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Scheduling Optimization Scheme Based on Genetic Algorithm for Integrated System of Inspection, Storage and Distribution of Electric Power Materials

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Abstract. *Traditional electric power material management systems often have problems with the separation of detection, storage and distribution, leading to inefficient resource utilisation and lagging scheduling decisions. With the expansion of the scale of the power grid and the improvement of the degree of intelligence, there is an increasing demand for the accuracy, real-time and intelligence of material management. In order to solve these problems, this paper proposes a scheduling optimisation method based on improved genetic algorithm. Firstly, the integrated optimisation of the whole process of material management is achieved by establishing a mathematical model that comprehensively considers the various aspects of power material management. Secondly, an improved genetic algorithm is designed, which introduces adaptive parameter adjustment and local search strategy to improve the convergence speed and the quality of the algorithm. The experimental results show that in large-scale problems, the Improved Genetic Algorithm (IGA) proposed in this paper needs only 580 iterations to reach a stable solution, which is 52% faster than the traditional genetic algorithm. The stability of the solution of the IGA is also significantly improved, and the standard deviation in large-scale problems is only 0.042, which is 55.8% lower than that of the traditional genetic algorithm. Although the computational time of the IGA is slightly longer than that of the traditional algorithm (287.6 s vs. 265.4 s), this additional computational cost is acceptable given the quality of the solutions it provides and the advantages in convergence speed. Compared to the state-of-the-art Reinforcement Learning Genetic Algorithm (RL-GA), the IGA achieves an 8.9% improvement in computational efficiency while maintaining similar convergence and stability. These results show that the method proposed in this paper has significant advantages in scheduling optimisation.*
Keywords: power material management; improved genetic algorithm; scheduling optimisation; intelligent decision-making

1. **Introduction.** With the rapid development of the electric power industry and the continuous expansion of the power grid scale, the management and scheduling of electric power materials has become a key factor affecting the safe and stable operation of the power system. As a new mode of material management in electric power enterprises, the integrated system [1] aims to integrate inspection [2], storage [3] and distribution [4] to improve the efficiency of material management and reduce the operating costs. However, the complexity and dynamics of this system bring great challenges to scheduling optimisation.

In recent years, Artificial Intelligence (AI) and optimisation algorithms have shown significant advantages in solving complex system scheduling problems. Among them, Genetic Algorithm (GA), as a heuristic algorithm simulating the biological evolution process [5, 6], performs well in dealing with large-scale and multi-constraint optimisation problems. Applying GA to the scheduling optimisation of power material is expected to overcome the limitations of the traditional methods and achieve a more efficient and intelligent scheduling strategy.

In addition, with the development of smart grid and IoT technologies, power material management is facing new challenges such as the surge in data volume and the requirement for higher real-time decision-making. This further highlights the importance and urgency of developing advanced scheduling optimisation schemes. In this context, it is of great theoretical significance and practical application value to explore the GA-based scheduling optimisation scheme for power material.

Despite the potential advantages of an integrated system in improving the efficiency of materials management, it still faces many challenges in actual operation. For example, multi-objective optimisation is very important in power material scheduling, which needs to simultaneously consider the objectives of cost minimisation, timeliness maximisation, and optimal resource utilisation [7, 8], which are often in conflict with each other. In addition, system operation is affected by complex constraints such as inventory capacity, transport capacity, time windows, and quality requirements [8]. Due to the fluctuation and uncertainty of factors such as power demand, material supply, and transport conditions, scheduling schemes must be highly adaptive and robust. As the scale of the grid continues to expand, the scheduling optimisation problem becomes larger and more complex, which places higher demands on the computational efficiency of the algorithms. Finally, in the face of emergency situations, the system must be able to quickly generate and adjust the scheduling scheme, which further tests the convergence speed of the algorithm.

Based on the above problems, this study aims to design a GA-based scheduling optimisation scheme for power materials. The scheme needs to be able to effectively handle multi-objective optimisation problems, satisfy complex constraints, adapt to the dynamics and uncertainty of the system, and maintain good computational efficiency in large-scale problems. It also needs to consider how to incorporate domain knowledge into the algorithm design to improve the interpretability of the optimisation effect and solution.

1.1. **Related work.** The integrated system is an advanced mode of materials management in electric power enterprises, aiming at integrating to achieve efficient and collaborative materials management [9]. The core of the system is to integrate the traditional scattered material management process into an organic whole, and to achieve the fine management of the whole life cycle of materials through information technology and intelligent means.

