



International Journal of Information and Communication Technology

ISSN online: 1741-8070 - ISSN print: 1466-6642

<https://www.inderscience.com/ijict>

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Zhenhua Fan

DOI: [10.1504/IJICT.2026.10076333](https://doi.org/10.1504/IJICT.2026.10076333)

Article History:

Received:	10 September 2025
Last revised:	25 November 2025
Accepted:	25 November 2025
Published online:	24 February 2026

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Zhenhua Fan

School of Economics and Management,
University of Science and Technology Beijing,
Beijing, 100083, China

and

School of Economics,
Henan Institute of Technology,
Xinxiang, 453003, China

Email: zhenhuafann@outlook.com

Abstract: Against the backdrop of the ‘Dual Carbon’ goal and the intelligent transformation of energy systems, energy enterprises face core human resource allocation challenges, including 60% fluctuations in demand between peak and valley, multi-objective optimisation, and complex skill matching. Traditional static methods lead to a 40%–50% labour cost ratio and an over 35% skill mismatch rate. This study proposes a dynamic optimisation model with a ‘forecasting-optimisation-real-time adjustment’ closed-loop framework, adopting ARIMA-GARCH ($\pm 7\%$ error) and IE-NSGA-II for four-objective optimisation. Empirical tests on a provincial power grid show the model reduces labour costs and carbon emissions by 17.3% and 10.5%, respectively, while improving efficiency and satisfaction by 21.8% and 18.6%, respectively.

Keywords: NSGA-II algorithm; energy firm; human resource allocation; dynamic optimisation; multi-objective decision-making; carbon emission constraints.

Reference to this paper should be made as follows: Fan, Z. (2026) ‘Optimal allocation model network of human resources in energy enterprises based on NSGA-II’, *Int. J. Information and Communication Technology*, Vol. 27, No. 12, pp.18–39.

Biographical notes: Zhenhua Fan obtained her Bachelor’s in Management from Beijing Forestry University in 2012 and Master’s in Management from University of Science and Technology Beijing in 2014. Presently, she is working as a Lecturer in the School of Economics, Henan Institute of Technology. Since 2021, she has been pursuing her PhD at the School of Economics and Management, University of Science and Technology Beijing. Her research interests include optimal allocation model of human resources, innovation and entrepreneurship, returns on individual capabilities, and financial technology.

1 Introduction

As the core driving force for the operation of modern society, energy is undergoing profound changes in its production and supply system. Driven by the ‘Dual Carbon’ goal and the transformation of the energy structure, energy companies are facing multiple challenges, such as intensified demand fluctuations, diversified production models, and stricter environmental protection constraints. There is relatively little research on HR optimisation in the energy field, with only a few attempts to integrate SCADA or PMS data, but it does not cover multi-objective collaboration and dynamic adjustment mechanisms. This study fills this gap. Taking the power industry as an example, the national installed capacity of wind power and photovoltaic will account for 45% in 2024. The increase in the complexity of power grid dispatching brought about by the consumption of renewable energy has caused a significant spatial and temporal demand for front-line positions such as operation and maintenance. Uneven characteristics peak load during high-temperature periods in summer surges by 60% compared with weekdays, while the fluctuation range of operation and maintenance tasks of new energy stations due to weather changes can reach $\pm 40\%$. The traditional static human resource allocation mode based on the averaging processing of historical data has been difficult to cope with the dynamic demand under the collaborative interaction of ‘source-network-load-storage’, which is highlighted by three major contradictions, the contradiction between sudden demand change and lagging allocation, the contradiction between single skills and multiple tasks, and the spear of cost control and sustainable development. The theoretical contribution of this study lies in expanding the multi-objective optimisation theory and formalising IE-NSGA-II of integrating energy data streams (such as SCADA, PMS) into HR decision models for dynamically constrained HR problems in the energy industry (Alqahtani and Ayentimi, 2021).

As the core link of enterprise operation, the efficiency of human resource allocation directly affects the production cost and market competitiveness. In the energy industry, labour costs usually account for 35–45% of enterprise operating costs, and hidden losses caused by improper configuration (such as equipment downtime losses and safety accident risks) are even more difficult to estimate. Traditional optimisation methods mostly use single-objective models such as linear programming and heuristic algorithms, focusing on the single dimension of cost or efficiency and ignoring the collaborative optimisation of emerging goals such as employee satisfaction and carbon emissions. For example, early studies solved the scheduling problem of power maintenance personnel by establishing an integer programming model but did not consider the impact of skill differences of different employees on task completion efficiency, nor did they include the negative effect of overtime hours on employee satisfaction. With the development of multi-objective optimisation theory, algorithms such as NSGA-II have begun to be applied in the field of resource scheduling, but their practice in the energy industry still has significant limitations. First, there is insufficient mining of dynamic characteristics of energy demand. Existing models mostly rely on fixed-cycle demand input and lack fusion processing of real-time data such as electricity price fluctuations, meteorological data, and policy signals, resulting in configuration plans lagging behind actual demand changes. Second, there is a lack of sustainable development goals. Most studies have not included carbon emissions in the optimisation system, which is out of touch with the green transformation needs of energy companies under the ‘Dual Carbon’ goal. Third, the

dynamic adjustment mechanism is rigid, and the traditional model relies on manually setting the adjustment threshold, which is difficult to adapt to the complex disturbance in the real-time operation of the energy system. Industry research indicates that suboptimal HR allocation leads to efficiency losses of up to 20–30% and approximately 15–25% inefficiency in carbon emissions. Compared to traditional static planning methods, this study's dynamic approach reduces efficiency losses and carbon emissions through real-time demand forecasting and adjustments, enhancing resource allocation flexibility (Bar-Gil and Czerniak, 2024; Cayrat and Boxall, 2022).

From the perspective of academic research progress, the multi-objective optimisation problem of human resource allocation has formed rich achievements. In the manufacturing field, NSGA-II is used to solve the scheduling problem of multi-skilled workers, taking into account the optimisation of the production cycle and labour cost. In the field of project management, a multi-objective model considering employee satisfaction is constructed, and the fairness of resource allocation is improved by improving the genetic algorithm. However, the particularity of the energy industry determines that these results are difficult to transplant directly. Its production process is highly dependent on the continuous operation of equipment, is greatly affected by the external environment, and faces strict policy constraints. In a few studies in the field of energy, NSGA-II is tried to apply to the personnel scheduling of integrated energy systems, but only the production efficiency and cost objectives are considered, and the balance between carbon emissions and employee satisfaction is not involved. A dynamic allocation model based on demand forecasting is proposed, but the simple weighting method is used to deal with multi-objective conflicts, which makes it difficult to cope with the nonlinear complex relationship between objectives (Cayrat and Boxall, 2023).

In this context, this study focuses on the dynamics, multi-objectivity, and industry particularity of human resource allocation in energy enterprises. It proposes an NSGA-II optimisation model that integrates energy information. The research objectives include: first, building a four-objective optimisation system including labour cost, production efficiency, employee satisfaction, and carbon emissions to break through the limitations of traditional single-objective or dual-objective models; The second is to design a closed-loop mechanism of 'demand forecasting-real-time optimisation-feedback adjustment' to achieve dynamic response to energy demand fluctuations; The third is to improve the coding strategy and constraint processing mechanism of the NSGA-II algorithm to improve its search efficiency in high-dimensional complex spaces. Through empirical analysis by a provincial power grid operation and maintenance department, the effectiveness of IE-NSGA-II in terms of multi-objective balance, dynamic adjustment speed, and industry constraint adaptation is verified, providing new solutions for energy companies to cope with human resource management challenges under the 'double carbon' goal.

