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Maintenance Scheduling Optimization Using MILP and Asset LCA

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Abstract: In asset lifecycle management, the increasing scale of power equipment and the complexity of the operating environment challenge traditional maintenance and scheduling methods to meet the requirements of high efficiency, economy, and reliability throughout the entire lifecycle of power equipment. This study, therefore, aims to minimize the total lifecycle maintenance cost while maximizing equipment reliability. The proposed approach combines a mixed-integer linear programming model and the Improved Aquila Optimizer (IOA) algorithm, incorporating asset lifecycle analysis for maintenance scheduling optimization. The Improved Aquila Optimizer (IOA) algorithm improves performance through quasi-inverse solution initialization, adaptive weighting, bubble predation, and perturbation strategies. Results demonstrate that the IOA achieves better convergence speed and precision than comparative algorithms, including the Generic Algorithm (GA) and Practical Swarm Optimization (PSO), in single-peak and multi-peak test function optimization. When applied to the case studies, the improved algorithms were 11.983 million yuan (Example 2) and 21.504 million yuan (Example 3), demonstrating short convergence time and high stability. The proposed scheme reduced total cost by 21.2% to 27.2%, fault losses costs by 45.7%, and increased average equipment reliability by 12.6% to 14.6%, and the load balancing rate by 13.8% to 16.8%, compared to the traditional scheme. These improvements effectively reduce the number of faults and power outage duration. This research provides a scientific and efficient decision-making framework for lifecycle maintenance and scheduling of power equipment assets, which can enhance the operational quality and economic benefits of power system asset lifecycle management.

Keywords: MILP, asset lifecycle, asset lifecycle management, maintenance scheduling, IAO, WOA.

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1. Introduction

In the context of global energy transition and rapid development of smart grids, the safety, reliability, and economy of asset lifecycle management face unprecedented challenges (Kumar et al., 2025). With the expansion of the scale of new energy grid connection, the increasing complexity of transmission networks, and the diversified growth of electricity loads, the operating environment of power equipment throughout its entire lifecycle is becoming increasingly harsh. Issues such as equipment aging and rising failure probability have put forward higher requirements for asset lifecycle maintenance and scheduling (Tirkolaee, 2024). As a key factor in ensuring the stable operation of the power system, Equipment Maintenance Scheduling (EMS) must arrange maintenance time, types, and resource allocation under limited constraints to balance costs with system reliability (Kraiem et al., 2025). Power equipment, being central to power system operation, is classified as machinery or production equipment from an asset management perspective and possesses typical asset attributes. According to accounting standards, it is recognized as an asset for three core reasons: 1) the enterprise controls the equipment through purchase or construction. 2) The equipment can generate continuous economic benefit, production, transmission, and distribution of electrical energy. 3) its initial cost and subsequent maintenance expenses can be reliably measured. Within the asset lifecycle management framework, the full cycle cost of power equipment includes explicit expenses such as purchase, maintenance, failure loss, as well as depreciation and amortization costs. The latter includes linear depreciation of the equipment's original value over its useful life and installment amortization of intangible assets, such as technology patents. These cost elements need to be systematically considered in the objective function of maintenance scheduling optimization. Traditional power EMS relies on periodic maintenance based on time intervals or post maintenance mode based on fault feedback. Although these methods are simple to operate, they often fail to match the equipment's actual operating status. This can lead to insufficient or excessive maintenance, which in turn increases fault losses, waste resources, and causes fluctuations in system reliability (Bökler et al., 2024). Furthermore, with the exponential growth in the number of devices and the emergence of massive, multiple-source heterogeneous data, traditional methods face significant limitations in computational efficiency and optimization accuracy when dealing with high-dimensional and nonlinear maintenance scheduling problems, making it difficult to meet the requirements of modern power systems for efficient operation and maintenance (Vilarinho et al., 2024).

Mixed Integer Linear Programming (MILP) is a mathematical optimization method utilized to maximize or minimize a linear objective function under linear constraints, where some or all variables are restricted to integers. Some or all of the variables are restricted to integers. Ghaithan et al. (2024) built a MILP model for optimizing the Hydrogen Refueling Stations (HRS) fused with grid connected concentrated solar energy, considering various constraints to minimize the overall lifecycle expenditure of the integrated system. This HRS could satisfy the local hydrogen needs, and the standardized cost was $7.17/kg. Talebi et al. (2024) combined stochastic minimization theory with an MILP model, taking product price as the decision variable and considering the interaction between demand and supply, to solve the pricing challenge in revenue management. The developed model demonstrated the feasibility of pricing with and without capacity supply. Shao et al. (2024) proposed a new linearization method and an adaptive strategy to adjust the number of piecewise linearization breakpoints, transforming the pump scheduling optimization problem from a non-convex mixed integer nonlinear programming problem to a MILP problem. Compared to traditional methods, this method saved 9.83% of energy costs in large-scale water distribution systems compared to genetic algorithms. Lee et al. (2024) constructed an MILP model based on the concept of spatiotemporal networks, considering the constraints of satellite space mission environments, to allocate tasks and communication time windows for the scheduling problem of multiple satellites and ground stations. Numerical experiments have verified that the model can effectively solve the scheduling problems of satellite tasks and communication. Lu et al. (2024) proposed a fast and accurate self-healing scheme for distribution networks based on MILP, constructing a centralized 5G communication network and linearizing the switch function in the fault location model. This method significantly enhanced the network's self-healing speed and precision of the network, effectively reducing the outage time after faults and narrowing the outage range.

