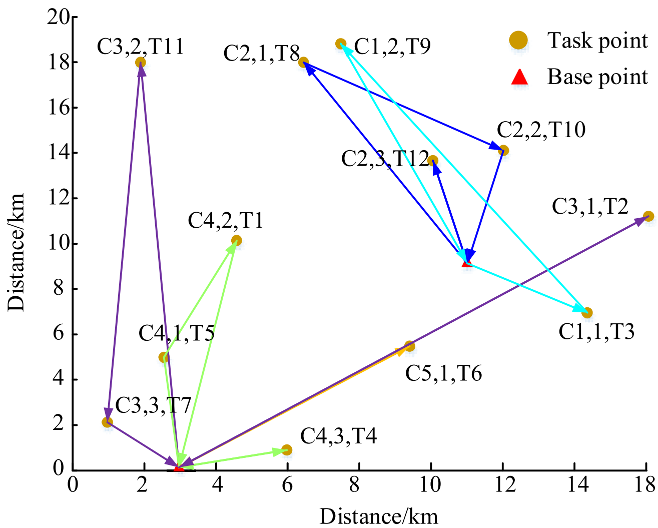

FIGURE 8. Team scheduling path planning diagram.

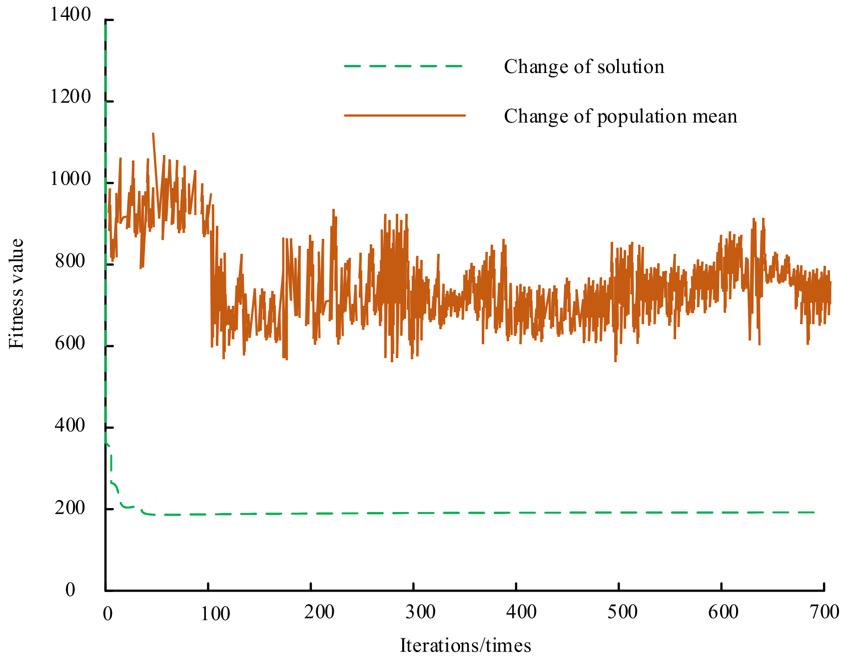

FIGURE 9. Algorithm efficiency results considering total task completion time.

model not only takes into account the distance of the total distance, but also solves the problem of severe uneven distribution. This may mean that in the task allocation, in addition to minimizing the distance of the total journey, the total time of the task is also taken into account, as well as the cost of idle hourly wages. By considering multiple indexes comprehensively, the scheduling model can find a better task allocation scheme thereby solving the previous model's issue of uneven task allocation. Figure 11 shows the team scheduling path planning diagram automatically generated according to the calculation results.

Considering the analysis of the optimization results of the total time to complete the task, the scheduling path of each team is reasonably optimized. The path mileage for team 3 has increased compared to the former planning, but it is still well-controlled. The optimization process took 2 minutes and 30 seconds to complete the scheduling path. The delay loss was 571,000 yuan, and there was also an overdue phenomenon in the plan. The overdue loss was 188,000, and there was also an overdue phenomenon in the overall plan. The completion time of the planned task was reduced to 14 hours, compared with the former 3 hours earlier, there is a significant