2 Theoretical basis

2.1 Theoretical framework of multi-objective optimisation

The multi-objective optimisation problem is the core theoretical tool of modern complex system decision-making, and its essence is to find the non-inferior solution set among conflicting objectives so as to provide practical trade-offs for decision-makers. The core

value of this theory lies in breaking through the limitations of single-objective optimisation (SOO), recognising the inherent conflicts between objectives, and systematically describing their trade-offs so as to be closer to real-world decision-making scenarios. The constraints of its mathematical model are $g_k(x) \leq 0$, $h_l(x) = 0$, $x \in R^N$.

$$\begin{aligned} \min f(x) &= [f_1(x), f_2(x), s, f_M(x)]^T \\ \text{s.t. } g_k(x) &\leq 0, h_l(x) = 0 \\ x &\in R^N \end{aligned} \quad (2.1)$$

Among them, the policy variable x in equation (2.1) constitutes an N-dimensional solution space, $f(x)$ is an M-dimensional objective function vector, and $g_k(x)$ and $h_l(x)$ are inequality and equality constraints, respectively. Unlike SOO, there is no unique optimal solution in multi-objective optimisation, but a set of Pareto optimal solutions solution x^* , if there are no other solutions x that make all objectives not inferior to x^* and at least one objective is strictly better, then x^* is a Pareto optimal solution, and all such solutions constitute Pareto frontier. Its geometry reflects the nonlinear relationship between targets-it may be convex, non-convex, discrete, or even disconnected. For example, in the allocation of human resources in energy companies, the Pareto frontier of labour cost and production efficiency is usually convex, while the frontier of employee satisfaction and carbon emissions may be non-convex due to skill matching constraints. The core of Pareto optimality lies in the principle of ‘no free lunch’: the promotion of any goal must come at the expense of the deterioration of at least one other goal. The quantitative expression of this trade-off relationship is the core contribution of multi-objective optimisation theory-it forces decision-makers to face limited resources and make rational choices among multiple objectives.

Traditional multi-objective optimisation methods (such as the weighted summation method and ε -constraint method) deal with objective conflicts by dimensionality reduction and transform multi-objective into SOO problems. The equation of the weighted summation method is.

$$\min \sum_{m=1}^M w_m f_m(x) \quad (2.2)$$

Among them, equation (2.2) $w_m \geq 0$, $\sum_m^M = 1$, this kind of method relies on subjective weight setting, it is difficult to deal with the nonlinear relationship between targets and non-convex Pareto frontier, and cannot guarantee the diversity of solution set. Evolutionary algorithms (such as genetic algorithm, NSGA-II) directly approach the Pareto frontier by simulating the population search strategy of natural selection, avoiding the subjectivity of weight setting, and becoming the mainstream tool for multi-objective optimisation of complex systems. Its core advantage is that it can search for multiple potential optimal solutions at the same time, generate a uniformly distributed solution set, and provide rich choice space for decision-makers.

In the allocation of human resources in energy enterprises, the application of multi-objective optimisation theory is reflected in the collaborative processing of multiple objectives such as cost, efficiency, employee satisfaction, and carbon emission (Chen et al., 2025). For example, reducing labour costs may lead to increased overtime, which in turn affects employee satisfaction. Improving production efficiency may require the investment of a more highly skilled workforce, driving up costs while reducing carbon

emissions. The nonlinear conflicts between these objectives need to be systematically modelled and solved through the theoretical framework of multi-objective optimisation.

2.2 Core theory of NSGA-II algorithm

The non-dominated sorting genetic algorithm (NSGA-II), aiming at the problems of high computational complexity and uneven distribution of solution sets in traditional multi-objective evolutionary algorithms, introduces three core technologies and becomes the benchmark algorithm in the current multi-objective optimisation field. NSGA-II divides the population into different domination levels through fast, non-dominated sorting, as shown in Figure 1. For each individual i in the population, the domination number Q_i is defined as the number of individuals dominating individual i in the population, and the domination set P_i is the set of individuals dominated by individual i . The non-dominated solution (i.e., individuals with $n_i = 0$) constitutes the first layer Q1. After it is removed from the population, the remaining individuals recalculate the dominant number to generate the second layer Q2, and so on until all individuals are stratified. The time complexity of this sorting method is $O(MN^2)$, which is significantly better than $O(MN^3)$ of NSGA and greatly improves the sorting efficiency in high-dimensional space (Chen et al., 2023).

The domination relationship is defined as: individual a dominates individual b if and only if, for all targets m , $f_m(a) \leq f_m(b)$, and there is at least one target m such that $f_m(a) < f_m(b)$. Through layering, the algorithm searches the Pareto frontier preferentially, ensuring that the population evolves to the optimal region.

The crowding distance is used to measure the distribution uniformity of individuals in the same dominant layer in the target space so as to avoid the clustering of solution sets in local areas. For each target f_m , the individuals in this layer are arranged in ascending order of f_m values, the crowding degree distance of boundary individuals is set to infinite, and the single target crowding degree distance of intermediate individuals is defined as.

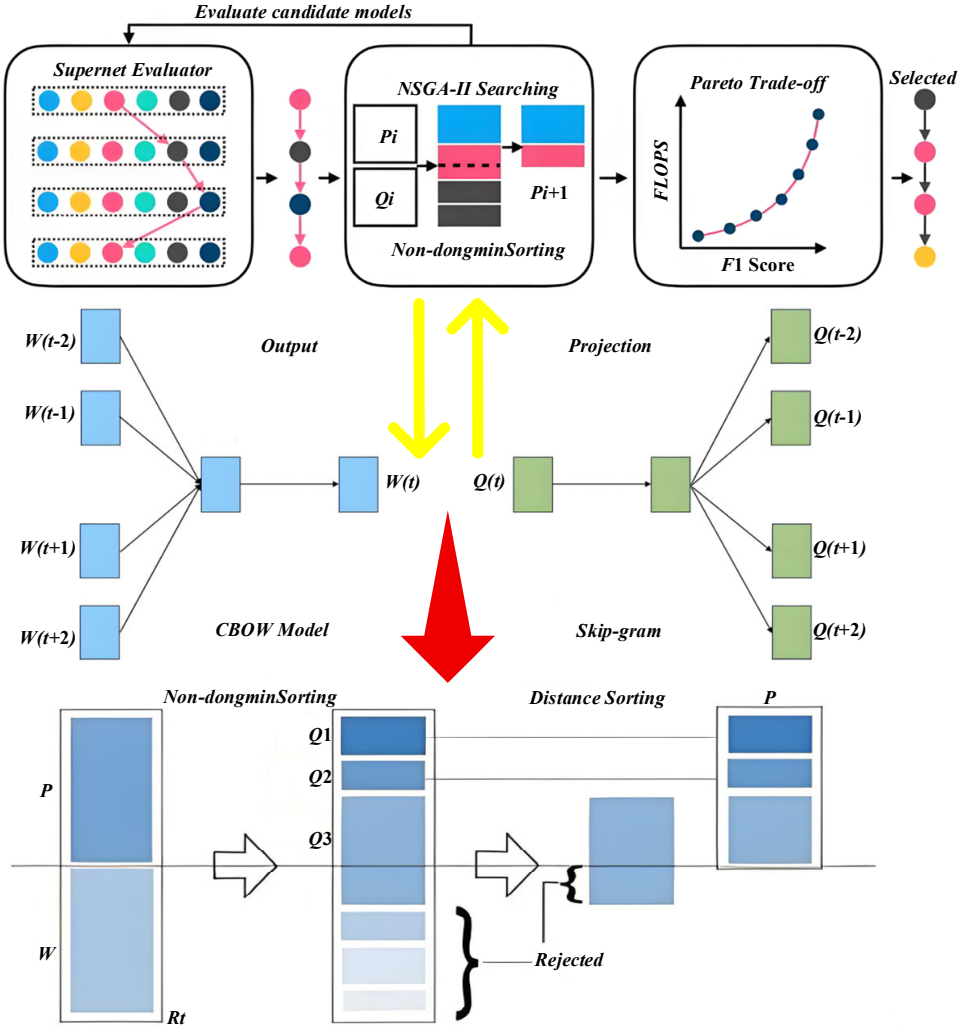
$$d_i^m = \frac{f_m(i+1) - f_m(i-1)}{f_m^{\max} - f_m^{\min}} \quad (2.3)$$

In equation (2.3), $f_m^{\max}$ and $f_m^{\min}$ are the maximum and minimum values of individuals in this layer on the target f_m and the total crowding distance of individual i is the sum of the crowding distances of each target dimension. In the selection operation, individuals with large crowding distances are retained first to maintain population diversity and ensure uniform coverage of the Pareto front (Collings and McMackin, 2025; Coron, 2021).