Effective scheduling optimisation is essential to improve the overall operational efficiency of the system, reduce costs and enhance service quality. For the scheduling optimisation problem of electric power material, researchers have proposed a variety of methods and strategies. These methods can be broadly classified into the following categories: (1) Traditional mathematical planning methods: linear programming, integer programming and mixed integer programming are widely used in scheduling optimisation problems [10]. These methods are able to find exact solutions in small-scale problems, but often face the challenge of high computational complexity when dealing with large-scale, nonlinear problems. (2) Heuristic Algorithms: In response to the limitations of traditional methods, researchers have developed various heuristic algorithms such as simulated annealing algorithm [11], ant colony algorithm [12] and particle swarm optimisation algorithm [13]. These algorithms are able to find an approximate optimal solution in an acceptable time, but may fall into local optimum. (3) Intelligent optimisation methods: with the development of artificial intelligence technology, methods such as deep reinforcement learning [14] and neural networks [15] are introduced into the field of scheduling optimisation. These methods have the advantages of being adaptive and capable of handling high-dimensional data, but often require a large amount of training data and computational resources. (4) Hybrid approaches: in order to combine the advantages of various methods, researchers have proposed a variety of hybrid optimisation strategies [16, 17]. For example, combining heuristic algorithms with mathematical planning, or fusing machine learning methods with traditional optimisation algorithms. (5) Multi-objective optimisation approaches: considering the multi-objective nature of material scheduling, some researchers have adopted multi-objective optimisation approaches, such as the NSGA-II algorithm [18] and the MOEA/D algorithm [19], in order to balance the trade-offs between different objectives. Although these methods have achieved some success in specific scenarios, there are still many challenges when facing the complexity, dynamics, and large-scale characteristics of the integrated system. In particular, in dealing with multi-objective, multi-constraint and real-time decision-making requirements, it is often difficult for existing methods to simultaneously balance solution quality and computational efficiency. This provides motivation and space for this study to propose a novel GA-based scheduling optimisation scheme.

1.2. **Motivation and contribution.** By reviewing and analysing the existing literature, we find that there are several major problems in the research on scheduling optimization of the integrated system. Firstly, most of the existing studies focus on a single link of power material management (e.g., inspection, storage or distribution) and lack a comprehensive consideration of the whole supply chain. This decentralised research method is difficult to capture the mutual influences between the links, leading to poor overall optimisation results. Secondly, traditional optimisation algorithms often face the problem of slow convergence and easy to fall into local optimum when dealing with large-scale, multi-constraint problems such as power material management. Existing algorithms lack effective adaptive mechanisms, making it difficult to maintain stable performance in problems of different sizes and complexities. In addition, most of the existing studies adopt a single coding approach, which makes it difficult to effectively handle both continuous variables (e.g., distribution quantity) and discrete variables (e.g., detection decisions) in power material management problems. This limits the effectiveness of the algorithms in complex problems. Existing genetic algorithms often lack effective local search mechanisms, leading to inefficiencies in the refined optimisation phase. This makes it difficult for algorithms to strike a good balance between global exploration and local exploitation. Power material management involves multiple conflicting objectives such as cost minimisation and service level maximisation; however, existing research mostly adopts simple multi-objective processing methods, making it difficult to achieve a good balance between multiple objectives. There are many complex constraints in power material management, such as inventory capacity, transport capacity, and inspection period, etc., however, existing studies often ignore these constraints.

To address the above issues, the main innovations and contributions of this work include:

(1) Integrated system model: This paper proposes for the first time a mathematical model that comprehensively considers the whole process of electric power materials. This integrated model breaks the limitations of the separation of the links in the traditional electric power material management system, achieves global optimisation, and improves the efficiency of resource utilisation and real-time decision-making.

(2) Design of Improved Genetic Algorithm (IGA): An improved GA is designed to address the characteristics of power material management system. The IGA introduces the following innovations: a) Adaptive parameter tuning mechanism: by dynamically adjusting the crossover probability and variance probability, the algorithm is able to automatically balance the global exploration and local exploitation during the searching process, which improves the algorithm's adaptability to the problems with different scales. Adaptability of the algorithm on problems of different scales is improved. b) Hybrid coding strategy: A hybrid coding scheme is designed to deal with continuous variables and discrete variables at the same time, which is better adapted to the characteristics of the power material management problem. c) Local search strategy: A local search strategy based on simulated annealing is introduced to enhance the fine search capability of the algorithm, which helps to obtain higher quality solutions.

(3) Multi-objective optimisation method: This paper proposes a multi-objective optimisation method combining the weighted sum method and penalty function, which effectively balances the two conflicting objectives of cost minimisation and service level maximisation, and provides decision makers with a more comprehensive optimisation scheme.

(4) Efficient constraint processing technology: an adaptive penalty coefficient strategy has been developed to effectively deal with a variety of complex constraints in power material management, such as inventory capacity, transport capacity, time window, etc., to ensure the feasibility and practicability of the optimisation results.

