International Journal of Engineering and Technology Innovation, vol. 14, no. 2, 2024, pp. 152-164

Grid Operation and Inspection Resource Scheduling Based on an Adaptive Genetic Algorithm

Bingnan Tang[1], Jing Bao[2,*], Nan Pan[2], Mingxian Liu[1], Jibiao Li[1], Zhenhua Xu[3]

[1]Lijiang Power Supply Bureau, Yunnan Power Grid Co., Ltd., Lijiang, China

[2]Faculty of Civil Aviation and Aeronautical, Kunming University of Science & Technology, Kunming, China

[3]Shanghai Ulsrobotics Co., Ltd., Shanghai, China

Received 26 November 2023; received in revised form 10 January 2024; accepted 11 January 2024

DOI: https://doi.org/10.46604/ijeti.2024.13129

Abstract

Grid operation and inspection a key links to ensure the safe operation of the power system, which requires efficient task allocation and resource scheduling. To address this problem, this paper proposes a resource scheduling model for grid operation and inspection based on bi-level programming. Firstly, the O&I process is analyzed and defined as a combined optimization problem of the multiple traveling salesman problem (MTSP) and the job-shop scheduling problem (JSP). Secondly, a bi-level programming model of MTSP and JSP is established according to the characteristics of the problem. Finally, an adaptive genetic algorithm is used to solve the problem. The feasibility of the model and the advancement of the algorithm are verified through the simulation of real scenarios and a large number of tests, which provide strong support for the sustainable development of the power system.

Keywords: power grid operation inspection, bi-level programming, resource scheduling, adaptive genetic algorithm (AGA)

1. Introduction

As one of the indispensable infrastructures of modern society, the reliability and economy of the power system are crucial for social and economic development. As the core link of power system management, grid operation, and inspection play a crucial role in ensuring the reliable operation and economy of the power system. With the continuous expansion of the scale of the power system and the rapid development of intelligent technology, grid operation, and inspection are facing more complex challenges. In response to these challenges, scholars have proposed to combine three-dimensional virtual scenarios with digital grids [1], thus enhancing the training of operation and inspection (O&I) employees.

In addition, due to the expansion of the grid scale, it is difficult to meet the demand for efficient operation and maintenance of the grid by relying entirely on human inspection methods, and scholars have proposed to introduce drones and other machines and equipment for grid inspection, and have conducted extensive research on their safety management systems [2] as well as inspection programs [3]. However, in some specific aspects of grid O&I, it is difficult for robots to effectively replace manual work due to restricted operating space, insufficient safety distance, and other problems, and manual inspection still occupies an important position. In recent years, scholars have researched the key issues of task allocation and resource scheduling involving machines, equipment, and personnel in grid O&I through various methods and techniques.

Task allocation aims to rationally assign different tasks to the right person or department to ensure that the tasks can move forward in an orderly manner. It has been widely studied in several specialized fields. In the field of machine planning, the problem of imbalance between multiple drones [4] and tasks, the linear task allocation problem of distributed multiple robots

* Corresponding author. E-mail address: baojing@stu.kust.edu.cn

English language proofreader: Chih-Wen Teng

[5], and the clustered collaborative task allocation of underwater robots [6] have all been effectively solved. In the field of personnel management, the allocation method between staff and tasks is also a hot research topic, and some scholars have conducted task allocation based on employees' preference awareness [7]. In addition, two-stage task allocation due to task failure has also been adequately considered [8]. Resource scheduling, on the other hand, is an effective guarantee to ensure that these tasks can be carried out according to the established plan [9-11], In the context of Industry 4.0, there are higher requirements for resource scheduling.

Nonetheless, the traditional grid O&I methods mainly focus on the optimization of the system as a whole, ignoring the units that work together with it. Analyzing the grid O&I resource scheduling problem, it can be learned that the goal of task allocation is to find the best combination of units to be inspected and inspection units, while the goal of resource scheduling is to find the optimal allocation of O&I tasks and resources, to achieve the optimal objective value. Both combinations involve discrete variables, therefore, the optimal scheduling of grid O&I resources is essentially a combinatorial optimization problem. Borrowing from classical combinatorial optimization problems, task allocation can be defined as a multiple traveling salesman problem (MTSP) [12-13], while resource scheduling can be defined as a job-shop scheduling problem (JSP) [14-15].

The MTSP is an extension of the traveling salesman problem (TSP), which is designed to solve the problem in which multiple travelers work together to complete a set of cities. In MTSP, multiple travelers are required to work together to complete the task, with each traveler being responsible for visiting a portion of the cities. The core of the problem lies in determining the path of each traveler to minimize the overall traveling cost. MTSP has a wide range of application scenarios, including logistics and distribution, inspection tasks, power grid O&I, etc. JSP is a classical problem considered in job shop environments, aiming to optimize the scheduling order of tasks in a set of job shops with limited resources. In summary, a two-layer planning model [16] is introduced to coordinate the task allocation and resource scheduling efforts for global optimization of the grid O&I system.

More and more scholars have found that meta-heuristic algorithms, due to their simplicity, efficiency, and wide applicability, show significant advantages in solving combinatorial optimization problems such as the MTSP [17-18] and the JSP [19-20], which provide the feasibility and effectiveness of the efficient solution of such complex problems. In terms of algorithm design, scholars have proposed hybrid meta-heuristic algorithms combining techniques such as the dragonfly algorithm (DA), firefly algorithm (FA), and genetic algorithm (GA) [21-22]. Compared with the traditional meta-heuristic algorithms, the hybrid meta-heuristic algorithms have strong adaptive and global search ability and can find more appropriate solutions in the search space of complex problems. However, there are fewer meta-heuristic algorithms for the two-layer planning problem, and research on scheduling resources for grid O&I is even scarcer.

To address these problems, this paper constructs a grid O&I resource scheduling optimization model combining MTSP and JSP with the shortest total O&I time to optimize the overall efficiency of grid O&I. In addition, an algorithm design based on an adaptive genetic algorithm (AGA) is proposed to solve the problem. The feasibility of the model and the advancement of the algorithm are verified by simulating the real environment and comparing the existing algorithms.