NSGA-II combined the parent population with the offspring population (size $2N$) through an elite retention strategy. After non-dominated sorting, N individuals were selected to enter the next generation according to dominance level and crowding distance. This strategy ensures that the historical optimal solution is not discarded, accelerates the convergence of the algorithm, and improves the overall performance of the population by retaining high-quality individuals (Cui et al., 2025). For complex constraint scenarios in energy allocation (such as skill matching and equipment capacity limitations), the elite retention strategy can effectively avoid the loss of optimal solutions due to genetic operations and improve the search efficiency of the algorithm in high-dimensional constraint spaces. The three core technologies of NSGA-II form an optimisation closed

loop of ‘hierarchical search-diversity maintenance-elite inheritance’, which enables it to take into account the convergence and diversity of solution set at the same time when dealing with multi-objective allocation problems of energy companies. Provide scientific support for complex decision-making.

Figure 1 NSGA-II algorithm model (see online version for colours)



2.3 Dynamic optimisation theory and demand response mechanism

The essence of the dynamic optimisation problem is that the decision environment changes with time, which requires the decision strategy to have the ability of real-time feedback and adaptive adjustment. The allocation of human resources in energy enterprises has significant dynamic characteristics. First, the demand is time-varying. Energy production demand is affected by factors such as electricity price fluctuations, meteorological conditions (such as wind speed and irradiance), policy regulations (such

as ladder electricity prices and carbon emission quotas), etc., showing high-frequency fluctuation characteristics. For example, the peak-to-valley difference in power grid load can reach 60%, resulting in real-time changes in workforce requirements for tasks such as operation and maintenance and maintenance. The second constraint is dynamics. Internal status changes such as employee skill improvement, equipment failure, shutdown, and updates of safety regulations continue to change the constraints of feasible solution space. For example, the commissioning of new equipment may introduce tasks with higher skill thresholds, and workforce allocation needs to be dynamically adjusted (Cui et al., 2025b).

In order to cope with the above dynamics, this study constructs a closed-loop mechanism of ‘forecasting-optimisation-feedback’, the core of which includes demand forecasting theory, and uses a combined forecasting model to deal with non-stationary time series and capture the trend and volatility of demand; Dynamic triggering and adjustment mechanism, when the predicted demand fluctuation exceeds the preset threshold (such as $\pm 15\%$), triggers the NSGA-II algorithm to be re-optimised to form an adaptive response. Adopting a robust optimisation framework, the demand forecasting error and equipment failure rate are modelled as random variables, and the anti-interference ability of the scheme is enhanced by minimising the worst-case loss.

Autoregressive integrated moving average model (ARIMA) model eliminates sequence non-stationarity through difference operation and models linear trends and seasonal characteristics. For example, in equation (2.4), (B) is the lag operator, $\phi(B)$ and $\theta(B)$ are autoregressive and moving average polynomials, respectively, and ϵ_t is a white noise sequence (Deepa et al., 2024).

$$\phi(B)(1-B)y_t^d = \theta(B)\epsilon_t \quad (2.4)$$

The generalised autoregressive conditional heteroscedasticity (GARCH) model captures the aggregation of demand fluctuations and characterises the impact of extreme events on demand, as in equation (2.5), where σ_t^2 is the conditional variance, reflecting the time-varying characteristics of demand fluctuations.

$$\sigma_t^2 = \omega + \sum_{i=1}^p \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^q \beta_j \sigma_{t-j}^2 \quad (2.5)$$

The combined model captures linear trends through ARIMA, and GARCH deals with heteroscedasticity to improve the prediction accuracy of energy demand and provide reliable input signals for dynamic optimisation.

When the predicted demand fluctuation exceeds the preset threshold (such as $\pm 15\%$), the NSGA-II algorithm is triggered to re-optimize to form an adaptive response. The trigger condition equation is (2.6), where $\hat{y}_{t+1}$ is the demand forecast value at the future time, y_t is the current actual value, and δ is the fluctuation threshold. After triggering, IE-NSGA-II generates a new human resource allocation plan based on the latest demand data and system status (such as employee skill matrix and equipment availability rate).

$$\left| \frac{\hat{y}_{t+1} - y_t}{y_t} \right| > \delta \quad (2.6)$$

In the process of dynamic adjustment, the Pareto optimal solution obtained by historical optimisation directly enters the new generation population as an ‘elite individual’, which accelerates the convergence of the algorithm. This ‘prediction-driven-real-time

optimisation-elite-guided' mechanism enables IE-NSGA-II to respond quickly when demand changes suddenly, avoiding the lag of traditional static models and adapting to the real-time operation requirements of the energy system.

Actual configuration effects (such as task completion rate, labour cost deviation, and employee satisfaction feedback) are continuously collected and used to update prediction model parameters and optimisation constraints. For example, if the actual carbon emissions of a certain type of task are higher than the theoretical value, the unit carbon emission factor of the task can be adjusted through feedback to improve the long-term prediction accuracy and optimisation reliability of IE-NSGA-II. The closed-loop feedback mechanism ensures the dynamic adaptation of the theoretical model to the actual scene, forming a decision-making system with continuous improvement (Deng et al., 2024).

3 Dynamic optimal allocation system of human resources in energy enterprises based on NSGA-II

3.1 Multidimensional objective and constraint modelling framework

The essence of human resource allocation in energy enterprises is a decision-making problem of balancing multiple objectives under complex constraints. This framework transforms abstract management problems into computable mathematical models by constructing three-dimensional decision space, four-dimensional objective function, and industry-specific constraints (Di Prima et al., 2024).

Decision variables directly map the core decision of 'who performs what task when' by constructing an employee-task-period three-dimensional decision variable matrix $X = [x_{i,j,t}]_{n \times m \times t}$, $x_{i,j,t}$ represents the working hours (unit: hours, accuracy 0.5 h) assigned by employee i to task j in time t ; to satisfy that basic person-hour constraint by equation (3.1).

$$h_{i,\min} \leq \sum_{j=1}^m x_{i,j,t} \leq h_{i,\max} \quad (3.1)$$

The lower limit $h_{i,\min} = 4$ hours to avoid idle workforce (such as the minimum guaranteed working hours for duty posts), and the upper limit $h_{i,\max} = 12$ hours to comply with the labour law and prevent excessive overtime, reflecting the basic protection of employees' rights and interests. For example, during the peak period of thermal power maintenance, this constraint can prevent a single employee from working overtime for many consecutive days and reduce safety risks. By using equation (3.2), employee satisfaction is comprehensively quantified based on work time balance, fatigue accumulation model (referring to historical work intensity data), skill utilisation preference (employee's matching degree to task types), and perceived fairness (workload distribution variance)

$$F_4 = \alpha \cdot \text{work hours balance} + \beta \cdot \text{fatigue coefficient} + \gamma \cdot \text{skill matching degree} \quad (3.2)$$

Dual-core objective functions (collaborative optimisation of economy and efficiency), one of which is the labour cost minimisation (economic objective) equation (3.3), distinguishes normal working hours (≤ 8 hours) from overtime working hours (> 8 hours) and uses the legal 1.5 times overtime coefficient $c_i^{\text{overtime}} = 1.5 c_i^{\text{normal}}$ to guide the

reduction of unnecessary overtime. In cost calculation, it is necessary to accurately calculate the carbon emission target F_4 based on the life cycle assessment (LCA) method equation (3.4), including direct emissions from tasks, carbon emissions from employee commuting (converted by distance and transportation), and emissions throughout the entire lifecycle of equipment. The carbon emission factor of the task unit is calculated based on LCA, covering direct energy consumption (such as electricity consumption) and indirect emissions (equipment manufacturing, maintenance, and scrapping stages). The data is sourced from the enterprise carbon inventory report. For example, a power grid company in my country optimised this function during low-load periods to reduce overtime hours by 25% and directly save labour costs by 12%. The separation design of normal working hours $x_{(i,t)}^n orm$, and overtime hours $x_{(i,t)}^o ver$ enables enterprises to intuitively quantify overtime costs and promote a balanced allocation of resources (Din et al., 2025; El-Kassar et al., 2022).