The optimization of the maintenance plan is the process of analyzing equipment failure modes and optimizing the scheduling of maintenance activities to improve equipment reliability, reduce maintenance costs, and minimize downtime. Dey et al. (2024) constructed a MILP model to decide the best preventive maintenance plan for equipment, to minimize total maintenance costs and downtime, with a focus on equipment maintenance in the mining industry. Compared with current practice, this model reduced maintenance costs by 14% and downtime by 41%. Xia et al. (2024) considered three types of faults and their maintenance measures and established a multi-objective MILP model to optimize distribution network maintenance scheduling. After optimization, both the cost and reliability indicators of the distribution network have been improved, but the deviation in failure rate will affect the maintenance plan, resulting in a maximum change of 30% in various indicators. Alhamad et al. (2024) considered decisions such as labor planning, training, and spare parts inventory management, and combined Genetic Algorithm (GA) and taboo search to solve the preventive maintenance planning problem of joint power plants. This hybrid method outperformed traditional methods in solution quality and convergence velocity, could generate better maintenance plans, improve production levels, and generate considerable hydropower surplus. Qureshi et al. (2024) conducted a comprehensive review of the application of Machine Learning (ML) in predictive maintenance of solar power plants, discussing related technologies, algorithms, and challenges, covering data acquisition and deployment. The role of ML technology in implementing proactive maintenance approaches could reduce downtime and lower maintenance expenditures. Kosanoglu et al. (2024) developed a hybrid solving algorithm. This algorithm combined deep reinforcement learning based on dual deep Q-networks and a simulated annealing algorithm to solve maintenance planning problems, while considering decisions such as labor planning, training, and spare parts inventory management. The algorithm found optimal solutions for small-scale problems and shows potential to surpass conventional meta-heuristic and machine learning (ML) algorithms.

In summary, while significant research has been conducted on MILP and maintenance scheduling, the adaptability and efficiency of the resulting model requires further improvement. Therefore, this study proposes a maintenance scheduling optimization method based on MILP and Asset Lifecycle Analysis (ALCA). This method comprehensively considers the maintenance cost, reliability, and resource utilization efficiency of the entire lifecycle of the equipment. A more universal, dynamic, and efficient maintenance scheduling optimization model has been established to improve the effectiveness of EMS.

The primary innovation of this work lies in the construction of a MILP model that integrates maintenance execution costs, fault loss costs, and inventory costs with ALCA to achieve multi-objective optimization of maintenance scheduling. Furthermore, an Improved Aquila Optimizer (IAO) algorithm is designed, incorporating quasi-reverse solution initialization, adaptive weighting, bubble predation, and perturbation strategies to enhance its global optimization capability and stability of large-scale problems.

2. Methods and Materials

2.1. MILP Model Construction

For maintenance scheduling optimization problems, the MILP model effectively handles complex problems involving integer variables and linear constraints. Informed by the practical requirements of maintenance scheduling combined with

ALCA, this study constructs an MILP model with the goal of minimizing total maintenance costs and maximizing equipment reliability, as shown in Fig. 1.

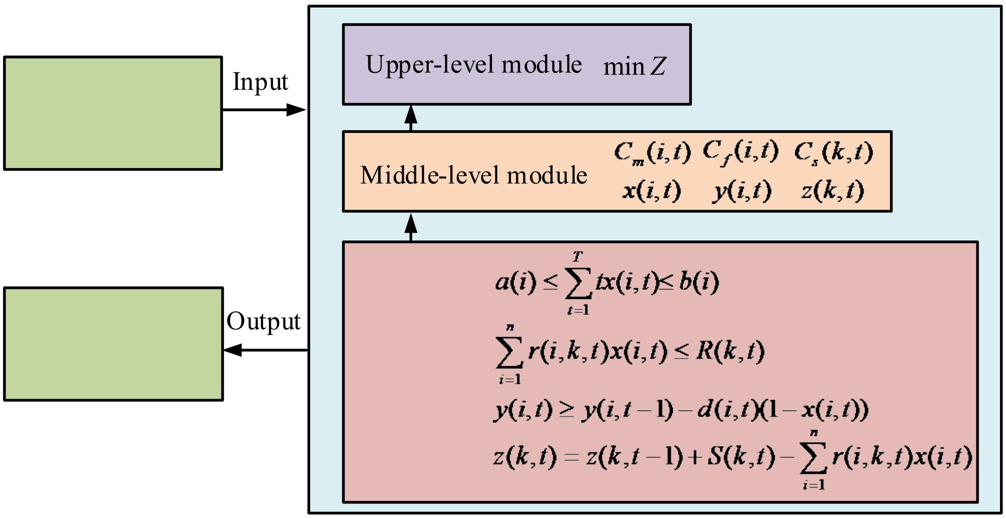


Fig. 1. MILP model

As illustrated in Fig. 1, the maintenance scheduling model aims to ensure reliable equipment operation while minimizing the total asset lifecycle cost. The total cost comprises three main components, lifecycle maintenance execution cost, lifecycle failure loss cost, and lifecycle inventory cost. The objective function is shown in Eq. (1).

$$\min Z = \sum_{i=1}^{n}\sum_{t=1}^{T} C_m(i,t)x(i,t) + \sum_{i=1}^{n}\sum_{t=1}^{T} C_f(i,t)(1-y(i,t)) + \sum_{k=1}^{m}\sum_{t=1}^{T} C_s(k,t)z(k,t) \tag{1}$$

In Eq. (1), Z is the total maintenance cost, n is the amount of devices, T is the duration of the planning cycle, and m is the number of types of maintenance resources. $C_m(i,t)$ means the maintenance execution cost of device i at time t, and $x(i,t)$ is a 0-1 variable. One indicates that i is undergoing maintenance at t, and 0 indicates that it is not being maintained. $C_f(i,t)$ is the cost of loss incurred by i due to a malfunction at t. $y(i,t)$ is the reliable state variable of i at t. One indicates normal operation, 0 indicates malfunction. $C_s(k,t)$ and $z(k,t)$ are the inventory cost and level of resource k at t. In the constraint conditions, the maintenance time window constraint, resource capacity constraint, equipment state transition constraint, and inventory balance constraint all need to meet the changing characteristics within the asset lifecycle. The maintenance time window constraint refers to each device having a specific maintenance time window. Maintenance operations need to be performed within this window, as defined in Eq. (2) (Paul et al., 2024).