2. System Modeling

Grid operation and maintenance play a crucial role in maintaining the safe operation of the power system, directly impacting the reliability of the energy supply and the stability of the electrical power system. In the process of grid operation and maintenance, effective task allocation and resource scheduling ensure the availability of grid equipment, prompt resolution of faults, and continuous power supply to the electrical system. The grid operation and maintenance problem typically involve multi-level decision-making, with task allocation and resource scheduling being two core levels.

2.1. Model framework

To enhance the efficiency of grid operation and maintenance and optimize resource utilization, this paper establishes a dual-layer planning-based optimization model for grid operation and maintenance resource scheduling. The goal is to achieve coordinated optimization of task allocation and resource scheduling.

The model framework is illustrated in Fig. 1. In this model, the task allocation layer focuses on finding matches between different units to be inspected and inspection units, thereby achieving the optimal allocation of units to be inspected. The problem at this level can be understood as a MTSP, where each inspection unit represents a traveling salesman.

Simultaneously, the resource scheduling layer concentrates on how to optimally schedule resources to execute grid operation and maintenance tasks given a task allocation scheme. Resource scheduling involves achieving the optimal match of multiple tasks and various resources in different "units to be inspected - inspection unit" combinations. At this level, the solutions of multiple JSP models form a set of solutions for MTSP. By iteratively optimizing task allocation and resource scheduling, the model ultimately achieves efficient execution of grid operation and maintenance tasks, optimal resource allocation, and cost reduction, and ensures the reliability and continuous power supply of the electrical system.

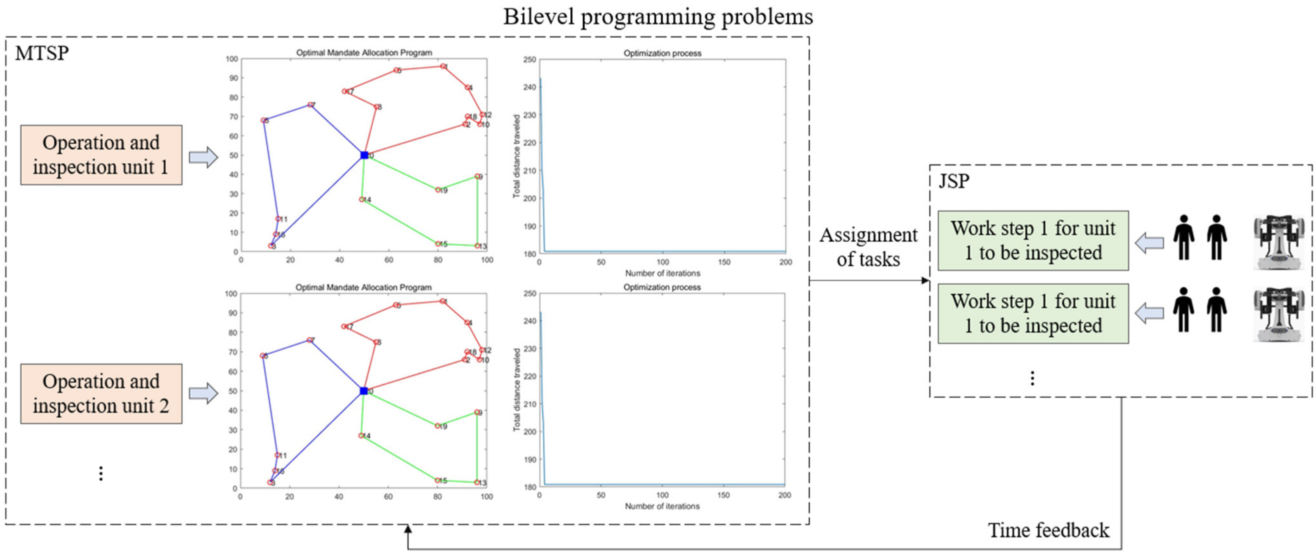

Fig. 1 Model framework diagram

2.2. Model assumptions

(1) All units awaiting inspection are of the same type, meaning the workflow for the operational inspection unit within them is identical.

(2) A singular unit awaiting inspection can only be assigned to a specific operational inspection unit.

(3) When the operational inspection unit undertakes tasks, they are carried out sequentially, one after another, and simultaneous execution is not permissible.

(4) The unit to be inspected is accessed only once.

2.3. Description of symbol

Before delving into the extensive research program, it is critical to understand the key terms and symbols used in this study. The inspection process is closely related to numerous interrelated components and therefore requires clear definitions. This paper describes the key symbols in Table 1, setting the stage for an informed scientific dialog.

Table 1 Description of symbol

Sign	Symbol description
T	Total duration of inspection
m	Number of inspection units
n	Number of units to be inspected
d_{ij}	The distance from unit i to j to be inspected
v_0	Transport inspection unit transfer speed
N_l	Number of working steps
w_{il}	The fifth step of the unit i to be inspected takes time
E_{ig}	The completion time of the ith unit to be inspected on the gth resource
Lt_{ig}	The execution time of the ith task on the gth resource

2.4. Upper task allocation model

In the assignment of power grid inspection tasks, the units awaiting inspection correspond to cities, and the operational inspection units correspond to travel agents. The model is established on a directed graph, where V is the set of n units awaiting inspection, and A is the set of arcs. Distinguishing itself from traditional MTSP models that do not account for the traveling agents' dwell time within cities, this paper proposes an MTSP that considers the dwell time in cities. In the context of actual power grid inspection work, which involves prolonged stays, the dwell time represents the duration of the operational inspection units working within the unit's awaiting inspection. The improved MTSP task assignment model is defined as follows:

$$T = \min \sum_{i=1}^{n} \sum_{j=1}^{n} \left(t_{ij} + t_{iw}\right) x_{ijk},\ k = 1, 2, \ldots, m \tag{1}$$

$$x_{ijk} = \begin{cases} 1 & \text{if } \mathrm{A}(i, j) \text{ is selected} \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