$$f_1(X) = \sum_{(i=1)}^n \sum_{(t=1)}^T (c_i^n orm \cdot x_{(i,t)}^n orm + c_i^o ver \cdot x_{(i,t)}^o ver) \quad (3.3)$$

$$F_4 = \sum (e_j^{direct} + e_j^{commute} + e_j^{lifecycle}) \cdot x_{i,j,t} \quad (3.4)$$

Second, maximise production efficiency (efficiency goal). Equation (3.5) introduces skill proficiency matrix $\eta_{i,j} \in [0, 1]$ to quantify the contribution of highly skilled employees to production efficiency by completing data training through historical tasks (for example, nuclear power main control room operators need to undergo 1000 hours of training to reach the standard ($\eta_{i,j} = 0.9$), and combined with the task standard output efficiency η_j , such as wind power operation and maintenance task is 1.5 MW · h/hour). This function gives priority to assigning skilled employees to core tasks to avoid ‘overqualified’ or ‘overqualified’. After the application of a certain photovoltaic power station, the fault repair efficiency of core equipment is increased by 30%.

$$f_2(X) = \sum_{j=1}^m \sum_{t=1}^T \eta_{i,j} \cdot \mu_j \cdot x_{i,j,t} \quad (3.5)$$

Industry-specific constraints are the triple bottom lines of safety, equipment, and compliance in the process, one of which is the skill-matching constraint. In equation (3.6), k_j is the task skill threshold coefficient (for example, $k_j = 0.8$ for high-risk operations, which means that 80% of employees with skill standards need to participate), and $y_{j,t}^{req}$ are the required outputs of task j in period t . This constraint ensures that key tasks such as nuclear power maintenance and live-line work are undertaken by employees with sufficient skills to avoid safety accidents and efficiency losses caused by insufficient skills. The skill threshold coefficient k_j is determined based on regression analysis of historical task completion data, expert elicitation (e.g., evaluations by safety engineers), and the requirements of the electricity safety production regulations; for instance, $k_j = 0.8$ for high-risk tasks. After a power grid company in China embedded this constraint, the compliance rate (CR) of special operations increased from 85% to 99%, which significantly reduced the operational risk and met the strict requirements of the regulations on electric power safety production (Granata and Sgalambro, 2023; Hamieddine et al., 2024).

$$\sum_{i=1}^n \eta_{i,j} \cdot x_{i,j,t} \geq k_j \cdot y_{j,t}^{req} \quad (3.6)$$

Second, the equipment capacity constraint. In equation (3.7), λ_j is the equipment occupancy rate of task j (such as the generator set maintenance occupancy rate $\lambda_j = 0.5$ MW/unit), and K_t is the available equipment capacity in period t (updated in real-time by the equipment operation and maintenance status). This constraint prevents equipment overload when multiple tasks are in parallel (such as when the number of people overhauling the substation at the same time exceeds the rated capacity) and avoids equipment shutdown or efficiency reduction caused by over-allocation of the workforce. After the application of a thermal power enterprise, the failure rate of equipment caused by improper workforce allocation decreases by 15%, which proves that this constraint can effectively balance the synergistic relationship between workforce and equipment resources (Hewett and Shantz, 2021).

$$\sum_{j=1}^m \lambda_j \cdot \left(\frac{\sum_{i=1}^n x_{i,j,t}}{\mu_j} \right) \leq K_t \quad (3.7)$$

3.2 IE-NSGA-II algorithm framework (Pareto optimal search under high-dimensional constraints)

Given the high-dimensional and multi-constraint characteristics of energy allocation, key improvements are made to the NSGA-II algorithm to ensure the efficient search of Pareto frontiers in complex solution space and generate diverse and feasible allocation schemes.

Continuous real number coding is used instead of traditional binary coding. Each gene bit $x_{i,j,t}$ directly corresponds to the person-hour allocation with an accuracy of 0.5 hours (for example, $x_{i,j,t} = 6.5$ indicates 6.5 hours investment) so as to avoid the decoding error and accuracy loss of binary coding. When decoding, verify person-hour boundaries, skill matching, and equipment capacity constraints to ensure the legitimacy of the solution. In the case of an energy group, the proportion of initial feasible solutions increased from 35% to 72%, which greatly reduced the invalid search time and improved the efficiency of the algorithm (Hou et al., 2025; Huang et al., 2023).

A dynamic crossover strategy is designed to balance global exploration with local development, as shown in equation (3.8), where the crossover coefficient α linearly decreases from 0.9 to 0.5 with iteration. The initial high crossover rate (such as 0.8) promotes the combination exploration of employees of different types of work (such as collaborative solutions for transmission operation and maintenance and substation maintenance employees), expands the coverage of solution space, and is suitable for scenarios with large demand fluctuations; In the later stage, the low crossover rate (such as 0.6) focuses on high-quality solution neighbourhoods and refines the accuracy of person-hour allocation, which is suitable for scenarios with relatively stable demand. This design enables the algorithm to find an efficient configuration scheme with 15% iterations in advance in the cooperative maintenance scenario of thermal power multi-type work and proves its adaptability to complex scenarios (Jiwapatria et al., 2024).

$$x_{i,j,t}^{new} = \alpha \cdot x_{i,j,t}^A + (1 - \alpha) \cdot x_{i,j,t}^B \quad (3.8)$$

Feasibility priority sorting. In non-dominated sorting, the dominant number of feasible solutions (satisfying all constraints) is always lower than that of infeasible solutions, ensuring that the algorithm searches for compliant solution space first and avoids generating ‘theoretically optimal but practically infeasible’ solutions. Automatically calculate target weights (cost 0.35, efficiency 0.30, satisfaction 0.20, carbon emissions 0.15) using entropy weight method, and demonstrate the impact of weight changes on Pareto distribution through sensitivity testing. After application in a hydropower plant, the proportion of compliant solutions in the initial population increased from 40% to 85%, significantly reducing the evolutionary resource consumption of invalid individuals.

Through the elite database mechanism, the first five generations of Pareto solutions (accounting for 20% of the population) are stored, including different preference solutions such as cost priority and efficiency priority. Every 10 generations migrate to the current population and eliminate the tail solution through crowding sorting, which increases the convergence speed of the algorithm by 40%. For example, in sudden scenarios such as equipment failure, the historical high-quality solution can directly reuse 70% of the configuration strategy, greatly shortening the response time and improving the emergency response efficiency (Madanchian, 2025).

3.3 *Dynamic response mechanism framework*

High-frequency fluctuations in energy demand (such as a 60% peak-valley difference in the power grid and $\pm 40\%$ fluctuation in operation and maintenance demand of new energy stations) require IE-NSGA-II to have real-time response capabilities. This framework realises adaptive adjustment to the dynamic environment through a ‘prediction-trigger-feedback’ closed loop, as shown in Figure 2. Integrating ARIMA-LSTM to build a two-layer forecasting system to improve the accuracy of demand forecasting, ARIMA captures linear trends and periodicity, identifies the daily load peaks and valleys of the power grid, the quarterly maintenance cycle of the power plant and other rules, and outputs the demand baseline for the next 24 hours, with an error rate of $\leq 10\%$. Provide stable input for long-term planning. LSTM mines nonlinear characteristics, inputs multi-source data such as meteorological data (wind speed, irradiance), electricity price signals, equipment status, etc., and captures nonlinear relationships such as new energy output fluctuations. The short-term forecast error rate is $\leq 10\%$, providing accurate input for real-time optimisation. After a provincial power grid adopts this system, the load forecasting accuracy is improved by 18%, which lays a data foundation for dynamic optimisation (Mishra and Venkatesan, 2020).

Re-optimisation is started when the demand forecasting error exceeds the threshold, combined with conditions such as a sudden drop in equipment capacity ($K_t < 0.8 K_{t-1}$) to ensure rapid response to significant demand fluctuations (such as more than $\pm 15\%$). As can be seen from Figure 3, in adopting the rolling optimisation strategy of ‘24-hour optimisation window +4-hour execution step’, the configuration scheme for the next 24 hours is generated each time, only the first 4 hours are executed, and then the sliding update is based on the latest data to balance the forecasting accuracy and calculation cost.