2. Rationale and methodology.

2.1. Electric power material integrated system model.

The integrated system of power material is shown in Figure 1, which mainly includes the following key components [20]:

Inspection subsystem: Responsible for the quality inspection before the materials are put into storage, regular sampling and functional testing before leaving the warehouse to ensure that the quality of materials meets the standards.

Storage subsystem: Manage the inventory, storage layout and environmental control of materials to achieve scientific storage and rapid positioning.

Distribution subsystem: Responsible for the allocation, transport and distribution of materials to ensure that they reach the place of need in a timely manner.

Information management subsystem [21]: integrates data from various subsystems to provide decision support and real-time monitoring.

In order to better optimise the scheduling of power supplies, we first build a comprehensive and accurate system model. The model covers all key components of the system and their interrelationships:

(1) Detection subsystem model: Let $Q = \{q_1, q_2, \ldots, q_n\}$ be the set of materials to be detected, where q_i denotes the i-th material. Define the detection function $D(q_i)$ to represent the detection result of the material q_i. Detection time function $T_d(q_i)$ denotes

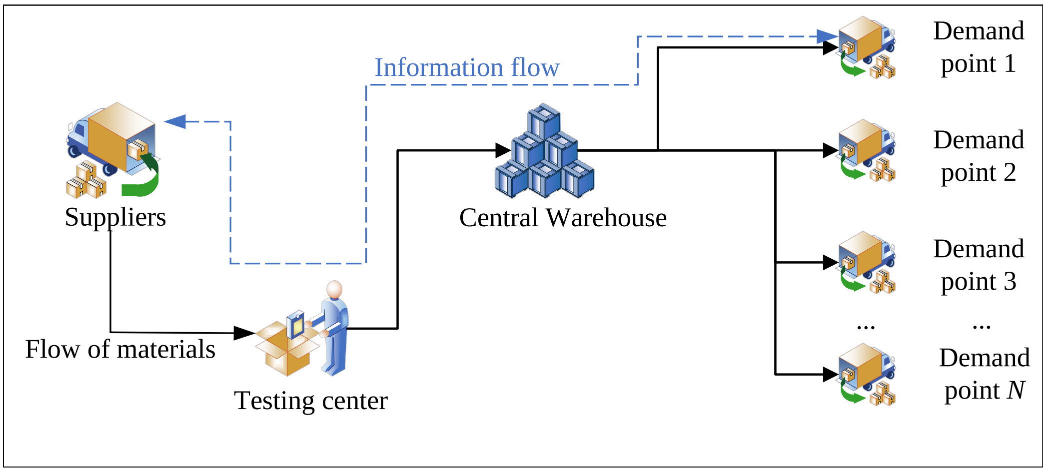

Figure 1. Schematic diagram of the integrated system for electric power materials

the time required to detect material q_i.

$$D(q) = \begin{cases} 1, & \text{If the material is qualified} \\ 0, & \text{If the material is not qualified} \end{cases} \tag{1}$$

(2) Stockpile subsystem model: Define the inventory state vector $I(t) = [I_1(t), I_2(t), \ldots, I_n(t)]$, where $I_i(t)$ denotes the inventory of material q_i at time t. Inventory capacity constraint: $\sum_{i=1}^{n} I_i(t) \leq C$, where C is the total inventory capacity. Define the storage cost function $C_s(I(t))$ to denote the inventory holding cost.
(3) Distribution subsystem model: Define the distribution route set $R = \{r_1, r_2, \ldots, r_m\}$, where r_j denotes the j-th distribution route. The distribution time function $T_r(r_j, q_i)$ indicates the time required to distribute the material q_i through the path r_j. Distribution cost function $C_r(r_j, q_i)$ denotes the cost of distributing the material q_i through the path r_j.
(4) Demand model: Define the demand function $D(t) = [D_1(t), D_2(t), \ldots, D_n(t)]$, where $D_i(t)$ denotes the demand for material q_i at t.
(5) System state transfer equation:

$$I(t+1) = I(t) + Q_{\text{in}}(t) - Q_{\text{out}}(t) \tag{2}$$

where $Q_{\text{in}}(t)$ and $Q_{\text{out}}(t)$ denote the inbound and outbound quantities at time t, respectively.
(6) Objective function: Minimising total cost:

$$\min\left(\sum_{t} C_s(I(t)) + \sum_{i,j} C_r(r_j, q_i)\right) \tag{3}$$

Maximising service levels:

$$\max\left(\sum_{i,t} \frac{D_i(t)}{D_i(t) + B_i(t)}\right) \tag{4}$$

where $B_i(t)$ denotes the out-of-stock quantity of material q_i at time t.
(7) Binding conditions: Inventory capacity constraints:

$$\sum_{i=1}^{n} I_i(t) \leq C, \ \forall t \tag{5}$$

Transport capacity constraints:

$$\sum_{i=1}^{n} q_i \cdot x_{ij}(t) \leq K_j,\ \forall j, t \tag{6}$$

Time window constraints:

$$T_{\text{arrive}}(j,t) \in [T_{\min}(j,t),\, T_{\max}(j,t)],\ \forall j, t \tag{7}$$