$$t_{ij} = \frac{d_{ij}}{v_0} \tag{3}$$

$$t_{iw} = \sum_{i=1}^{n} \sum_{l=1}^{N_l} w_{il} \tag{4}$$

$$\sum_{j=2}^{n} x_{1j} = m \tag{5}$$

$$\sum_{j=2}^{n} x_{j1} = m \tag{6}$$

$$\sum_{i=1}^{n} x_{ij} = 1,\ j = 2, \ldots, n \tag{7}$$

$$\sum_{j=1}^{n} x_{ij} = 1,\ i = 2, \ldots, n \tag{8}$$

$$p_i - p_j + \left(n - m\right) x_{ij} \le n - m - 1 \tag{9}$$

$$2 \le i \ne j \le n \tag{10}$$

$$x_{ij} \in \left\{0, 1\right\}, \forall (i, j) \in A \tag{11}$$

where, Eq. (1) represents the total time, including transfer time and working time; Eq. (2) is a 0-1 variable indicating whether the path $\mathrm{A}(i, j)$ is selected; Eq. (3) calculates the transfer time; Eq. (4) calculates the working time; Eqs. (5)-(6) ensure that exactly m operational inspection units depart from unit 1 awaiting inspection and return to unit 1; Eqs. (7)-(8) ensure that each unit awaiting inspection is visited only once (except for unit 1); Eq. (9) prevents the formation of operational routes that do not include unit 1 awaiting inspection, where represents the number of nodes passed by the operational unit from departure to unit i awaiting inspection. Eqs. (10)-(11) specify the range of values for each index variable.

2.5. Upper task allocation model

In the scheduling of operational inspection resources, operational inspection resources correspond to machines, operational steps correspond to processes, and operational inspection tasks correspond to workpieces. The model is established based on these correspondences. Distinguishing itself from traditional JSP models where tasks require specific resources, this paper adopts a perspective of ensuring resources meet tasks and conducts pre-scheduling of operational inspection resources. The improved JSP resource scheduling model is defined as follows:

$$w_{il} = \min_{1<i<n} \max_{1<g<n_g} E_{ig} \tag{12}$$

$$E_{1g} - Lt_{ig} + \delta(1 - a_{igh}) \geq E_{ih} \tag{13}$$

$$E_{l} - E_{ig} + \delta(1 - b_{igh}) \geq Lt_{ig} \tag{14}$$

$$E_{ig} \geq 0 \tag{15}$$

$$a_{igh}, b_{igh} \in \{0,1\} \tag{16}$$

$$\forall l \in N_l, \forall g \in N_g, \forall h \in N_h \tag{17}$$

where Eq. (12) represents minimizing the maximum completion time; Eq. (13) ensures that the completion time of the current step is greater than the difference between the completion time of the previous step and the processing time. Here, δ is a non-negative slack variable introduced to ensure the satisfaction of the constraint. a_{igh} represents the priority of resource g to fulfill the demand of task i; Eq. (14) represents the non-blocking relationship between steps, which indicates that task i prioritizes the use of resource g; Eqs. (15)-(17) specify the range of values for the relevant variables.

3. Algorithm Description

In the current academic context, the two-layer planning problem faces problems such as difficulty in solving and local optimization. Therefore, the proposal of a population intelligent optimization algorithm is of great academic importance. The technical details of the AGA algorithm are described in the following section.

3.1. Standard genetic algorithm (SGA)

The GA is a heuristic algorithm proposed by J. Holland in 1975, inspired by the simulation of biological evolution processes. The execution process of the algorithm includes encoding, decoding, selection, crossover, mutation, and recombination. GA is characterized by its simplicity, strong parallel search capability, and minimal requirements for optimization problems. It is widely applied in engineering and scientific fields to address optimization problems.

3.1.1. Data encoding and decoding

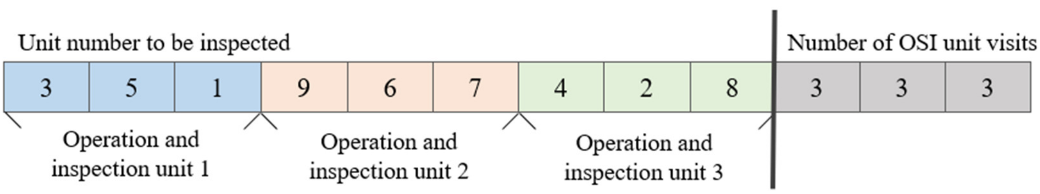

Fig. 2 MTSP layer genetic algorithm coding

In MTSP, assuming there are 10 units awaiting inspection, numbered 0-9, and there are 3 operational inspection units. Initially, all three operational inspection units start from unit 0 awaiting inspection. The encoding of the MTSP layer is illustrated in Fig. 2. The number to the left of the black vertical line indicates the PIU number assigned to the O&I unit, while the number to the right indicates the number of PIUs to which the O&I unit is assigned.

Chromosome individuals are divided into two parts by vertical lines. The left side represents the number of units awaiting inspection (excluding unit 0), and the right side represents the number of units awaiting inspection passed by each operational inspection unit. Following a decimal encoding, no decoding is required.

In JSP, assuming there are 2 units awaiting inspection, each with 2 steps for maintenance, and there are 4 resources available for selection. Each step requires one or more of these resources. The encoding of the JSP layer, using a double-layer structure, is illustrated in Fig. 3.

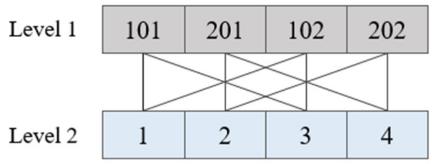

Fig. 3 JSP layer genetic algorithm coding

Layer 1 encodes task step sequences, and Layer 2 encodes resource types. The decoding format for this dual-layer structure is as follows: If a chromosome with 10112 genes is formed, it signifies that the first step of task 1 is executed using resources 1 and 2.

3.1.2. Fitness function

To ensure the continuous evolution of the population towards superior individuals, it is crucial to establish an evaluation function that aligns with the model. The objective of the dual-layer scheduling system is to minimize the overall time without violating work rules. Hence, this criterion can be used to assess the quality of individuals. Based on this principle, the fitness function (Y) is formulated to have a mapping relationship with the objective function, as shown in the following equation.

$$fitness = \sum_{i=1}^{n} \sum_{j=1}^{n} t_{ij} + t_{iw} \tag{18}$$

3.1.3. Population initialization

During the population initialization stage, a set number of individuals are randomly generated, and their feasibility is examined. If the task allocation and resource scheduling scheme represented by an individual violates constraints, a repair process is conducted to ensure compliance with the specified constraints.