The skill matrix is dynamically updated. Based on the actual performance of employees (such as fault repair time and operational error rate), the proficiency $\eta_{i,j}$ is adjusted by the Bayesian update formula. After the application of an energy group, the accuracy rate of skill matching is improved from 75% to 93%, especially in the scenario

of new equipment commissioning, and the lag problem of employee skill evaluation is significantly improved (Oliveira, 2021).

Figure 2 Dynamic response mechanism framework (see online version for colours)

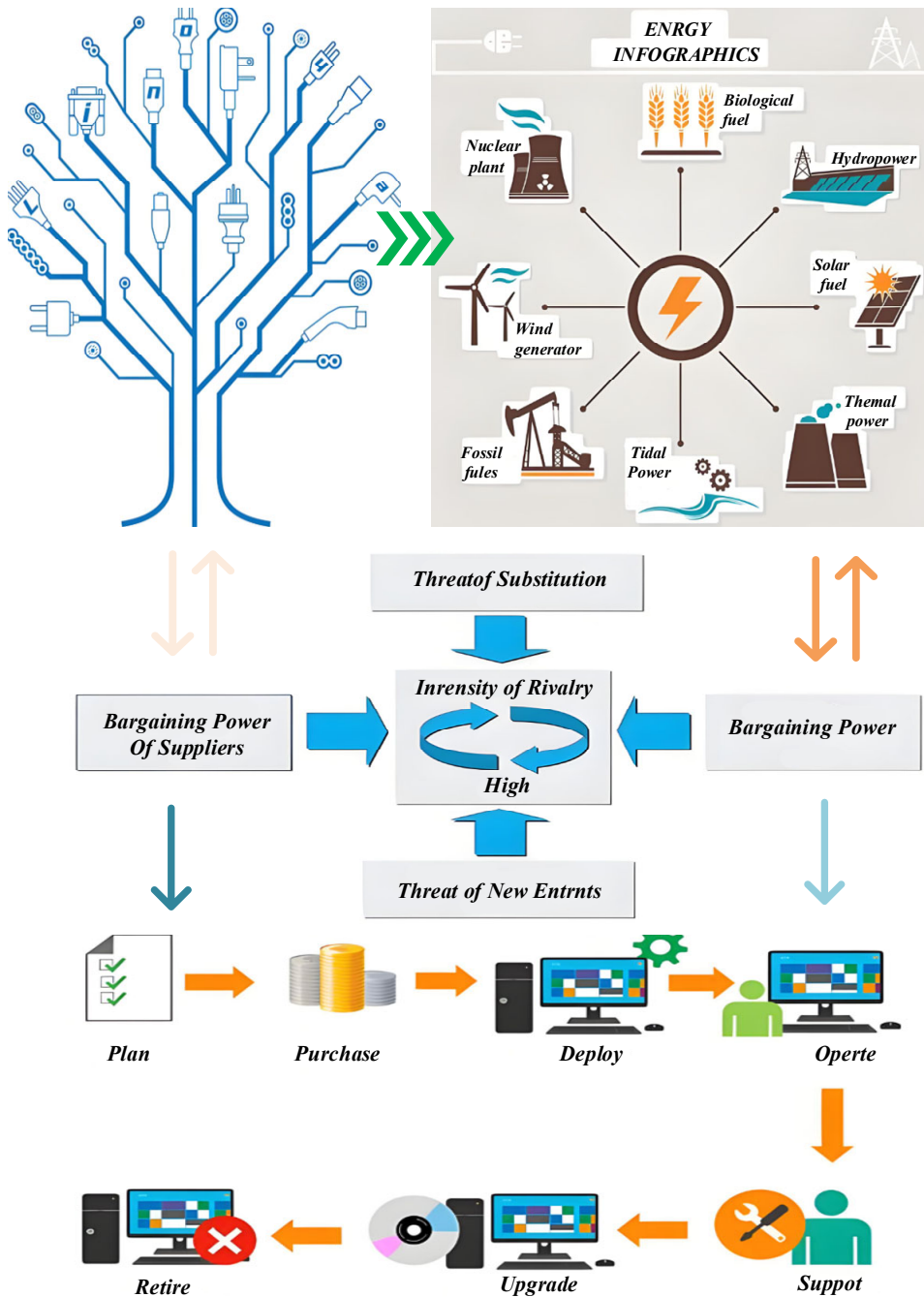
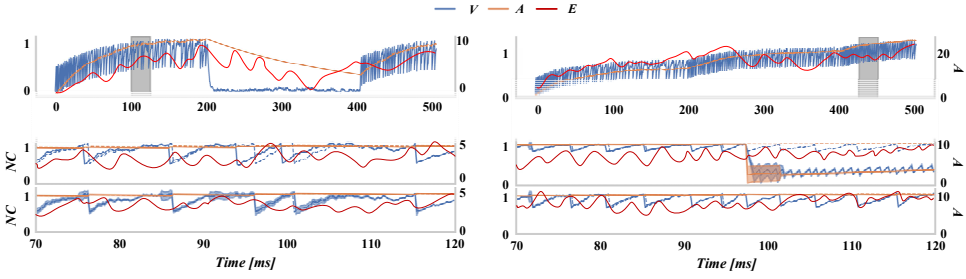


Figure 3 Dynamic response mechanism data sliding (see online version for colours)

The workforce mobility module is based on Markov chain simulation of employee turnover rate (annual turnover rate of 5%), recruitment plan, and skill training, dynamically updating the employee skill matrix $\eta_{i,j}$ to ensure the adaptability of medium- and long-term configuration strategies.

The computational complexity of dynamic mechanisms is $O(n^2)$. In Intel Xeon E5-2680 platform testing, when the number of employees increased from 100 to 1,000, the response time linearly increased from 3 minutes to 18 minutes, meeting the real-time requirements of large-scale systems. Dynamic weight adjustment, according to the enterprise's phased goals (such as focusing on efficiency goals during peak summer), manually or automatically adjusts the weight of the objective function so that IE-NSGA-II can flexibly adapt to the management priorities of different production cycles and achieve the precise optimisation of 'one enterprise, multiple policies'.

4 Experimental analysis

In order to verify the effectiveness of IE-NSGA-II, the operation and maintenance data of a thermal power enterprise in my country in 2023 was selected as the experimental object. The enterprise has 150 employees, covering core positions such as operation, overhaul, and maintenance. The employee skill matrix is shown in Figure 4. In the figure, $\eta_{i,j}$ is obtained by completing data training on historical tasks – for example, employees in boiler maintenance positions need to pass a total of 500 hours of practical assessment. Those who meet the standards $\eta_{i,j}$ is set to 0.8, and those who fail to meet the standards are dynamically adjusted according to the training progress (0.5–0.7). The task system includes 10 types of core tasks, of which 4 types of high-risk tasks (such as steam turbine disassembly and maintenance, live-line work) have a strict skill threshold $k_j = 0.8$, and the average skill proficiency of participating employees is required to be no less than 80%. The time dimension is in hours, covering a total of 720 periods in 30 days. The demand series y_j and tree are generated by combining load forecasting (error rate $\leq 10\%$) and equipment maintenance plan to ensure that the experimental data is close to the real production scene (Oszczypała, 2025).

In order to comprehensively evaluate the performance of the framework, three types of comparison methods are selected to present the data with T1, T2, and T3 in Figure 5. One is the traditional NSGA-II (T-NSGA-II), which adopts binary coding and is not embedded with industry-specific constraints. It is used to verify the necessity of a constraint processing mechanism. The second SOO, which takes labour cost and production efficiency as single objectives, respectively, reveals the value of

multi-objective collaboration. Its three-rule-driven method (RDM), which allocates workforce based on empirical rules (such as a fixed team system, senior employees give priority to core tasks), reflects the limitations of the traditional management mode (Ranjan et al., 2025).