Quality requirements constraints:

$$D(q_i) = 1,\ \forall i \tag{8}$$

where $x_{ij}(t)$ denotes the quantity of material i distributed through path j at t time, K_j denotes the transport capacity of path j, $T_{\text{arrive}}(j,t)$ denotes the arrival time of path j at t time, and $[T_{\min}(j,t), T_{\max}(j,t)]$ denotes the time window.

2.2. **Principle of genetic algorithm.** GA is a heuristic search algorithm that simulates the process of biological evolution [22]. In this study, we choose GA as the core optimisation method, and its basic principle is as follows: Represent the solution to the problem as a chromosome $X = [x_1, x_2, \ldots, x_L]$, where L is the chromosome length. Randomly generate an initial population $P(0) = \{X_1, X_2, \ldots, X_N\}$, where N is the population size. Define the fitness function $F(X)$ for evaluating the degree of superiority or inferiority of each chromosome X. Use roulette selection method with selection probability p_i. Define the crossover operator $C(X_1, X_2) = \{X'_1, X'_2\}$. Define the mutation operator $M(X) = X'$. Set the maximum number of iterations $G_{\max}$.

Improvements to conventional GA:

(1) Adaptive parameter tuning: we use adaptive crossover rate p_c and mutation rate p_m to adapt to different stages of the search process. The crossover rate and mutation rate are calculated as follows:

$$p_c = p_{c1} - (p_{c1} - p_{c2}) \cdot \frac{f' - f_{\text{avg}}}{f_{\max} - f_{\text{avg}}} \tag{9}$$

$$p_m = p_{m1} - (p_{m1} - p_{m2}) \cdot \frac{f_{\max} - f'}{f_{\max} - f_{\text{avg}}} \tag{10}$$

where f' represents the higher adaptability score among the two selected individuals in crossover operation; f_{avg} refers to the average of the fitness scores of all individuals in the current population; $f_{\max}$ represents the highest adaptability score in this group; p_{c1} represents the upper limit of the crossover rate (usually 0.9); p_{c2} represents the lower limit of the crossover rate (usually 0.6); p_{m1} represents the upper limit of the variability (usually 0.1); p_{m2} represents the lower limit of the variability (usually 0.001). This adaptive mechanism works in such a way that when the fitness of the individuals is low (below average), the algorithm uses higher crossover and mutation rates to increase the diversity of the population; when individuals show high adaptability, the frequencies are reduced to maintain the stability of better solutions.

(2) Multi-objective processing: a multi-objective optimisation strategy based on the Pareto front [23] is used to define the non-dominated ranking function $\text{ND}(P) = \{F_1, F_2, \ldots\}$.

(3) Parallel computation: use the island model and define the migration operation $M(P_1, P_2) = \{P'_1, P'_2\}$. With these improvements, our genetic algorithm is able to better handle the complexity and dynamics of the integrated system, and provides a powerful tool for achieving efficient and intelligent scheduling optimisation.

3. **Design of scheduling optimisation schemes based on genetic algorithms.**

3.1. **Problem formulation.** Based on the previously described model, we now combine the problem formulation with the genetic algorithm framework to construct a complete optimisation scheme.

Objective function:

(1) Minimising total costs:

$$\min f_1 \;=\; \sum_{t=1}^{T}\left(\sum_{i=1}^{n}\sum_{j=1}^{m} C_r(r_j, q_i)\, x_{ij}(t) \;+\; \sum_{i=1}^{n} C_s(I_i(t)) \;+\; \sum_{i=1}^{n} C_d(q_i)\, y_i(t) \right) \tag{11}$$

(2) Maximising service levels:

$$\max f_2 \;=\; \frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{n} \frac{D_i(t)}{D_i(t)+B_i(t)} \tag{12}$$

In order to combine a multi-objective optimisation problem with an improved genetic algorithm, an overall strategy is used. Firstly, by applying the weighted synthesis method, the problem that originally contained multiple objectives was reconstructed into a single objective problem, and then the multi-objective solution was implemented. Second, the penalty function method is used to handle the constraints and ensure the feasibility of the solution. Next, a hybrid coding scheme is designed to handle both continuous and discrete variables. Specific selection, crossover and mutation operations are also designed as part of the genetic operations for the problem characteristics. Finally, a local search strategy is introduced to improve the search efficiency of the algorithm and to ensure that a better quality solution can be found globally.