3.1.4. Select individual operation

During the selection stage, the algorithm employs a roulette wheel approach to choose individuals within the population. In other words, the probability of selection for each individual is determined based on its fitness function value. The higher the fitness of an individual, the greater the probability it will be retained. However, individuals with lower fitness also have a certain probability of being retained. The formula for calculating the selection probability is given by,

$$select_i = \frac{fitness_i}{\sum_{i=1}^{N} fitness_i} \tag{19}$$

3.1.5. Crossover operation

During the crossover stage, individuals exchange parts of their genes from the parental chromosomes to achieve genetic recombination. This process generates two new individuals, each containing genes from both parents. The algorithm employs a partially matched crossover method with a certain probability for the crossover operation. The crossover points and the number of crossovers are randomly selected using a random function. Subsequently, the genes of the parents are crossed to produce two new offspring individuals.

3.1.6. Mutation operation

In the mutation stage, a key process takes place. Here, two mutation positions labeled A and B, are pinpointed on the individual using a random function, diversifying the gene pool. The genes positioned between A and B then undergo a reversal. This strategic switch in their order results in the creation of a mutated individual, introducing variability and fueling the potential for evolutionary developments.

The initiation of GAs is contingent upon the creation of an initial population, achieved by the random generation of a specific set of chromosomes. The subsequent phase encompasses the evaluation of each chromosome by leveraging a fitness function, thereby determining its subsequent precedence during the selection phase.

Thereafter, a selection phase engages, where, prompted by their respective fitness evaluations, the superior chromosomes undergo a crossover to engender the next generation. This inexorably incites the mutation phase, instigating random alterations within the chromosomes, and consequently promoting genetic diversity within the population. The process then reverts to a fresh cycle of evaluation, selection, crossover, and mutation, persisting in this trajectory until it satisfies preset termination criteria, such as the attainment of a specified number of iterations or an optimal solution deemed satisfactory is unearthed. The flowchart for the SGA is illustrated in Fig. 4.

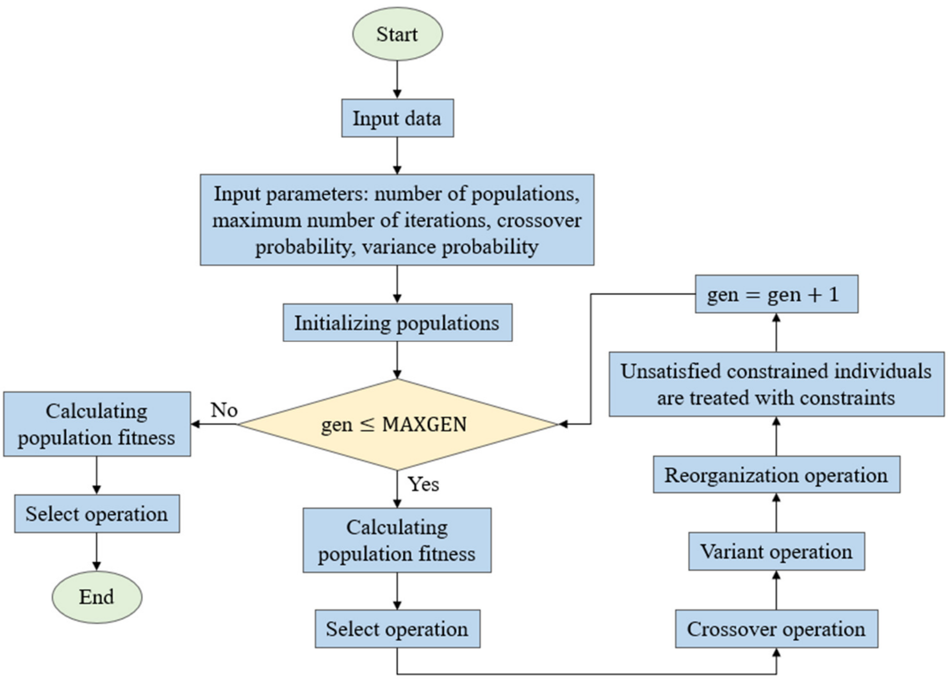

Fig. 4 Standard genetic algorithm flow chart

3.2. Adaptive genetic algorithm (AGA)

While the SGA demonstrates good convergence speed and optimization capabilities, it still has shortcomings such as unstable optimization performance and relatively weak global optimization ability. To address these issues, this paper introduces adaptive and selective strategies to optimize the algorithm.

3.2.1. Adaptive strategy

In the crossover and mutation stages of the SGA, the fixed values of crossover probability p_c and mutation probability p_m often lead to significant uncertainty in the algorithm's convergence speed and search range. Adaptive strategies allow the crossover and mutation probabilities to change with the fitness of individuals, providing better global search capabilities compared to fixed values.

The update of the adaptive strategy relies on individual performance. When the fitness of individuals in a generation surpasses the average level, it indicates better performance, prompting a reduction in crossover and mutation probabilities. Conversely, if the fitness is below average, an increase in crossover and mutation probabilities is warranted. The update of crossover probability and mutation probability can be expressed as shown in:

$$p_c = \begin{cases} p_{c\max} - \dfrac{(p_{c\max} - p_{c\min})(f_a - f_{aver})}{f_{\max} - f_{aver}}, f_a \geq f_{aver} \\ p_{c\max}, f_a < f_{aver} \end{cases} \tag{20}$$

$$p_m = \begin{cases} p_{m\max} - \dfrac{(p_{c\max} - p_{c\min})(f_{\max} - f_b)}{f_{\max} - f_{aver}}, f_b \geq f_{aver} \\ p_{m\max}, f_b < f_{aver} \end{cases} \tag{21}$$

where $p_{c\ \min}$, $p_{c\ \max}$, $p_{m\ \min}$, and $p_{m\ \max}$ are the minimum crossover probability, maximum crossover probability, minimum mutation probability, and maximum mutation probability for the GA. $f_{\max}$ and f_{aver} represent the maximum and average fitness values, while f_a and f_b indicate the current individual's fitness.