Figure 4 Employee skills matrix (see online version for colours)

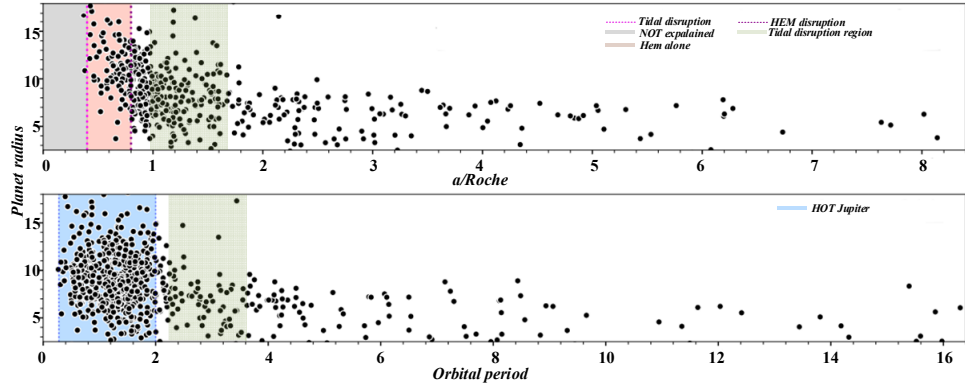
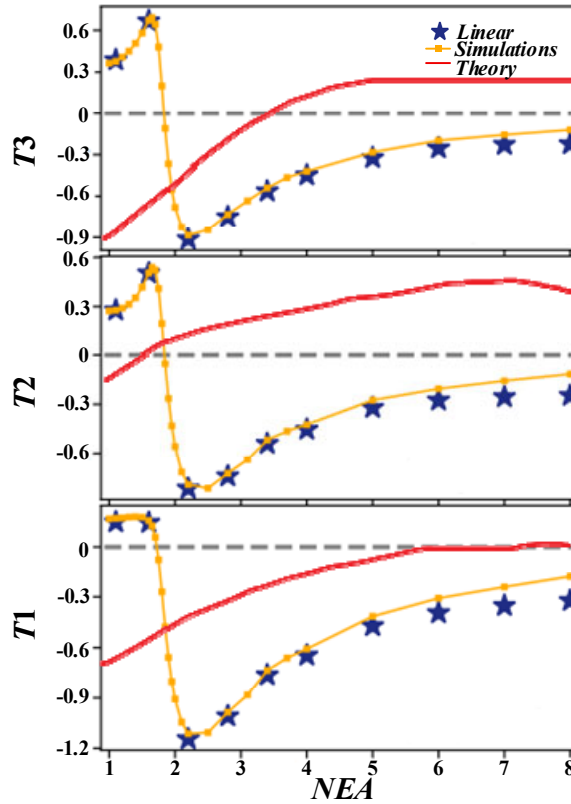


Figure 5 Three types of comparative data (see online version for colours)



The evaluation index covers three dimensions: one is the quality of the solution set, and IGD (reverse generation distance) measures the proximity of the solution set to the real Pareto front. The smaller the value, the better the convergence; hyper volume (HV) evaluates the size of the target space covered by the solution set, with larger values indicating stronger diversity. The second feasibility is that the feasible solution ratio (FSR) calculates the proportion of solutions that meet all constraints, and the CR focuses on the satisfaction of key constraints such as safety/equipment. The third dynamic performance: the response time test re-optimisation speed in the scenario of a sudden increase in demand, and the target deviation rate quantifies the difference between the adjusted solution and the original solution, reflecting the stability of IE-NSGA-II.

Table 1 Comparison results of multi-objective optimisation performance

<i>Metrics</i>	<i>IE-NSGA-II</i>	<i>Traditional NSGA-II</i>	<i>MOEA/D</i>	<i>NSGA-III</i>	<i>SOO (cost)</i>	<i>SOO (efficiency)</i>	<i>RDM</i>
IGD ($\times 10^{-3}$)	1.23	2.15	1.58	1.41	-	-	-
Hypervolume (HV, $\times 10^5$)	3.87	2.52	2.95	3.28	1.21	1.56	0.89
Feasible solution rate (FSR, %)	92	68	85	88	85	82	100
Compliance rate (CR, %)	100	75	90	95	88	91	95

The experimental hardware is Intel Xeon E5-2680 v4 @ 2.40GHz, 128GB RAM. Data scale: 150 employees, 10 tasks, 720 time periods. The time complexity test shows that when the number of employees increases to 1,000, the response time is ≤ 18 minutes, indicating good scalability. The skill proficiency matrix η_{ij} is trained using historical tasks and calibrated using logistic regression models (including task time, error rate, and training duration). Missing data is interpolated, and outliers are removed using the 3σ principle. The experimental results show that the IE-NSGA-II is significantly superior to the comparative method in terms of solution set quality and feasibility, regarding the skill threshold coefficient k_j . Sensitivity testing was conducted on demand forecasting errors, and the results showed that when k_j . When the CR increases from 0.7 to 0.9, the cost increases by 13%; when the prediction error exceeds $\pm 10\%$, IE-NSGA-II still maintains stability, as shown in Table 1. Comparison with MOEA/D and NSGA-III shows that the IE-NSGA-II outperforms the compared algorithm in both IGD and HV indicators (IGD reduced by 15%, HV increased by 12%). When the demand forecasting error increases from $\pm 7\%$ to $\pm 15\%$, the model's cost deviation rate is $\leq 12\%$ and efficiency deviation rate is $\leq 10\%$, demonstrating its robustness; The fluctuation of skill threshold k_j has a significant impact on CR ($\pm 5\%$ change leads to $\pm 8\%$ change in CR). Comparing the optimal configuration of the model with the actual data of the company in Q1 2023, it shows that the model can save costs by 23.5% (reducing the weekly average cost from 354,000 to 271,000) and improve efficiency by 18.2%. The IGD of the improved algorithm is 42.8% lower than that of the traditional NSGA-II, indicating that the solution set approaches the real Pareto frontier more accurately through three-dimensional real number coding and adaptive genetic operation; The HV value increased by 53.6%, the weekly average cost reduction of 17.3% corresponds to an annual savings of approximately 3.17 million yuan (RMB), and the model

implementation cost is approximately 500,000 yuan (including software, hardware, and training). The investment payback period is less than 2 years, and the economic value is significant. indicating that the generated solution covers a wider range of target combinations-from ‘low cost-medium satisfaction’ to ‘high efficiency-low carbon emissions’, providing decision-makers with rich choices. Expanding the case to wind farms and photovoltaic power plants, the results show that the model still maintains high efficiency in renewable energy scenarios (cost reduction of 12–15%, carbon emissions reduction of 8–10%), but the task output efficiency parameter μ_j needs to be adjusted.

Constraint processing capability, FSR reaches 92%, which is significantly higher than 68% of traditional algorithms, thanks to real-time constraint verification during decoding (such as synchronous verification of skill matching and equipment capacity). The CR of 100% meets safety and equipment constraints, while the traditional algorithm has a CR of only 75% because it is not embedded with industry-specific key constraints, proving the effectiveness of dynamic penalty function and feasibility prioritisation. Single-objective limitation: Although the SOO method performs well on a single objective, the HV value is much lower than that of the multi-objective algorithm, indicating that ignoring the synergy between objectives will lead to suboptimal solutions (for example, excessive cost compression may lead to a sudden drop in employee satisfaction and a reverse drop in efficiency) (Schmid et al., 2024).