$$a(i) \le \sum_{t=1}^{T} tx(i,t) \le b(i) \tag{2}$$

The parameters in Eq. (2), $a(i)$ and $b(i)$ correspond the earliest and latest maintenance times allowed for i. Resource capacity constraint refers to the limitation that various resources used during maintenance cannot exceed their available capacity, as shown in Eq. (3).

$$\sum_{i=1}^{n} r(i,k,t)x(i,t) \le R(k,t) \tag{3}$$

In Eq. (3), $r(i,k,t)$ represents the demand for k by i during maintenance at t. $R(k,t)$ denotes the available capacity of k at t. The device state transition constraint considers the reliability degradation law of assets at various stages of their lifecycle. Maintenance operations can restore the health status of the device and extend its effective lifecycle, as shown in Eq. (4) (Gharibi & Abdollahzadeh, 2025).

$$y(i,t) \ge y(i,t-1) - d(i,t)(1-x(i,t)) \tag{4}$$

In Eq. (4), $d(i,t)$ represents the reliability decrease coefficient of i from time $t-1$ to t when it is not under maintenance. The inventory balance constraint is shown in Eq. (5).

$$z(k,t) = z(k,t-1) + S(k,t) - \sum_{i=1}^{n} r(i,k,t)x(i,t) \tag{5}$$

In Eq. (5), $S(k,t)$ denotes the replenishment amount of k at t. By analyzing the asset lifecycle, this study has determined the above objective functions and constraints, forming a complete MILP model and providing a mathematical framework for maintenance scheduling optimization.

2.2. Design of Model Solving Algorithm

In the process of solving MILP models, traditional algorithms may face the problem of low computational efficiency when dealing with large-scale problems (Shoukat, 2024). To this end, this study introduces multiple strategies and designs the IAO algorithm, as shown in Fig. 2.

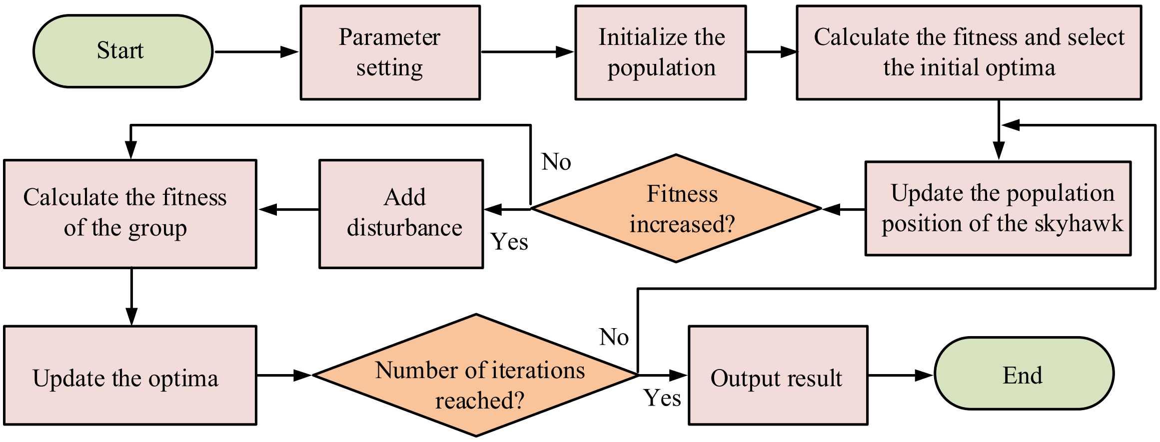


Fig. 2. IAO algorithm process

In Fig. 2, the algorithm is initialized after startup. Then, the original solution and reverse solution are generated, and individuals are selected for screening. During the iteration process, the search capability of the algorithm is adjusted through adaptive weight factors (Mecheter et al., 2024). By using the Whale Optimization Algorithm (WOA) bubble predation strategy, the exploration of local areas is strengthened. The perturbation update strategy helps individuals break free from limitations. During the initialization process of the population, the original solution X is represented as shown in Eq. (6).

$$X = (x_1, x_2, \cdots, x_d) \tag{6}$$

In Eq. (6), d represents the number of original solutions. The representation of the reverse solution $\bar{X}$ is shown in Eq. (7).

$$\bar{X} = (U_1 - x_1, U_2 - x_2, \cdots, U_d - x_d) \tag{7}$$

In Eq. (7), U_d is the upper bound of variable d. The fitness comparison between the original solution and the inverse solution is shown in Eq. (8).

$$X_{init}(i') = \begin{cases} X(i'), & f(X) \le f(X) \\ \bar{X}(i'), & otherwise \end{cases} \tag{8}$$

In Eq. (8), $X_{init}(i')$ means the i'-th solution in the initial population. $f(X)$ denotes the fitness function value of solution X. This study introduces an adaptive weight factor dynamic adjustment algorithm to enhance the global and Local Search Capabilities (LSC). The weight factor ω increases linearly with the number of iterations t', as shown in Eq. (9).

$$\omega = \omega_{max} - \frac{(\omega_{max} - \omega_{min})t'}{T_{max}} \tag{9}$$

In Eq. (9), ω_{max} and ω_{min} are the maximum and minimum values of the weight factors. T_{max} is the maximum number of iterations. During the iteration process, the size of the weight factor corresponds to the size of the algorithm's search range (Kim et al., 2025). The bubble predation strategy diagram of WOA is shown in Fig. 3.