3.2. **Coding strategy.** For the characteristics of the integrated system, we design a hybrid coding strategy to handle both continuous and discrete variables. The chromosome structure is shown below:

$$X \;=\; [\,X_1,\, X_2,\, X_3\,] \tag{13}$$

where X_1 denotes the distribution decision, encoded as a vector of real numbers, $X_1 = [x_{111}, \ldots, x_{ijt}, \ldots, x_{nmT}]$, and x_{ijt} denotes the quantity of material i distributed through path j at time t; X_2 denotes the detection decision, encoded as a binary string, $X_2 = [y_{11}, \ldots, y_{it}, \ldots, y_{nT}]$, and y_{it} denotes whether or not material i is detected (0 or 1) at time t; X_3 denotes the inventory allocation decision, encoded as a vector of real numbers, $X_3 = [z_{11}, \ldots, z_{it}, \ldots, z_{nT}]$, and z_{it} denotes the amount of inventory allocated to material i at time t. The length of X_1 is $n \times m \times T$, the length of X_2 is $n \times T$, and the length of X_3 is $n \times T$. Therefore, the total coding length is:

$$L \;=\; n \times m \times T \;+\; 2n \times T \tag{14}$$

Feasibility strategies:

(1) For X_1, we use normalisation to ensure that the distribution on each path does not exceed the transport capacity:

$$x_{ijt} \;=\; K_j \cdot \frac{x'_{ijt}}{\sum_{i=1}^{n} x'_{ijt}} \tag{15}$$

where x'_{ijt} is the original value in the code and K_j is the transport capacity of path j.

(2) For X_2, we use binary encoding directly without special handling.

(3) For X_3, we use a similar normalisation process to ensure that the total inventory does not exceed the inventory capacity:

$$z_{it} \;=\; C \cdot \frac{z'_{it}}{\sum_{i=1}^{n} z'_{it}} \tag{16}$$

where z'_{it} is the original value in the code and C is the total inventory capacity. This hybrid coding strategy is able to represent all decision variables of the problem efficiently while guaranteeing the feasibility of the solution through normalisation.

3.3. **Weighted penalty fitness function design.** The fitness function is the key to evaluate the individual merits. Considering that our problem is a multi-objective optimisation problem, we use the weighted sum method to transform it into a single-objective problem and use the penalty function to handle the constraints. The fitness function is designed as follows:

$$F(X) = w_1 \cdot (-f_1) + w_2 \cdot f_2 - \sum_{k=1}^{K} p_k \cdot v_k(X) \tag{17}$$

where w_1, w_2 are the weights of the objective function satisfying $w_1 + w_2 = 1$; f_1, f_2 are the total cost and service level objective functions (as defined in Section 3.1), respectively; p_k is the penalty coefficient for the k-th constraint; and $v_k(X)$ is the degree of violation of the k-th constraint.

Constraint violation terms:

$$v_1(X) = \max\left(0, \sum_{i=1}^{n} I_i(t) - C\right) \tag{18}$$

$$v_2(X) = \max\left(0, \sum_{i=1}^{n} q_i \cdot x_{ijt} - K_j\right) \tag{19}$$

$$v_3(X) = \max\left(0, D_i(t) - \sum_{j=1}^{m} x_{ijt} - B_i(t)\right) \tag{20}$$

$$v_4(X) = \left| y_{it} \cdot D(q_i) - 1 \right| \tag{21}$$

Adaptive penalty coefficients:

$$p_k(t) = p_k(0) \cdot (1 + \beta)^t \tag{22}$$

where $p_k(0)$ is the initial penalty coefficient, β is the growth rate, and t is the current number of generations.

3.4. **Selection, crossover and mutation operations.** (1) Selection: We use an elite retention strategy combined with a roulette wheel selection method. The N_e individuals with the highest fitness in the current population are retained to go directly to the next generation. Apply roulette wheel selection to the remaining individuals with selection probability:

$$p_i = \frac{F(X_i)}{\sum_{j=1}^{N} F(X_j)} \tag{23}$$

where $F(X_i)$ is the fitness value of individual X_i.

(2) Crossover: For the real-coded parts X_1 (distribution decision) and X_3 (inventory allocation decision), arithmetic crossover is used:

$$X' = \alpha X^{(1)} + (1 - \alpha) X^{(2)}, \qquad X'' = (1 - \alpha) X^{(1)} + \alpha X^{(2)} \tag{24}$$

where $\alpha \in [0, 1]$ is a randomly generated number and $X^{(1)}, X^{(2)}$ are the corresponding parts of the two parent individuals. For the binary-coded part X_2 (detection decision), a single-point crossover is used.