3.2.2. Preference strategy

To enhance the global convergence speed of the algorithm, this paper employs a selective operation favoring dominant individuals. Specifically, the top N individuals in terms of fitness within the population are retained, while the bottom N individuals are replaced. This accelerates the selection process within the population, improving the algorithm's global effectiveness and convergence speed.

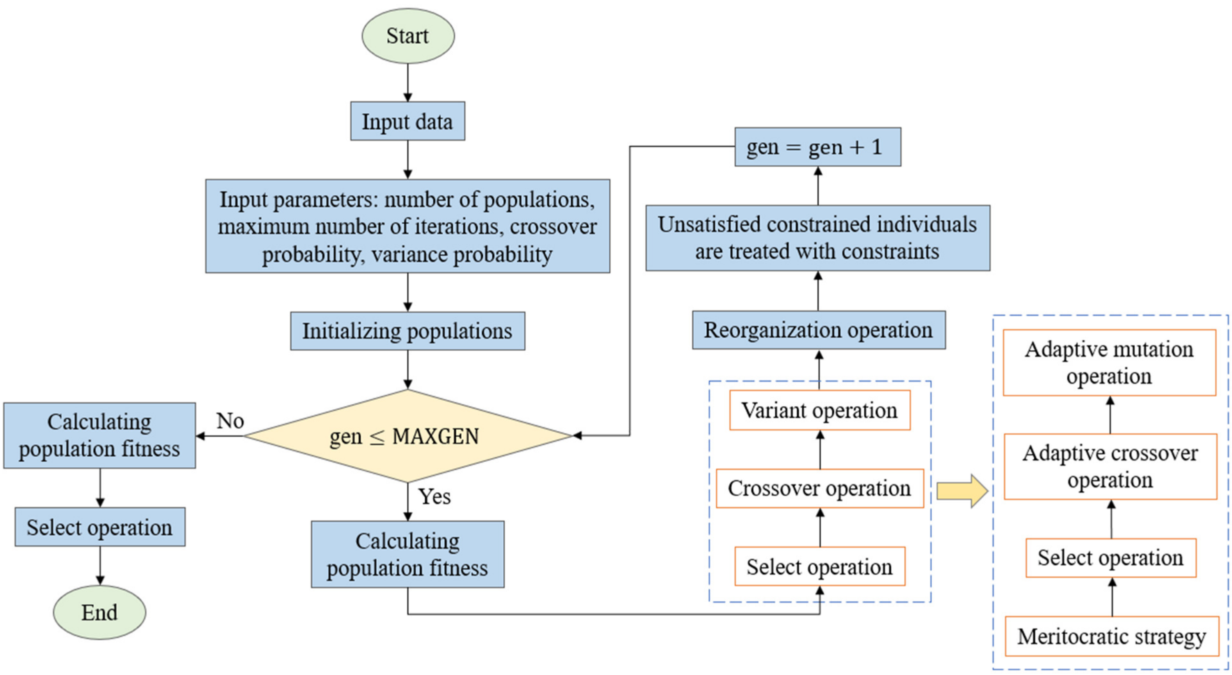

Fig. 5 Flow chart of adaptive genetic algorithm

Based on the aforementioned improvements, Fig. 5 describes an improved GA flowchart incorporating adaptive and selection strategies. This improved model further optimizes the traditional GA and achieves an enhancement of the GA operation mechanism by flexibly adjusting the input parameters and prioritizing the use of dominant chromosomes in the selection phase.

4. Case Simulation

To measure the efficiency and efficacy of the models and algorithms presented in this study, a case simulation approach has been adopted. These simulations have been specifically designed and adapted to be practical platforms for testing, validating, and empirically measuring their performance.

4.1. Case background

Relying on the actual grid O&I scenario, a two-dimensional simulation case is abstracted. Twenty units to be inspected are randomly generated as shown in Fig. 6, and the detailed coordinates are shown in Table 2. They will be assigned to three O&I units.

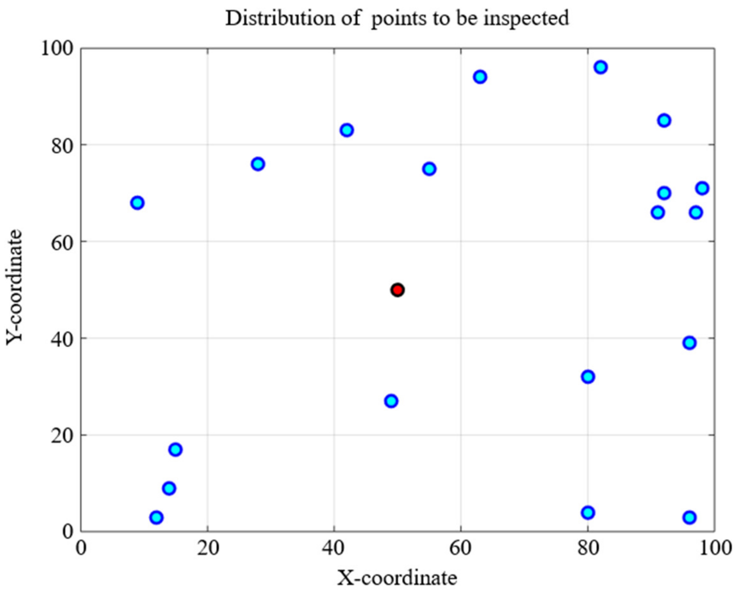

Fig. 6 Schematic diagram of the distribution of inspection points

Table 2 X and Y coordinates of 20 points

Point	X	Y	Point	X	Y
1	82	96	11	15	17
2	91	66	12	98	71
3	12	3	13	96	3
4	92	85	14	49	27
5	63	94	15	80	4
6	9	68	16	14	9
7	28	76	17	42	83
8	55	75	18	92	70
9	96	39	19	80	32
10	97	66	20	50	50

Each unit to be inspected has the same four inspection steps, and each inspection unit is equipped with operational tools specialized for each step, as well as general-purpose operational tools, sequentially numbered from 1 to 8, which contain specialized exoskeleton equipment as shown in Fig. 7. In addition, the resources and time spent for the different O&M steps are shown in Table 3.