In Fig. 3, the bubble predation strategy in WOA draws inspiration from the bubble net feeding method of humpback whales. When hunting, humpback whales release bubbles around the school of fish, constructing a spiral bubble net to surround the prey, and then swim at high speed from below to launch an attack. This strategy can trap prey, reduce their chances of escape, thereby increasing the success rate of predation. In the WOA, this predation behavior is considered a deep search method. When the algorithm identifies potential high-quality solutions, the remaining individuals take the optimal solution as their center of gravity and refer to the spiral structure of the bubble network to generate new candidate solutions around it. By continuously narrowing the search scope, refined exploration is conducted on the local area near the optimal solution, gradually approaching a more optimal solution, thereby enhancing the algorithm's search accuracy and development capabilities in the local area. The individual eagle generates new solutions around the current optimal solution, as shown in Eq. (10).

$$X_{new} = X_{best} + A \cdot e^{bl} \cdot cos(2\pi l) \tag{10}$$

In Eq. (10), X_{best} is the current optima, A is the coefficient vector, b is a constant, and l means a random number within [0,1]. Meanwhile, to avoid the algorithm dropping into local optima, a perturbation update strategy is introduced. The formula for a randomly perturbed individual with a certain probability p is shown in Eq. (11).

$$X_{perturbed}(i) = \begin{cases} X(i') + \delta \cdot (U_{i'} - L_{i'}), rand < p \\ X(i'), \quad otherwise \end{cases} \tag{11}$$

In Eq. (11), δ is the disturbance intensity factor, $U_{i'}$ and $L_{i'}$ are the upper and lower bounds of the variables. $rand$ means the same as l.

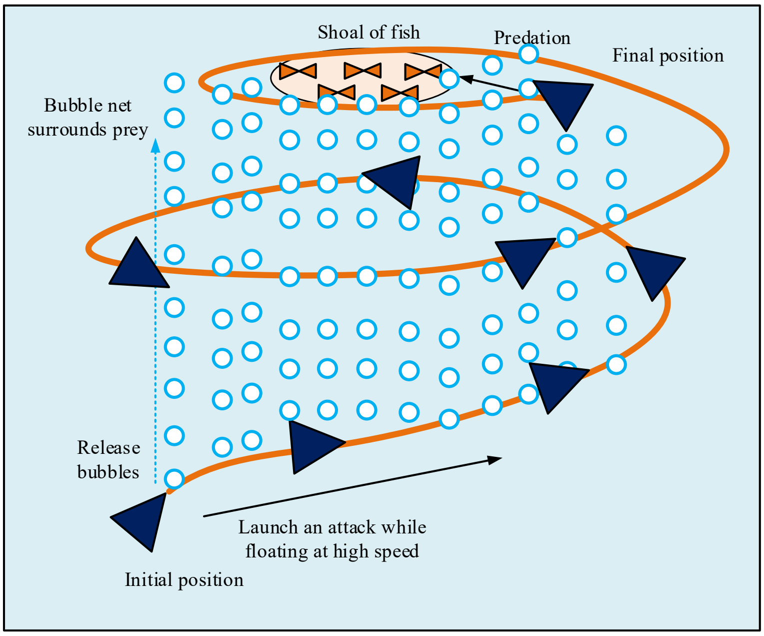


Fig. 3. Schematic diagram of the WOA bubble predation strategy

2.3. Design of Optimization Method for Power EMS

To address the specific requirements of power equipment, this study integrates the MILP model and IAO algorithm to design a tailored maintenance scheduling optimization method. This equipment is characterized by high reliability requirements, complex operating environments, and significant maintenance costs. Consequently, effective maintenance scheduling must account for factors such as equipment aging, load demand, and impact of power outage (Zangina et al., 2025). The set of electrical equipment is shown in Eq. (12).

$$E = \{e_1, e_2, ..., e_{n'}\} \tag{12}$$

Eq. (12) defines the set number of power equipment, is represented by n', and the operating status of each piece of equipment used is represented by the health index $H(n',t)$. The objective function for optimizing power equipment maintenance and scheduling is shown in Eq. (13).

$$\min Z' = \sum_{i=1}^{n'} \sum_{t=1}^{T} C_m^{'}(i,t)x(i,t) + \sum_{i=1}^{n'} \sum_{t=1}^{T} C_{out}(i,t)(1 - y(i,t)) + \sum_{k=1}^{m} \sum_{t=1}^{T} C_s^{'}(k,t)z(k,t) \tag{13}$$

In Eq. (13), Z' is the total target cost of power equipment maintenance. $C_m^{'}(i,t)$ represents the maintenance execution cost of power equipment i at t. Due to the specialized nature of power equipment maintenance, this cost category encompasses expenses for specialized tools and technical personnel. $C_{out}(i,t)$ is the loss cost caused by the power outages of i at t, which is related to the load borne by the device and the duration of the power outage. In special constraint conditions, the load balance constraint of the power system refers to maintenance and scheduling needs to ensure the load balance of the power system during the maintenance period, avoiding overload or insufficient power supply, as given by Eq. (14).

$$\sum_{i=1}^{n'} P(i,t)y(i,t) \geq L(t) \tag{14}$$

In Eq. (14), $P(i,t)$ is the rated power supply of i at t. $L(t)$ is the system load demand at t. Maintenance priority constraint refers to setting maintenance priorities based on the importance and health status of the equipment. Important equipment and equipment with low health index should be prioritized for maintenance, as shown in Eq. (15).

$$\rho(i)x(i,t) \geq \rho(j)x(j,t), \; if \; \rho(i) > \rho(j) \tag{15}$$

In Eq. (15), $\rho(i)$ is the priority coefficient, where a larger value corresponds to a higher maintenance priority for the equipment. Fig 4 outlines the implementation steps of the power EMS optimization method. The first step involves data collection and preprocessing, which includes gathering basic parameters, operational history, and maintenance records for the power equipment, followed by calculating the health index and failure probability for each unit. The next step is to establish a MILP model based on the maintenance requirements of power equipment and determine the objective function and constraint conditions. On this basis, the IAO algorithm is utilized to manage the model and obtain the best maintenance scheduling scheme. Finally, the solution results are evaluated and refined by accounting for operational uncertainties to enhance their practical robustness.