(3) Mutation: For X_1 and X_3, Gaussian variation is used:

$$x_{ijt} \leftarrow x_{ijt} + \mathcal{N}(0, \sigma^2) \tag{25}$$

where $\mathcal{N}(0, \sigma^2)$ denotes a normal distribution with mean 0 and variance σ^2. For X_2, a bit-flip mutation is used (flip 0↔1 with a certain probability). The mutation probability p_m uses the adaptive strategy as described previously.

3.5. **Local search strategy.** In order to improve the search efficiency of the algorithm, we perform local search on some elite individuals in each iteration. We use the simulated annealing algorithm [24] as the local search strategy; the pseudo-code is shown in Algorithm 1.

With this local search strategy, we can improve the overall performance of the algorithm by performing local refinement based on the global search.

4. Simulation experiments and results analysis.

4.1. **Experimental design and data sources.** In order to comprehensively evaluate the performance of the scheduling optimisation method based on improved genetic algorithm for the integrated system of electric power materials proposed in this paper, a series of simulation experiments were designed. The experiments were conducted in a hardware environment equipped with Intel Core i7-10700K CPU @ 3.80GHz and 32GB RAM, and MATLAB R2021a was used as the software platform.

We constructed three datasets of different sizes to test the performance of the algorithm at different complexities. The small-scale dataset contains 10 types of materials and 5 distribution routes with a planning cycle of 30 days; the medium-scale dataset contains 50 types of materials and 20 distribution routes with a planning cycle of 90 days; and the large-scale dataset contains 200 types of materials and 50 distribution routes with a planning cycle of 180 days. These datasets are designed to simulate various situations that may be encountered in a real power material management system.

The experimental data is generated by simulation based on historical data from 2020–2022 of a provincial power company. Material demand data are generated by analysing historical demand patterns using time series forecasting methods. Transportation costs are calculated based on actual transport distances and fuel costs, inventory costs refer to actual warehousing costs and capital occupancy costs, and inspection costs are set based on the inspection complexity of different materials. This simulation method based on actual data ensures the practicality and reliability of the experimental results.

In order to evaluate the advantages of the algorithms proposed in this paper, we selected traditional GA, PSO, SA, NSGA-II [18], MOEA/D [19] and Reinforcement Learning-based Genetic Algorithm (RL-GA) [25] as comparison algorithms. We use convergence speed, computation time and stability of the solution as evaluation metrics to comprehensively compare the performance of the algorithms.

The main parameters of the improved genetic algorithm proposed in this paper are set as shown in Table 1. These parameters are determined based on preliminary experiments and empirical values, and are intended to balance the algorithm's exploratory ability and convergence speed.

These parameters play an important role in different stages of the algorithm. The population size N and the maximum number of iterations $G_{\max}$ affect the algorithm's global search capability and computational time. The crossover probability P_c and the mutation probability P_m control the evolutionary process of the population. The number of elite individuals N_e ensures that the optimal solution is not lost during the evolutionary process. The local search related parameters (T_0, $T_{\min}$, α, δ, P_{flip}) are used in the algorithm to simulate the annealing local search process, which enhances the algorithm's ability to fine-tune the search in the local region.

Algorithm 1 Pseudo-code for local search strategy based on simulated annealing

Input: current solution X_{current}, initial temperature T_0, termination temperature $T_{\min}$, coefficient of cooling α, maximum number of iterations *MaxIter*, neighbourhood perturbation range δ, binary flip probability p_{flip}.
Output: optimal solution X_{best} after local search.

begin
$T \leftarrow T_0$, $iter \leftarrow 0$
$X_{\text{best}} \leftarrow X_{\text{current}}, \quad F_{\text{best}} \leftarrow F(X_{\text{current}})$
while $T > T_{\min}$ **and** $iter < MaxIter$ **do**
  $X_{\text{new}} \leftarrow$ GENERATENEIGHBOR(X_{current}) ▷ Generate new solutions in the neighbourhood
  $\Delta F \leftarrow F(X_{\text{new}}) - F(X_{\text{current}})$
  if $\Delta F > 0$ **then**
    $X_{\text{current}} \leftarrow X_{\text{new}}$
    if $F(X_{\text{current}}) > F_{\text{best}}$ **then**
      $X_{\text{best}} \leftarrow X_{\text{current}}$
      $F_{\text{best}} \leftarrow F(X_{\text{current}})$
    end if
  else
    $p \leftarrow \exp(\Delta F / T)$
    if RANDOM$(0, 1) < p$ **then**
      $X_{\text{current}} \leftarrow X_{\text{new}}$
    end if
  end if
  $T \leftarrow T \times \alpha$ ▷ cool down
  $iter \leftarrow iter + 1$
end while
return X_{best}
end
function GENERATENEIGHBOR(X)
  $X_{\text{new}} \leftarrow X$
  for each component i in X_{new} **do**
    if i belongs to X_1 **or** X_3 **then** ▷ real number encoding section
      $X_{\text{new}}[i] \leftarrow X_{\text{new}}[i] +$ RANDOM$(-\delta, \delta)$
    else
      if i belongs to X_2 **then** ▷ binary encoded section
        if RANDOM$(0, 1) < p_{\text{flip}}$ **then**
          $X_{\text{new}}[i] \leftarrow 1 - X_{\text{new}}[i]$ ▷ Flip the bit values.
        end if
      end if
    end if
  end for
  return X_{new}
end function