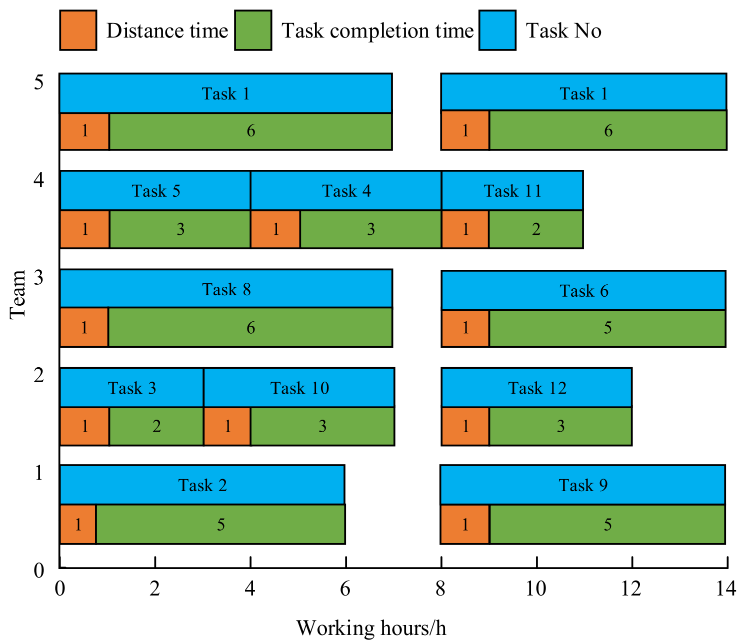

FIGURE 10. Gantt chart of task scheduling generated considering the total time of task completion.

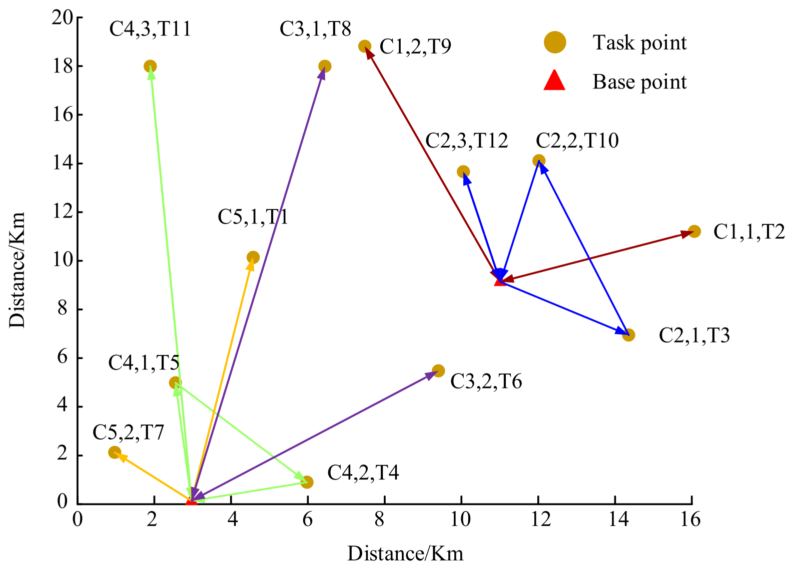

FIGURE 11. Automatically generated team scheduling path planning chart.

optimization effect. The driving cost generated is 25,700, compared with the former, the cost is reduced to a certain extent. The idle hour wage cost is 1,500, and the former idle hour wage. The cost of calculation is 5,800 yuan. By comparison, in this optimization, the cost of human resources is significantly lower. The total cost is 784,700 yuan. Compared with the former, the cost has generally increased, but the assignment of tasks to each team is more reasonable. The experiment verifies that the model considering the total task completion time and idle hour conditions has better performance from the internal way, and the performance of the GA needs to be verified. A comparison between Particle Swarm Optimization (PSO) algorithm and Back propagation neural network (BPNN), and the results are shown in Figure 12.

It can be seen from Figure 12 that the scheduling model of power mobile operation is optimized by PSO algorithm and BPNN algorithm, and the model error value is higher than that of the model optimized by the GA. When the PSO algorithm iterates about 250 times, the error value is stable at about 0.01. After 100 iterations of the BPNN algorithm, the error value remains at about 0.007. After 50 iterations of the GA, the error value remains at about 0.005. Therefore, it can be known

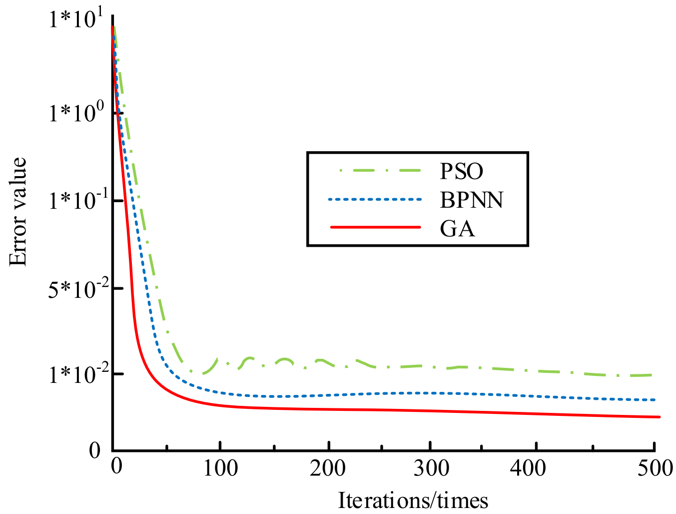

FIGURE 12. Comparison of error values of different algorithms.