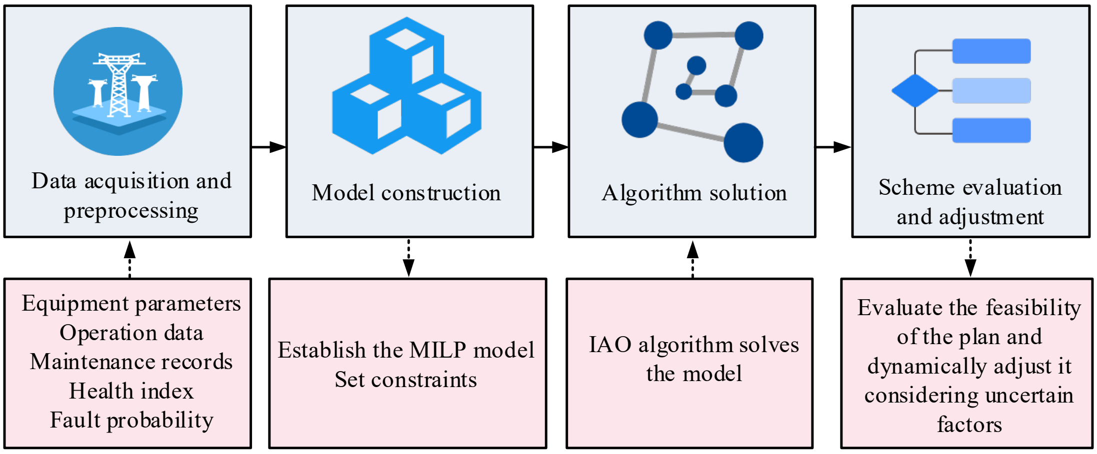


Fig. 4. Implementation step diagram of the optimization method for power equipment maintenance and dispatching

3. Results

3.1. Experimental Environment and Example Introduction

This study was implemented in Python 3.9. The Gurobi 10.0 solver was used to verify the MILP model's exact solution, and the performance of the IAO algorithm was compared against it. All experiments were conducted on a computer with an Intel Core i7-12700H processor (2.7GHz, 12 cores), 32GB RAM, running Windows 11 Professional Edition. The maximum number of iterations of the IAO algorithm is set at 200, and the population size at 50. This is based on the results of balancing convergence efficiency and computational cost in the previous pre-experiments. The maximum and minimum weight factors were set to 0.9 and 0.1, referring to the parameter configuration practices from similar optimization algorithms in power equipment maintenance. The perturbation probability of 0.3 was chosen to balance between avoiding local optima and ensuring solution stability. For the bubble predation strategy, a shrinkage coefficient of 2 is suitable for search accuracy requirements dictated by the maintenance of resource constraints in this study. To validate the approach, three case studies of different scales were designed: small-scale (Example 1), medium-scale (Example 2), and large-scale (Example 3) maintenance scheduling problems, as shown in Table 1. Example 1 corresponds to the maintenance scenario of a local area of the distribution network (such as a community-level distribution network), and the equipment types cover the core equipment of the real power grid (transmission lines, transformers, circuit breakers). Its initial health index (0.8-0.9) and failure rate (0.01-0.02 times per day) refer to the actual operation data of similar equipment in the "Guidelines for Reliability Assessment of Electric Power Equipment". Example 2 corresponds to the county-level regional power grid scenario, and the load demand range (300-500 MW) matches the typical load of the county-level power grid. Example 3 corresponds to the municipal regional power grid scenario. The initial inventory capacity (100-400 units) is set based on the municipal power grid maintenance resource reserve standards. Across all cases, the linear decline rate of the equipment health index (0.005 per day) and its post maintenance recovery value (0.95) align with established aging and maintenance characteristics of real power equipment.

Table 1. Basic parameters of the calculation example

Basic parameters	Example 1	Example 2	Example 3
Quantity of equipment	10	30	50
Planning period (days)	30	60	90
Types of resources	3	5	7
Maintenance time window range (days)	[5, 25]	[10, 40]	[15, 60]
Initial inventory capacity	[50, 80, 100]	[80, 100, 120, 150, 200]	[100, 150, 200, 250, 300, 350, 400]
Load demand range (MW)	[200, 300]	[300, 500]	[500, 800]

This example includes three typical types of power equipment: transmission lines, transformers, and circuit breakers. The key parameters, such as initial health index, failure rate, and maintenance cost, are defined in Table 2. Example 1 is used to verify the basic logic of the model. Examples 2 and 3 focus on the efficiency analysis of algorithms in large-scale problems. All examples consider a linear decrease in equipment health index over time (with a rate of 0.005 per day) and maintain a recoverable health index of 0.95. The inventory holding cost was set at 5% of the remaining resource value, while a fixed cost of 100,000 yuan was applied for each supply order.