4.2. Algorithm performance evaluation.

4.2.1. *Convergence analysis.* We first analyse the average number of iterations required for each algorithm to reach a stable solution on problems of different sizes, as shown in

Table 1. Parameter setting of IGA

Parameter description	Numerical value
Population size N	100
Crossing probability P_c	0.8
Initial variation probability P_m	0.1
The maximum number of iterations $G_{\max}$	1000
Number of elite individuals N_e	5
Initial temperature T_0	100
Termination Temperature $T_{\min}$	0.01
Cooling factor α	0.95
Neighbourhood perturbation range δ	0.1
The binary flip probability P_{flip}	0.05

Figure 2. Both IGA and RL-GA proposed in this paper show the fastest convergence speed on all sizes of problems, and their performance is almost the same. On medium-scale problems, the IGA requires an average of 320 iterations to reach a stable solution, while the conventional GA, PSO and SA require 620, 680 and 550 iterations, respectively. For large-scale problems, IGA requires 580 iterations while RL-GA requires 585 iterations to reach a stable solution, both of which are significantly better than the other algorithms. NSGA-II and MOEA/D, although they perform better than the conventional algorithms, still do not converge as fast as IGA and RL-GA.

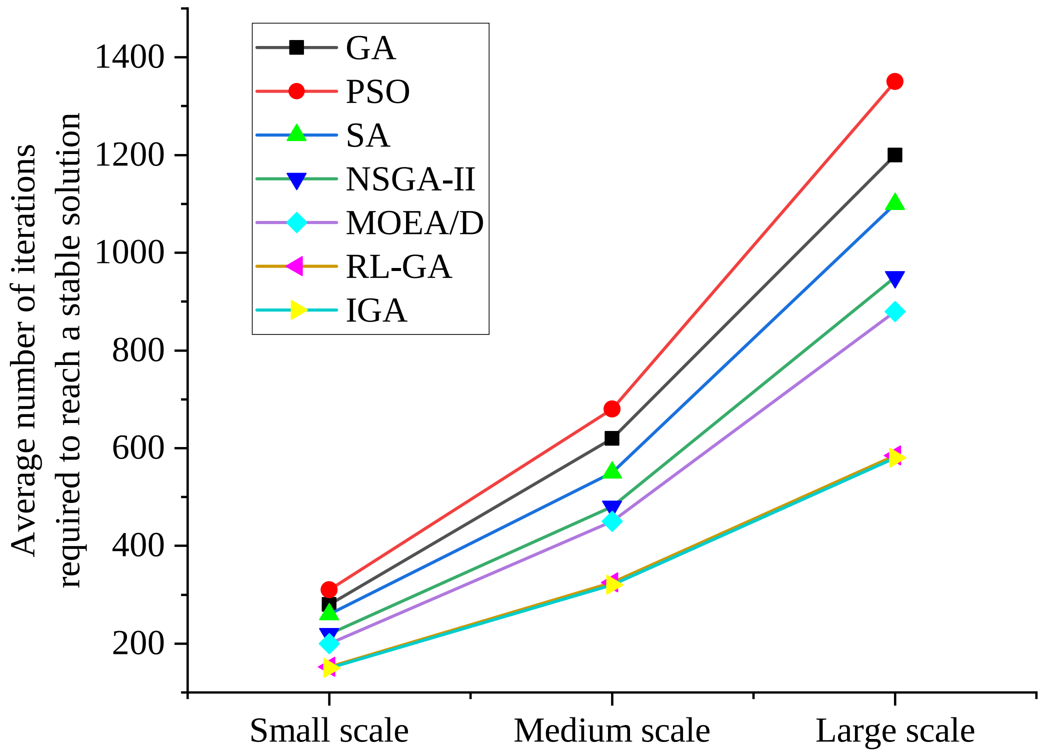

Figure 2. Average number of iterations for each algorithm to reach a stable solution on problems of different sizes

The fast convergence of IGA is mainly due to its improved genetic operation and local search strategy. Especially in complex large-scale problems, IGA is able to explore the solution space more efficiently and avoid falling into local optima. In contrast, traditional

GA and PSO tend to converge slowly in the later stages, while the SA algorithm, although converging faster in the early stages, improves less as it approaches the optimal solution.