TABLE 2. Analysis of scheduling performance of different algorithms.

Algorithm	Scheduling path length (Km)	Summary cost (ten thousand yuan)	Scheduling time (s)
References [19]	67.63	79.89	154
References [20]	67.28	79.21	156
Research method	66.74	78.47	150

that using the GA to optimize the power mobile job scheduling model has better performance. In order to further verify the proposed method, a comparative analysis was conducted using literature [19] and literature [20]. And three indexes of scheduling path length, total cost and scheduling time were used for evaluation. The results are shown in Table 2.

In the results of Table 2, the path length obtained by the research method is 66.74 km, which is slightly shortened compared with 67.63 km in literature [19] and 67.28 km in literature [20]. This indicates that the research method is more cost-effective in managing scheduling expenses and can complete the scheduling task at a lower cost. In terms of cost, the cost of the research method is 784,700 yuan, while the cost of literature [19] and literature [20] are 798,900 yuan and 792,100 yuan, respectively. This result shows that the research method is more effective in controlling the scheduling cost and can complete the scheduling task at a lower cost. In terms of scheduling time, the research method only uses 150 seconds, which is more efficient than the 154 seconds in literature [19] and the 156 seconds in literature [20]. This means that the research method is faster in processing speed and can complete the scheduling task in a shorter time. These results indicate significant enhancements in scheduling path optimization, cost control, and efficiency, ultimately improving the overall performance of power mobile job scheduling. Therefore, it can be concluded that the proposed method shows obvious advancement and practicability in the field of power mobile job scheduling.

V. DISCUSSION AND CONCLUSION

With the rapid development of the power industry, an increasing number of locations are utilizing electricity. At the same time, the distribution range of power is expanding, which increases the likelihood of power outages. In order to eliminate faults, the mobile operation of power is essential. The research uses the GA to optimize the scheduling of electric power mobile operations, and establishes an intelligent job-scheduling model. The model was tested by simulation experiments. Compared to the model that only considers the total time for task completion and idle hours, the model considering the total time for task completion and idle hour wages has higher total cost, but its job scheduling is more reasonable. Teams of different levels can obtain a more uniform number of task assignments. The task plan completion time is shortened by 3 hours, and the idle hour wages are saved by 4300 yuan. The cost of labor has significantly decreased, and the task route has been effectively managed. Compared with the current methods, the research method has better insights in the following three points: One is the comprehensive optimization considering multiple factors. The GA method adopted in the research considers several variables, including the total time to complete the task and the hourly wage for idle hours during the task scheduling. By optimizing these factors comprehensively, a more reasonable task scheduling scheme can be obtained. This comprehensive optimization considers the timeliness and cost factors of the task, resulting in the scheduling scheme more in line with the actual demand and improving the overall efficiency of scheduling. The second is to balance the task allocation and fairness. The research utilizes the GA methods to achieve more fair task allocation between different levels of teams and groups. By considering the class level and execution efficiency of the groups in the

GA, the task can be distributed more evenly, and some of the groups can avoid overloading or under-loading. This feature of balanced task allocation helps to improve the overall work efficiency, so that all teams can participate in the task and improve the utilization of human resources. The third is to control the task route in the best state. By iteratively optimizing using the GA, the system can identify the ideal allocation and path planning, reducing distances and eliminating time wastage. This control over the optimal task route can enhance the efficiency and accuracy of power mobility operations and better meet the needs of users. In the study, there are many uncertain factors in mobile power operation, such as traffic conditions, equipment failures, etc., which may lead to the delay of mobile power operation or other problems. In this paper, the unexpected uncertainties in operation are reduced by multi-objective optimization, including task types, team members, team abilities, operating standards and idle time. The research on intelligent scheduling of mobile jobs in the power industry using computers is still few in China, so there are still some deficiencies in the research. The GA used in the study can be further improved in the efficiency of the algorithm. Only the existing tasks are considered in the task scheduling, and the tasks in emergency situations are not considered. Therefore, the follow-up research is mainly aimed at improving the deficiencies. Its goal of helping the power industry is to establish automatic dispatching assignments, to deal with power failures in a timely and efficient manner, and to ensure normal power consumption in life.

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