Table 2. Key parameters of the calculation example

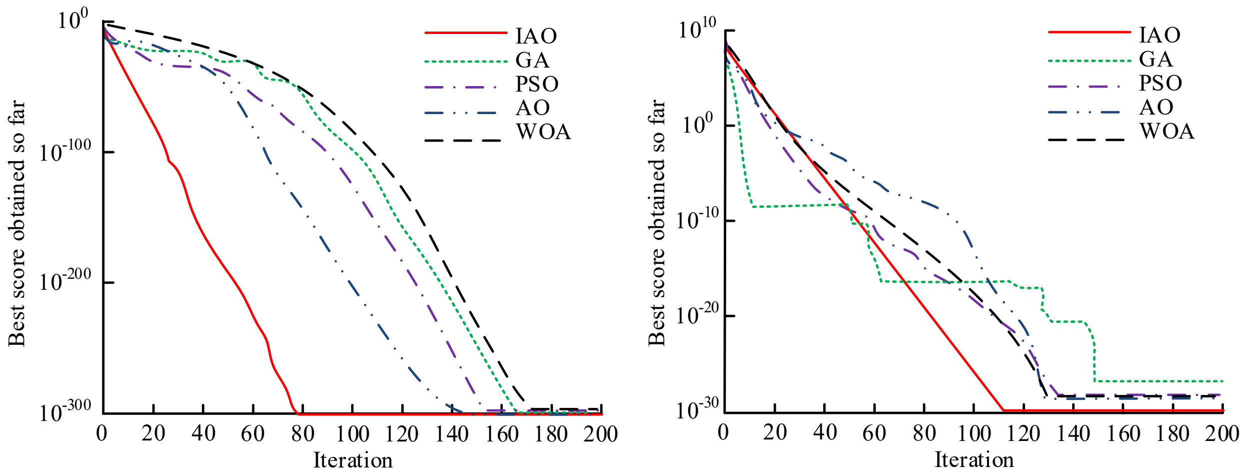
Key parameters	Transmission line	Transformer	Circuit breaker
Initial value of health index	0.90	0.85	0.80
Failure rate (times/day)	0.015	0.010	0.020
Maintenance execution cost/Fault loss cost (10,000 yuan/time)	5/20	8/30	6/15
Rated power supply (MW)	150	200	100
Priority coefficient	3	4	2

3.2. Performance Analysis of IAO Algorithm

The performance of the IAO was verified against several comparison algorithms: GA, Particle Swarm Optimization (PSO), Aquila Optimizer (AO), and WOA. Fig. 5 shows the convergence curves of the compared algorithms. The unimodal test function shown in Fig. 5(a) has convergence iterations of 80, 165, 157, 147, and 171 for IAO, GA, PSO, AO, and WOA. Fig. 5(b) shows the multimodal test function, and the IAO has a convergence iteration of 115 times. Its global optimal value is closer to 10-30 compared to other algorithms. This indicates that IAO has a faster convergence speed and higher accuracy.

The performance of the algorithms on the case studies is presented in Fig. 6. In Example 2 of Fig. 6(a), the optimal solution obtained by the IAO is 11.983 million yuan, which is lower than that achieved by GA and PSO. Additionally, the convergence time of the IAO is 32.6 seconds, demonstrating the fastest convergence rate among all algorithms. Furthermore, the standard deviation of the IAO is also the smallest. In Example 3 of Fig. 6(b), the optimal solution of the IAO is 21.504 million yuan, with a convergence time of 45.4 s, both of which outperform comparative algorithms. The data indicates that when addressing optimization problems, the IAO identifies the optimal solution efficiently, thereby reducing optimization costs.

To verify the effectiveness of quasi-reverse initialization, adaptive weights, bubble hunting strategy, and perturbation strategy, the ablation experiment of the algorithm is conducted in Example 3. The results of the ablation experiment are shown in Table 3. After removing the quasi-reverse initialization, the optimal solution increases by 3.2%. After removing the bubble hunting strategy, the average solution rises by 2.7%. After removing the perturbation strategy, the standard deviation of the solution increases by 18.6%. Comprehensive analysis shows that quasi-reverse initialization makes the algorithm closer to the optimal solution. The bubble hunting strategy can effectively improve the quality of the solution and reduce the value of the average solution. The perturbation strategy can reduce the standard deviation of understanding and avoid the algorithm falling into a local optimum.



(a) The convergence curve of unimodal function (b) The convergence curve of the multimodal function

Fig. 5. Comparison of convergence curves of algorithms

3.3. Analysis of the Optimization Effect of Power EMS

The proposed optimization scheme (MILP+IAO) was evaluated against two benchmarks: the MILP model solved with a standard solver and a traditional regular maintenance scheme. A cost comparison of different scheduling schemes is presented in Fig. 7. For example, 1 (Fig. 7(a)) t the MILP+IAO scheme achieved a total cost of 7.643 million yuan, which is 27.2% lower than the traditional solution. Notably, the fault loss cost was reduced significantly by 45.7%. Fig. 7(b) shows the cost comparison of Example 2. The total cost of the MILP+IAO solution is 17.503 million yuan, representing a 21.2% reduction over the traditional solution and a 9.9% improvement over that of the MILP. These two examples show that the MILP+IAO scheme significantly reduces the total cost and fault loss cost, demonstrating its efficiency and economy in optimizing the scheduling scheme.