4.2.2. *Stability analysis.* To assess the stability of the algorithms, we performed 30 independent runs of each algorithm on each problem size and calculated the standard deviation of the final objective function values, as shown in Table 2. IGA showed the best stability on all problem sizes. The standard deviation of IGA is 0.042 (normalised) for the large-scale problems. IGA and RL-GA show the smallest standard deviation on all problem sizes, indicating that they are the most stable in producing high-quality solutions. The performance of the two algorithms is very close to each other and slightly better than the other algorithms. NSGA-II and MOEA/D also show better stability than the conventional algorithms, but still slightly inferior to IGA and RL-GA.

Table 2. Standard deviation of objective function values for 30 runs (normalised)

Algorithm	Small scale	Medium scale	Large scale
GA	0.038	0.067	0.095
PSO	0.042	0.073	0.108
SA	0.031	0.058	0.087
NSGA-II	0.024	0.045	0.068
MOEA/D	0.022	0.041	0.063
RL-GA	0.016	0.029	0.043
IGA	0.015	0.028	0.042

The superior stability of IGA stems from its improved genetic operation and adaptive parameter tuning mechanism. These improvements enable the algorithm to converge stably to high-quality solutions under different initial conditions, which is crucial for decision reliability in practical applications.

4.2.3. *Computational efficiency analysis.* The average computational times of the algorithms on problems of different sizes are given in Table 3. The computational time of IGA is slightly longer than that of the conventional GA, PSO and SA, but significantly shorter than that of RL-GA. Although RL-GA is comparable to IGA in terms of convergence and stability, it is slightly less computationally efficient, especially when dealing with large-scale problems. Considering that IGA and RL-GA are able to converge faster to higher-quality solutions, their computational time increase is acceptable.

Table 3. Average computation time for each algorithm (seconds)

Algorithm	Small scale	Medium scale	Large scale
GA	10.2	59.7	265.4
PSO	9.8	57.2	258.9
SA	11.7	63.5	278.2
NSGA-II	13.8	72.6	305.4
MOEA/D	13.2	70.8	298.7
RL-GA	14.1	75.2	315.8
IGA	12.5	68.3	287.6

These data tables clearly demonstrate the advantages of IGA over traditional optimisation algorithms and other improved algorithms. IGA is comparable to the state-of-the-art RL-GA in terms of convergence speed and stability of the solution, while slightly outperforming it in terms of computational efficiency. Although other improved algorithms such as NSGA-II and MOEA/D also show better performance than the conventional algorithm, IGA and RL-GA are slightly better in all aspects.

These results further confirm the applicability and effectiveness of IGA in the optimisation problem of the integrated system of power materials. IGA not only outperforms the traditional optimisation algorithms, but also shows obvious advantages in comparison with other advanced and improved algorithms. In particular, IGA exhibits better computational efficiency while maintaining a solution quality comparable to that of RL-GA, which is particularly important for large-scale complex problems in practical applications.

5. **Conclusion.** In this paper, an IGA-based scheduling optimisation method for the integrated system of power materials is proposed, which effectively solves the problems of inefficient resource utilisation and decision lag in the traditional electric power materials management system. By establishing a mathematical model that comprehensively considers the whole process and introducing adaptive parameter adjustment and local search strategy, the efficiency and accuracy of scheduling optimisation are significantly improved. The following conclusions can be drawn by conducting experiments on simulated datasets of different sizes:
(1) The integrated model can effectively improve the overall efficiency of power material management and reduce the waste of resources and decision-making delays.
(2) IGAs show significant advantages in dealing with large-scale complex problems, especially in terms of convergence speed and stability of solutions.
(3) The adaptive parameter tuning mechanism of IGA effectively balances global exploration and local exploitation, and improves the adaptability of the algorithm under different problem sizes.
(4) Compared with other state-of-the-art algorithms (e.g., RL-GA), IGA exhibits better computational efficiency while maintaining the solution quality, which is particularly important for large-scale problems in practical applications.

The experiments in this paper are mainly based on simulation-generated datasets, which may not fully reflect all the complexities of real-world operations, although they are referenced to historical data from actual power companies. Future work should consider applying and validating the method in more actual cases to further improve its usefulness. In addition, techniques such as deep learning can be explored to be combined with the method proposed in this paper to cope with more dynamic and uncertain power material management environments.

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