Fig. 7 Physical illustration of the auxiliary task exoskeleton equipment

Table 3 Corresponding resources and time required for each inspection step

Workpiece	Operation	Machines	Processing time(s)
1	1	1, 2, 3, 4, 5, 7, 8	5, 3, 5, 3, 3, 10, 9
1	2	1, 3, 4, 5, 6, 7, 8	10, 5, 8, 3, 9, 9, 6
1	3	2, 4, 5, 6, 7, 8	10, 5, 6, 2, 4, 5
1	4	/	/
2	1	1, 2, 3, 4, 5, 7	5, 7, 3, 9, 8, 9
2	2	2, 3, 4, 5, 6, 7, 8	8, 5, 2, 6, 7, 10, 9
⋮	⋮	⋮	⋮
8	3	1, 2, 4, 5, 6, 7, 8	9, 9, 8, 5, 6, 7, 1
8	4	1, 3, 4, 5, 6, 7	9, 3, 7, 1, 5, 8

4.2. Simulation results

This article uses MATLAB R2023a as the simulation programming tool, operating on Windows 11, with 16 GB of memory, and a 13th Gen Intel(R) Core (TM) i9-13900HX processor. The GA has a population size of 50 and a maximum iteration of 200. Through simulation, the iterative process of the objective function and task assignment plan is shown in Fig. 8, and the resource scheduling plan is illustrated in Fig. 9. The specific results are detailed in Table 4.

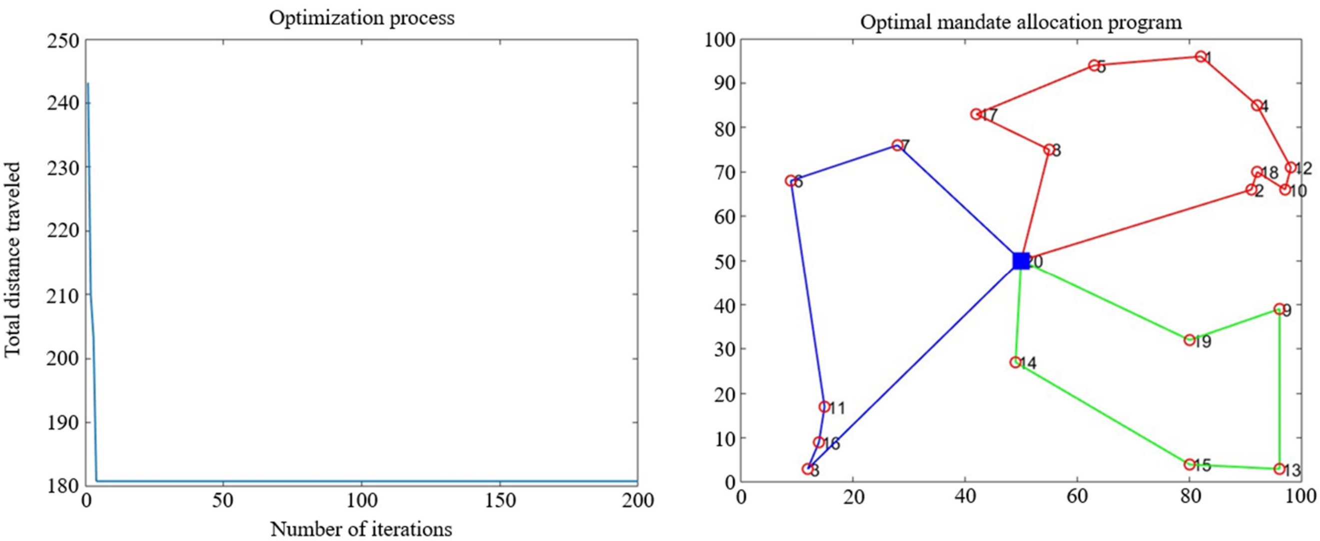

Fig. 8 Results of the MTSP

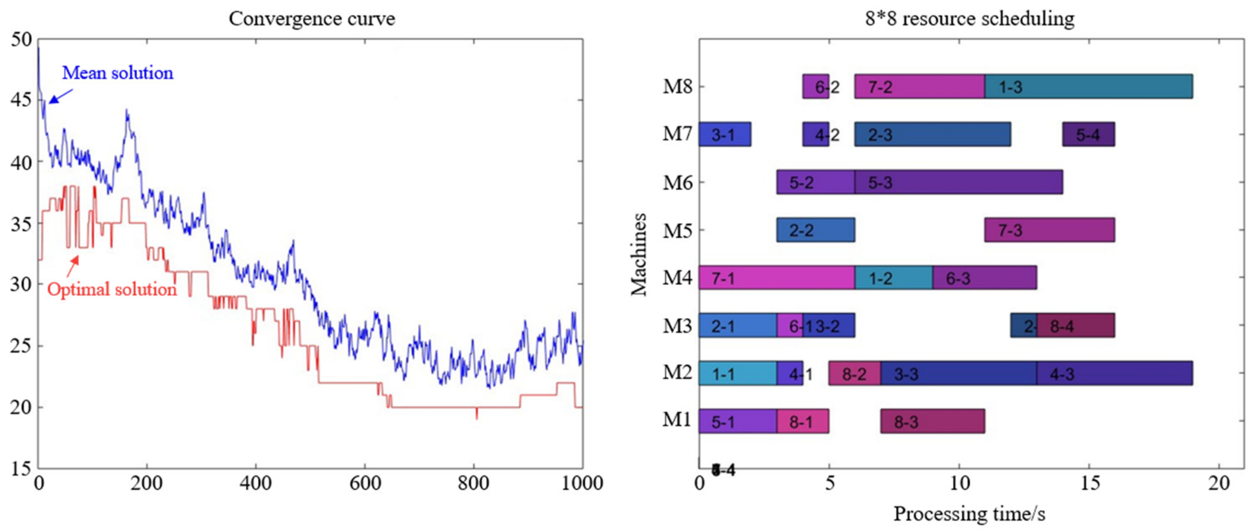

Fig. 9 Results of the JSP

Table 4 Task assignment plan

Operational inspection unit serial number	Collection of units to be inspected
1	20→2→18→10→12→4→1→5→17→8→20
2	20→19→9→13→15→14→20
3	20→3→16→11→6→7→20
Objective function value (s)	56.427

After an in-depth analysis of the above simulation results, it is concluded that both layers of the problem of the two-layer planning model are solved better. The final objective function values of the AGA and original GA are 74.427 and 81.786 respectively, in comparison, the time of AGA is shortened by 9.89%, which is better in solving the problem. Optimization of task allocation: the simulation results show that the optimized task allocation scheme using a GA significantly improves the efficiency of the O&I unit.