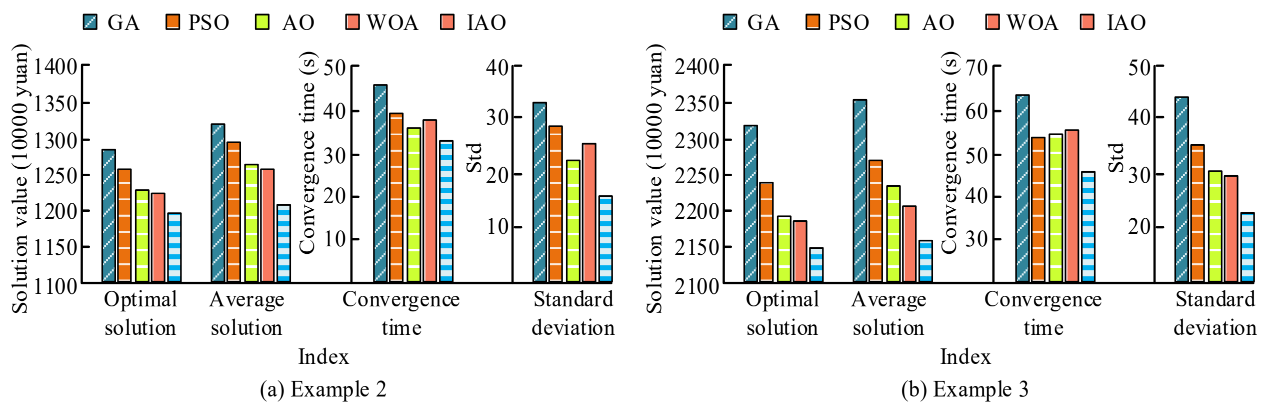


Fig. 6. Performance comparison of different algorithms in case analysis

Table 3. Results of ablation experiment

Strategy combination	Optimal solution (10000 yuan)	Average solution (10000 yuan)	Convergent algebra	Trapped in local optimum times
Complete IAO	2150.4	2165.2	150	0
Without reverse initialization	2219.3	2230.8	180	2
Without adaptive weight	2198.7	2210.5	175	1
Without bubble hunting strategy	2215.6	2225.3	165	1
Without perturbation strategy	2170.2	2185.9	160	3

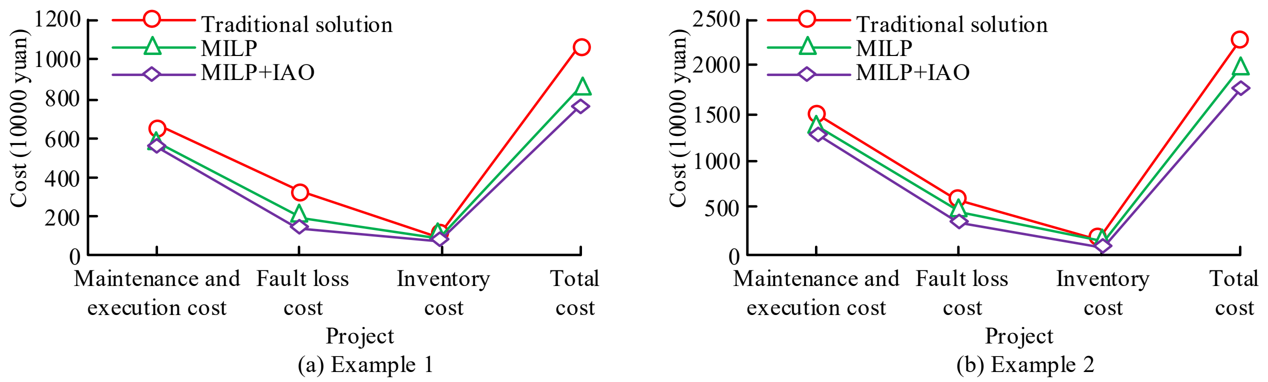


Fig. 7. Cost comparison of different scheduling schemes

In the comparison of reliability and load balancing indicators in Fig 8, the MILP+IAO scheme has significant advantages. In Example 1 of Fig. 8 (a), the average reliability of the equipment under the traditional scheme is 75.3%, while under the MILP+IAO scheme it can reach 86.7%. In Example 2, the average reliability of the equipment in the MILP+IAO scheme is 84.6%, which is much higher than 72.1% in the traditional scheme. Fig. 8 (b) shows the comparison of load balancing rates. In Example 1, the load balancing rate under the MILP+IAO is 102.3%, which is higher than 88.5% of the traditional scheme. In Example 2, the load balancing rates of the MILP+IAO and the traditional scheme are 101.5% and 85.2%. Overall, the application effect of the MILP+IAO in both examples are significantly better than that of the traditional scheme.

Fig. 9 shows the comparison between the number of faults and the duration of power outages. In Fig. 9 (a), Example 1, the traditional scheme experiences 12 failures, while the MILP+IAO scheme only has 7. In Example 2, the number of failures in the traditional scheme is 18 times, while that in the MILP+IAO is reduced to 10 times. Fig. 9 (b) shows that in Example 1 and Example 2, the power outage time of the MILP+IAO scheme is 22.5 hours and 30.1 hours, both lower than that of the traditional scheme. In contrast, the MILP+IAO solution can significantly reduce the frequency of faults and shorten the duration of power outages caused by faults, which is conducive to enhancing the stability of the power system.

In Example 1, the comparison of the effects of different priority strategies is shown in Table 4. When scheduling based on comprehensive priority (health index + importance), the cost of power outage losses is the lowest, which is 12.2% lower than scheduling based solely on health index, indicating the necessity of multi-dimensional priority constraints.