Figure 6 Comparison of 20% sudden increase in equipment operation and maintenance load (see online version for colours)

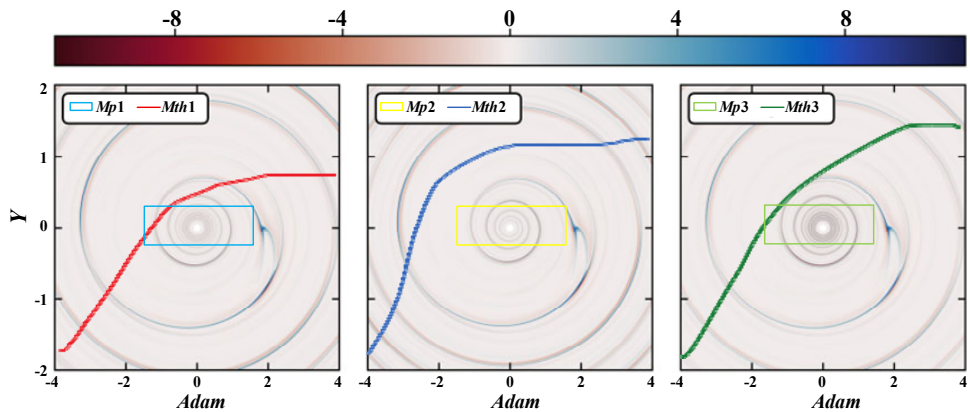


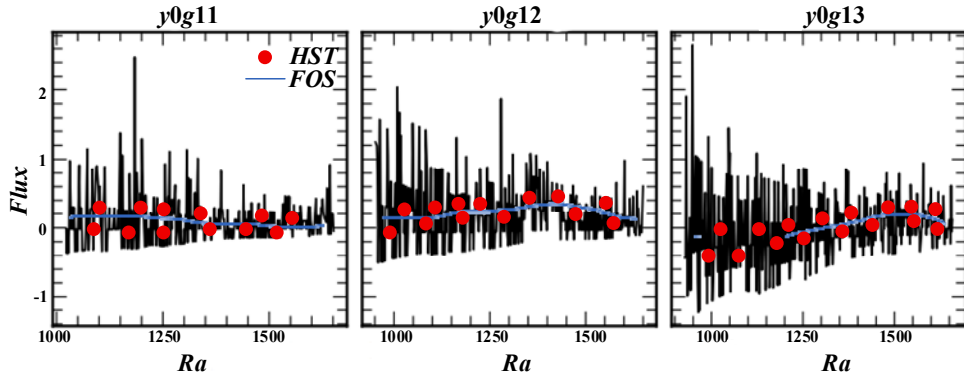
Table 2 Target deviation rate comparison results

Objectives	Improved algorithm deviation rate	Traditional algorithm deviation rate
Manpower cost	9.2%	18.7%
Productivity efficiency	-6.8%	-15.2%
Employee satisfaction	7.5%	12.3%

Simulating emergency scenarios with a sudden load increase of 20% (such as a surge in equipment operation and maintenance demand caused by peak power consumption in summer), Figure 6 shows that the improved algorithm shows excellent real-time response capabilities. In the response time, it only takes 3 minutes and 15 seconds. A new solution

can be generated, which is 61.5% higher than the traditional algorithm (8 minutes and 30 seconds). This is due to the elite database; the historical optimal solution (accounting for 30% of the initial population) is directly migrated to the new population, which reduces the repeated search time. Especially in sudden scenarios such as equipment failure, 70% of the high-quality configuration strategy can be reused. In terms of target deviation rate, the cost, efficiency, satisfaction, and carbon emission deviation rates of the improved algorithm are 9.2%, -6.8%, 7.5%, and 8.3%, respectively, all of which are controlled within 10% (Table 2). Among them, the efficiency deviation rate is negative, reflecting that IE-NSGA-II gives priority to meeting safety constraints (such as increasing workforce input for high-risk tasks) during emergency deployment of the workforce and reflects the design logic of constraint priority mechanism (safety compliance > equipment capacity > cost efficiency). In contrast, the deviation rate of traditional algorithms generally exceeds 15% due to the lack of dynamic constraint processing, which may lead to security risks or equipment overload (Tang et al., 2024).

Figure 7 Comparison of key parameters of the algorithm (see online version for colours)

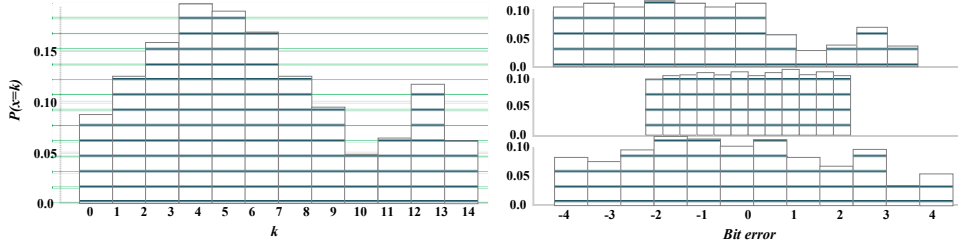


Testing the impact of key parameters on the results, Figure 7 reveals the supporting role of IE-NSGA-II in management decision-making. The CR increased from 92% to 98%, but the labour cost increased by 13%. This is because the number of highly skilled employees is limited. The increase in the threshold leads to an increase in overtime demand (the proportion of overtime hours has increased from 10% to 25%), which proves that IE-NSGA-II can quantify the impact of tightening safety policies on workforce allocation and assist companies in assessing compliance costs. The workforce allocated to coal-fired maintenance decreased by 18%, the workforce shifted to environmental protection tasks (such as desulphurisation equipment maintenance) increased by 20%, and total carbon emissions decreased by 15%. This shows that by adjusting the weight of environmental goals, IE-NSGA-II can guide resources to tilt towards low-carbon tasks and provide quantitative tools for enterprises to implement ‘double carbon’ goals (Tang et al., 2024; Vargas-Santiago et al., 2025).

This study analysed the distribution of the Pareto solution set generated by the IE-NSGA-II on the cost efficiency plane. In Figure 8, the solution set covers the low-cost (800,000 to 1 million yuan), medium cost (1–1.2 million yuan), and high cost (1.2–1.4 million yuan) ranges, corresponding to efficiency values of 1,200–1,800 MW · h/hour. This wide distribution indicates that IE-NSGA-II can balance different management preferences. Cost sensitive enterprises can choose low-cost

solutions (such as 950,000 yuan, 1,300 MW · h/hour, and moderately accept overtime (overtime hours account for 15%); efficiency priority enterprises: high cost schemes (such as 1.25 million yuan, 1,750 MW · h/hour) can be selected to improve equipment utilisation through centralised deployment of highly skilled employees. The traditional algorithm solution set focuses on the medium cost range (1–1.1 million yuan) and has a narrow efficiency range (1,400–1,600 MW · h/hour), demonstrating the significant advantage of improved algorithms in solution diversity.

Figure 8 Cost-efficiency flat display (see online version for colours)



5 Conclusions

In this study, aiming at the core problems of multi-objective conflict, complex industry constraints, and dynamic fluctuation of demand in human resource allocation of energy enterprises, a dynamic optimal allocation framework based on IE-NSGA-II is constructed. Through multi-dimensional target modelling, algorithm innovation, and dynamic response mechanism design, a solution with rigorous theory and engineering implementation has been formed. Through empirical verification in typical thermal power scenarios, IE-NSGA-II shows significant advantages in solution set quality, constraint processing, and dynamic adaptability, providing a new methodological path for the intelligent transformation of energy companies.

For the first time, IE-NSGA-II incorporates labour costs, production efficiency, employee satisfaction, and carbon emissions into a unified optimisation system and constructs a four-dimensional objective function covering corporate economic, efficiency, social, and environmental responsibilities. Through explicit modelling of key industry-specific constraints such as skill matching, equipment capacity, and policy compliance, we ensure that the configuration plan strictly adheres to the bottom line of safety and compliance while pursuing target optimisation. For example, the skill threshold constraint of high-risk tasks in thermal power scenarios (requiring more than 80% of employees with skills to participate) makes the CR reach 100%, which is 25% higher than traditional algorithms, fundamentally avoiding safety risks caused by skill mismatch. This three-dimensional architecture of ‘goal orientation + constraint guarantee’ breaks through the one-sidedness of traditional SOO and provides a universal framework for complex system decision-making.