In particular, in the MTSP results presented in Fig. 8, the path optimization of the O&I units reduces the ineffective round-trip time and ensures the shortest path to cover all the units to be inspected; improvement of resource utilization: the task allocation scheme in Table 3 demonstrates the efficient utilization of the resources of the units to be inspected and the O&I tools. By reasonably allocating the workload to each O&I unit, a balanced use of resources is achieved, which reduces resource idleness; minimization of job time: in the JSP simulation results, the overall job completion time is significantly reduced by optimizing the machining time and machine allocation of each workpiece on different processes. This time optimization is essential to improve the overall efficiency of the job shop.

4.3. Sensitivity analysis

Table 5 Task assignment plan for two inspection units

Operational inspection unit serial number	Collection of units to be inspected
1	1→11→32→27→48→6→14→25→24→43→23 →7→26→8→31→28→22→1
2	1→3→36→35→20→29→21→34→30→39→33 →45→15→10→49→9→50→16->2→1
3	1→38→5→37→17→44→42→19→40→41→13 →18→4→47→12→51→46→1
Objective function value (s)	166.068

In the sensitivity analysis section, this paper significantly extends the size of the simulation model from the initial 20 points to 50 points, while fixing the transportation and inspection units to 3. The results are shown in Fig. 10 and Table 5, which show that the objective function value is increased by 294% with a 250% increase in the number of inspection points, which is within a reasonable range. The purpose of this change was to evaluate the sensitivity of the model to an increase in the number of pending inspection points and how this change affects the performance of the solution to the MTSP and the GA. A more comprehensive assessment of the effectiveness and robustness of the algorithm in dealing with more complex problems can be made.

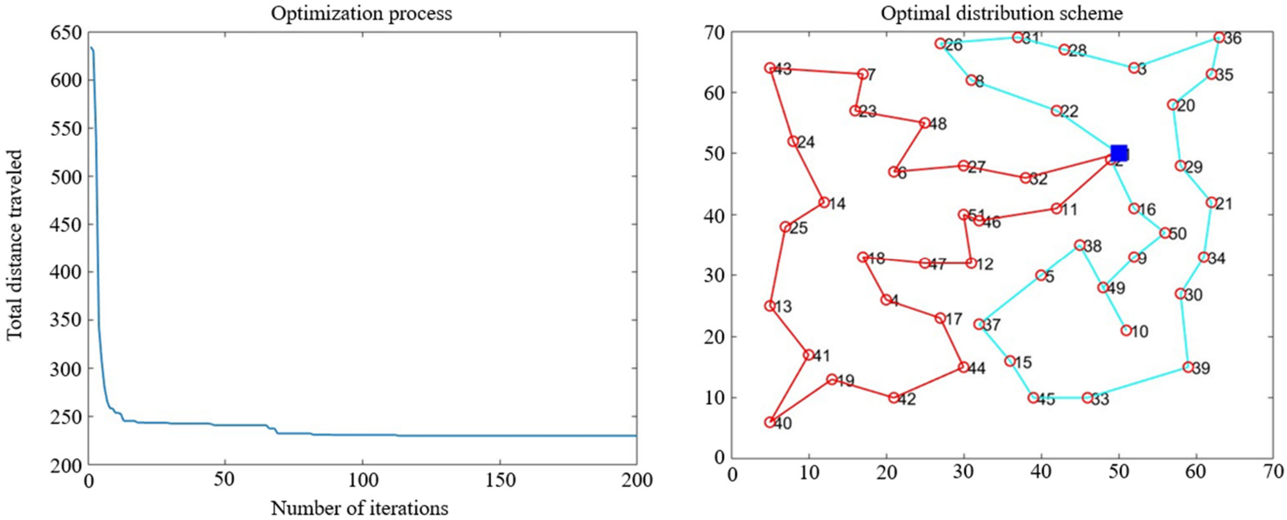

Fig. 10 Task assignment plan for 50 inspection points

5. Conclusions

Traditional MTSP and JSP have been widely studied, but less research has been done on combining the two as a two-tier planning problem. In addition, existing optimization methods often do not take both into account at the same time. Therefore, this study proposes a two-layer planning model in a grid O&I scenario to achieve global optimization while effectively improving the efficiency of O&I. The main contributions of the study are as follows:

(1) In this paper, a bi-level planning model specialized for complex grid O&I scenarios has been successfully designed and validated. The model consists of MTSP and JSP and is simulated in a MATLAB environment, which proves its feasibility and practicability in theoretical and practical applications, especially in improving the overall efficiency of O&I.

(2) AGAs are adjusted according to model requirements to improve their convergence and performance.

(3) This study compares the performance of different algorithms. The results show that the AGA reduces the overall O&I time by 9.89% compared to the traditional GA. In terms of sensitivity analysis, when the units to be inspected are increased from 20 to 50, the growth of the objective function value is controlled at 294%, which satisfies the actual situation.

In the future, the two-layer planning model for grid O&I will be further researched and applied to provide effective solutions for complex scheduling problems such as grid O&I and open up new research directions for optimization problems in similar fields. In addition, the methodology proposed in this study will have a wide range of application potential in scenarios with limited resources and stringent requirements for operational efficiency. In summary, this study demonstrates the possibility of realizing efficient task allocation and resource scheduling in complex grid O&I scenarios but also provides valuable experience and insights for future research in similar fields.

Acknowledgments

This work was supported by a Science and technology project of China Southern Power Grid Co., Ltd. under Grant YNKJXM20220216.

Conflicts of Interest

The authors declare no conflict of interest.