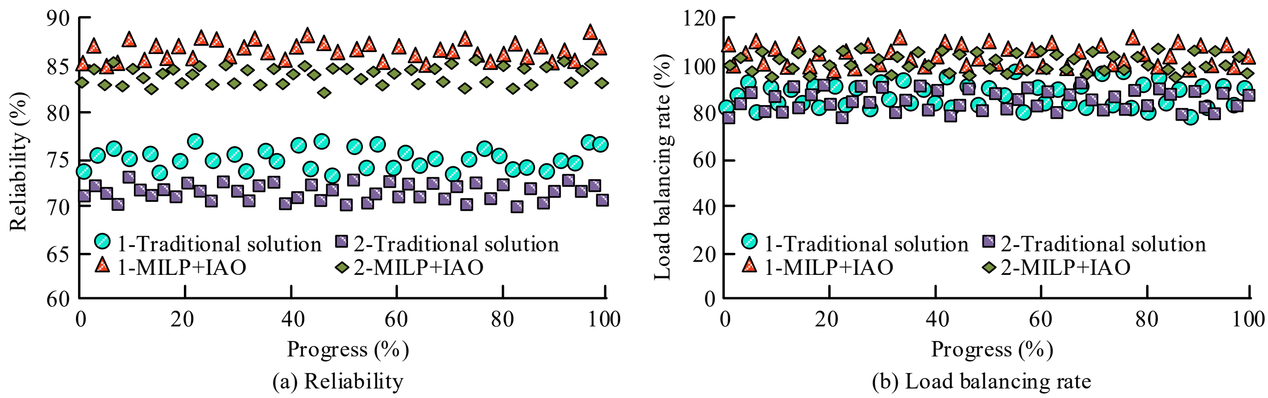


Fig. 8. Comparison of reliability and load balancing indicators

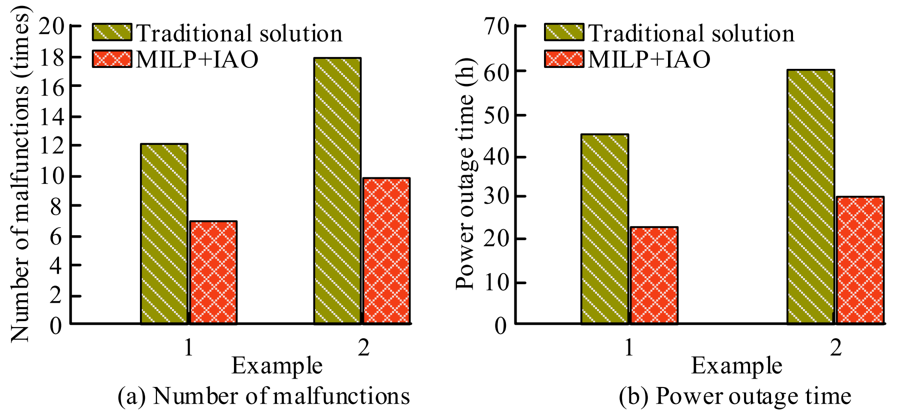


Fig. 9. Comparison of fault frequency and power outage time

Table 4. Comparison of the effectiveness of different priority strategies

Priority Policy	Maintain order	Power outage loss cost (10000 yuan)	Timely maintenance rate of high priority equipment	Over maintenance rate of low priority devices
No priority	stochastic scheduling	210.5	60.7%	35.5%
According to health index	Health index priority	164.3	85.8%	20.4%
By importance	Priority coefficient priority	180.6	90.5%	25.8%
Comprehensive priority	Health + Importance	144.5	95.1%	15.4%

4. Discussion and Conclusion

This study addresses the maintenance scheduling optimization problem by integrating ALCA to minimize total maintenance costs and maximize equipment reliability. A maintenance scheduling optimization model was constructed using MILP and solved using the IAO algorithm. At the same time, maintenance scheduling optimization methods have been designed for the special characteristics of power equipment. In the experiment, IAO reached the global optimum through 80 iterations under the unimodal function and converged through 115 iterations under the multimodal function. The convergence speed and accuracy were both better than the comparative algorithms. In Example 2, the optimal solution of IAO was 11.983 million yuan, which was 873,000 yuan less than GA, with a convergence time of only 32.6 seconds and stronger stability. In the optimization scheme of power EMS, the MILP+IAO scheme reduced the total cost by 27.2% compared to the traditional scheme in Example 1, reduced the cost of fault losses by 45.7%, improved the average reliability of equipment to 86.7%, achieved a load balancing rate of 102.3%, and reduced the number of faults to 7. Under the comprehensive priority strategy, the cost of power outage loss was reduced by 12.2% compared to scheduling based solely on the health index, which verified the necessity of multi-dimensional constraints. Public utility companies can first integrate the operation data and maintenance records of the SCADA system to automatically calculate the equipment health index. In combination with the adjustment of resource constraints based on the annual maintenance budget, the maintenance time window should be optimized according to the peak load of each season. Finally, the maintenance plan is connected to the dispatching system, giving priority to the maintenance of high-priority equipment and coordinating with spare parts procurement to reduce inventory issues. For instance, it can be used to support decision-making on replacing old transmission lines and enhance operation and maintenance efficiency. However, the study did not fully consider the data of sudden changes in equipment performance caused by extreme environments (such as typhoons and heavy snowstorms). Such sudden situations might cause the decline rate of equipment health index to deviate from the preset 0.005 per day. Moreover, in actual operation and maintenance, there were errors in sensor data (such as ±0.5°C deviation of temperature sensors), which would affect the accuracy of fault probability calculation. This further led to deviations in the maintenance plan. In the current model, in ultra-large-scale power grids with over 100 devices and more than 10 types of resources (such as cross-provincial power grids), the convergence time of the IAO algorithm would increase from 45.4 seconds (for 50 devices) to over 100 seconds, and the number of constraints of the MILP model grew exponentially. The computational efficiency of the Gurobi solver has significantly declined, making it difficult to meet the real-time scheduling requirements. It is necessary to further optimize the model structure (such as decomposing constraints by region) or introduce parallel computing technology.

Author Contributions

Qiqi Zhang contributed to conceptualization, methodology, software, validation, analysis, investigation, data collection, draft preparation, manuscript editing, and visualization. Xufeng Zhou contributed to validation, analysis, investigation, and data collection. Yi Cao contributed to validation, analysis, investigation, and data collection.

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Declaration of Artificial Intelligence (AI) Tools

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