References

[1] J. Yan, J. Huang, L. Zhou, C. Chen, Q. Wu, and J. Zhao, "Transmission Line Operation and Inspection Training Simulation Based on Multiple Time Scales and VR," Journal of System Simulation, vol. 34, no. 2, pp. 212-220, 2022.
[2] Y. Zhang, J. C. Guo, and J. D. Liao, "Construction and Research of Safety Management System for Machine Patrol Operation," Mathematical Problems in Engineering, vol. 2021, article no. 4529169, 2021.
[3] Z. Li, Y. Zhang, H. Wu, S. Suzuki, A. Namiki, and W. Wang, "Design and Application of a UAV Autonomous Inspection System for High-Voltage Power Transmission Lines," Remote Sensing, vol. 15, no. 3, article no. 865, February 2023.
[4] W. Wang, M. Lv, L. Ru, B. Lu, S. Hu, and X. Chang, "Multi-UAV Unbalanced Targets Coordinated Dynamic Task Allocation in Phases," Aerospace, vol. 9, no. 9, article no. 491, September 2022.
[5] O. Shorinwa, R. N. Haksar, P. Washington, and M. Schwager, "Distributed Multirobot Task Assignment via Consensus ADMM," IEEE Transactions on Robotics, vol. 39, no. 3, pp. 1781-1800, June 2023.
[6] J. Ru, D. Hao, X. Zhang, H. Xu, and Z. Jia, "Research on a Hybrid Neural Network Task Assignment Algorithm for Solving Multi-Constraint Heterogeneous Autonomous Underwater Robot Swarms," Frontiers in Neurorobotics, vol. 16, article no. 1055056, January 2023.
[7] F. Yucel and E. Bulut, "Online Stable Task Assignment in Opportunistic Mobile Crowdsensing with Uncertain Trajectories," IEEE Internet of Things Journal, vol. 9, no. 11, pp. 9086-9101, June 2022.
[8] Q. Zhang, Y. Wang, G. Yin, X. Tong, A. M. V. V. Sai, and Z. Cai, "Two-Stage Bilateral Online Priority Assignment in Spatio-Temporal Crowdsourcing," IEEE Transactions on Services Computing, vol. 16, no. 3, pp. 2267-2282, May-June 2022.
[9] M. A. Isah and B. S. Kim, "Integrating Schedule Risk Analysis with Multi-Skilled Resource Scheduling to Improve Resource-Constrained Project Scheduling Problems," Applied Sciences, vol. 11, no. 2, article no. 650, January 2021.
[10] K. Lin, J. Gao, G. Han, H. Wang, and C. Li, "Intelligent Blockchain-Enabled Adaptive Collaborative Resource Scheduling in Large-Scale Industrial Internet of Things," IEEE Transactions on Industrial Informatics, vol. 18, no. 12, pp. 9196-9205, December 2022.
[11] L. Zhu, J. Li, Z. Liu, and D. Zhang, "A Multi-Resource Scheduling Scheme of Kubernetes for IIoT," Journal of Systems Engineering and Electronics, vol. 33, no. 3, pp. 683-692, June 2022.
[12] Y. Wu, C. Guo, J. Zhao, X. Jin, and J. Xu, "RSKNet-MTSP: Effective and Portable Deep Architecture for Speaker Verification," Neurocomputing, vol. 511, pp. 259-272, October 2022.
[13] P. He and J. K. Hao, "Memetic Search for the Minmax Multiple Traveling Salesman Problem with Single and Multiple Depots," European Journal of Operational Research, vol. 307, no. 3, pp. 1055-1070, June 2023.
[14] Y. Li, J. Wang, and Z. Liu, "A Simple Two-Agent System for Multi-Objective Flexible Job-Shop Scheduling," Journal of Combinatorial Optimization, vol. 43, no. 1, pp. 42-64, January 2022.
[15] Y. Li, Z. Tao, L. Wang, B. Du, J. Guo, and S. Pang, "Digital Twin-Based Job Shop Anomaly Detection and Dynamic Scheduling," Robotics and Computer-Integrated Manufacturing, vol. 79, article no. 102443, February 2023.
[16] B. Shi, C. Xiao, K. Peng, L. Feng, J. Chen, and X. Zhang, "Two-Layer Joint Expansion Planning Strategy of Grid-Source-Storage for Distribution Network Based on Cluster Partition," Automation of Electric Power Systems, vol. 47, no. 14, pp. 43-51, 2023. (In Chinese)
[17] J. Zheng, Y. Hong, W. Xu, W. Li, and Y. Chen, "An Effective Iterated Two-Stage Heuristic Algorithm for the Multiple Traveling Salesmen Problem," Computers & Operations Research, vol. 143, article no. 105772, July 2022.
[18] Y. D. Wang, X. C. Lu, and J. R. Shen, "Improved Genetic Algorithm (VNS-GA) Using Polar Coordinate Classification for Workload Balanced Multiple Traveling Salesman Problem (mTSP)," Advances in Production Engineering & Management, vol. 16, no. 2, pp. 173-184, June 2021.
[19] X. Long, J. Zhang, K. Zhou, and T. Jin, "Dynamic Self-Learning Artificial Bee Colony Optimization Algorithm for Flexible Job-Shop Scheduling Problem with Job Insertion," Processes, vol. 10, no. 3, article no. 571, March 2022.
[20] B. Liu, X. Yuan, and X. Ming, "A NovelMethod for Flexible Job Shop Scheduling Based on Genetic Algorithm and Variable Neighborhood Search," Machine Design and Research, vol. 37, no. 1, pp. 177-182, 2021.
[21] T. T. Ngoc, L. V. Dai, and L. B. Minh, "Effects of Data Standardization on Hyperparameter Optimization with the Grid Search Algorithm Based on Deep Learning: A Case Study of Electric Load Forecasting," Advances in Technology Innovation, vol. 7, no. 4, pp. 258-269, October 2022.
[22] B. Modi and M. Lalwani, "Power Sharing and Control by Droop Controller with Advanced Filter Design: A Case Study in Lock-Down Periods," Proceedings of Engineering and Technology Innovation, vol. 18, pp. 49-60, April 2021.