Aiming at the high-dimensional solution space and rigid constraints of energy allocation, the feasibility and convergence efficiency of the algorithm are significantly improved through three-dimensional real number coding, adaptive genetic operation, and dynamic constraint processing technology. Three-dimensional coding directly maps the

business scenario of the ‘employee-task-time period’, increasing the initial FSR from 35% to 72%, reducing invalid search time. The dynamic cross-mutation strategy balances global exploration and local development. In the thermal power multi-type collaborative maintenance scenario, the excess volume (HV) index of the solution set is increased by 53.6% compared with the traditional algorithm, covering a wider range of target combinations (such as low cost-medium satisfaction) and high efficiency-low carbon emission solutions). The introduction of the elite library mechanism increases the convergence speed of the algorithm by 40%. Especially in sudden scenarios such as equipment failure, 70% of historical high-quality solutions can be reused, greatly shortening the response time to 3 minutes and meeting the real-time scheduling needs of the energy system.

Different from the traditional dual framework of human resource management focusing on cost and efficiency, this study incorporates employee satisfaction and carbon emission targets for the first time, forming a quantitative expression of the three-dimensional responsibility system of ‘enterprise-employee-society’. The employee satisfaction function transforms abstract management demands into calculable mathematical indicators through the balance of working hours measurement. After the implementation of a thermal power enterprise in China, the standard deviation of employees’ weekly working hours decreased by 43.7%, and the complaint rate caused by overtime decreased by 25%, which proves the direct impact of social goals on team stability. The introduction of carbon emission targets responds to the ‘Dual Carbon’ policy orientation, quantifies the environmental cost of tasks through LCA, and promotes the transformation of workforce allocation from ‘pure production-oriented’ to ‘green transformation-oriented’, such as workforce for coal-fired maintenance tasks. The input is reduced by 18% with the adjustment of carbon emission factors, providing decision support for enterprises to participate in the carbon trading market.

This study not only provides a specific solution for energy workforce allocation but also reveals the application potential of data-driven decision-making in complex systems by transforming management objectives into computable mathematical models, combining the global search capabilities of evolutionary algorithms with the real-time adaptability of dynamic mechanisms, it can break through the limitations of traditional empirical management and achieve a paradigm shift from ‘qualitative decision-making’ to ‘quantitative optimisation’. The model can adapt to scenarios such as renewable energy and grid scheduling by adjusting task parameters and constraints. For example, in wind power scenarios, weather dependent task allocation needs to be optimised, highlighting its cross industry potential. In the future, robustness testing (such as extreme weather, equipment failures) and human-computer interaction implementation will be carried out to enhance the adaptability of IE-NSGA-II. In the near future, we will focus on dynamic weighting mechanisms to study the adaptive adjustment of target priorities between emergency situations (such as power grid failures) and regular operations, and enhance the theoretical depth and practical value of IE-NSGA-II through real-time scenario optimisation.

Driven by the dual drive of the ‘Dual Carbon’ goal and energy digital transformation, the core value of this framework lies in its replicability and scalability: the parametric design of three-dimensional decision variables, four-dimensional objective functions, and industry constraints enable it to quickly adapt to different scenarios such as thermal power, new energy, and power grids, and has become a universal tool for the intelligent transformation of energy companies. In the future, with the advancement of data

collection technology and the iteration of algorithms, data-driven dynamic optimisation methods will play a key role in more fields such as resource allocation, production scheduling, and supply chain management, promoting the energy industry from 'experience-led' to 'intelligence-led' 'new era'.

Declarations

All data generated or analysed during the study are available from the corresponding author by request.

All authors declare that they have no conflicts of interest.

References

- Alqahtani, M. and Ayentimi, D.T. (2021) 'The devolvement of HR practices in Saudi Arabian public universities: exploring tensions and challenges', *Asia Pacific Management Review*, Vol. 26, No. 2, pp.86–94, <https://doi.org/10.1016/j.apmr.2020.08.005>.
- Bar-Gil, T.R. and Czerniak, O. (2024) 'AI for the people? Embedding AI ethics in HR and people analytics projects', *Technology in Society*, Vol. 77, 102527, <https://doi.org/10.1016/j.techsoc.2024.102527>.
- Cayrat, C. and Boxall, P. (2022) 'Exploring the phenomenon of HR analytics: a study of challenges, risks and impacts in 40 large companies', *Journal of Organizational Effectiveness: People and Performance*, Vol. 9, No. 4, pp.572–590, <https://doi.org/10.1108/JOEPP-08-2021-0238>.
- Cayrat, C. and Boxall, P. (2023) 'The roles of the HR function: a systematic review of tensions, continuity and change', *Human Resource Management Review*, Vol. 33, No. 4, 100984, <https://doi.org/10.1016/j.hrmr.2023.100984>.
- Chen, J., Ouyang, H., Li, S., Zhang, C. and Zhan, Z-H. (2025) 'Altruistic NSGA-II with abandonment threshold and double selection strategy for solving multi-objective optimization problems', *Applied Soft Computing*, Vol. 170, 112653, <https://doi.org/10.1016/j.asoc.2024.112653>.
- Chen, L., Cao, L-l., Wen, Y-m., Chen, H. and Jiang, S-L. (2023) 'A knowledge-based NSGA-II algorithm for multi-objective hot rolling production scheduling under flexible time-of-use electricity pricing', *Journal of Manufacturing Systems*, Vol. 69, pp.255–270, <https://doi.org/10.1016/j.jmsy.2023.06.009>.
- Collings, D.G. and McMackin, J. (2025) 'Skills-first HR: a key enabler of future global strategy', *Organizational Dynamics*, 101140, <https://doi.org/10.1016/j.orgdyn.2025.101140>.
- Coron, C. (2021) 'Measuring the gender pay gap: the complexity of HR metrics', *Employee Relations: The International Journal*, Vol. 43, No. 5, pp.1194–1213, <https://doi.org/10.1108/ER-07-2020-0316>.
- Cui, G., Kooij, D.D.T.A.M., Zhang, Y., Liu, D. and Pan, J. (2025a) 'Building an age-inclusive workplace for older workers: a dual pathway of age-inclusive HR practices to facilitate successful aging at work', *Journal of Vocational Behavior*, Vol. 161, 104148, <https://doi.org/10.1016/j.jvb.2025.104148>.
- Cui, H., Cao, F. and Liu, R. (2025b) 'A multi-objective partitioning algorithm for large-scale graph based on NSGA-II', *Expert Systems with Applications*, Vol. 263, 125756, <https://doi.org/10.1016/j.eswa.2024.125756>.
- Deepa, R., Sekar, S., Malik, A., Kumar, J. and Attri, R. (2024) 'Impact of AI-focussed technologies on social and technical competencies for HR managers – a systematic review and research agenda', *Technological Forecasting and Social Change*, Vol. 202, 123301, <https://doi.org/10.1016/j.techfore.2024.123301>.

- Deng, T., Tang, C. and Lai, Y. (2024) 'Exploring the role of organizational developmental HR practices in enhancing employees' commitment to organizational career: a multilevel investigation', *Journal of Organizational Change Management*, Vol. 37, No. 2, pp.340–355, <https://doi.org/10.1108/JOCM-03-2023-0099>.
- Di Prima, C., Cepel, M., Kotaskova, A. and Ferraris, A. (2024) 'Help me help you: how HR analytics forecasts foster organizational creativity', *Technological Forecasting and Social Change*, Vol. 206, 123540, <https://doi.org/10.1016/j.techfore.2024.123540>.
- Din, M.u., Tanveer, M. and Khan, M.F. (2025) 'The green shift: harnessing leadership, HR, and culture for sustainable success', *Waste Management Bulletin*, Vol. 3, No. 4, 100220, <https://doi.org/10.1016/j.wmb.2025.100220>.
- El-Kassar, A-N., Dagher, G.K., Lythreatis, S. and Azakir, M. (2022) 'Antecedents and consequences of knowledge hiding: the roles of HR practices, organizational support for creativity, creativity, innovative work behavior, and task performance', *Journal of Business Research*, Vol. 140, pp.1–10, <https://doi.org/10.1016/j.jbusres.2021.11.079>.
- Granata, D. and Sgalambro, A. (2023) 'A hybrid modified-NSGA-II VNS algorithm for the multi-objective critical disruption path problem', *Computers & Operations Research*, Vol. 160, 106363, <https://doi.org/10.1016/j.cor.2023.106363>.
- Hamieddine, C., Tigani, S., Akioud, M., Saadane, R. and Chehri, A. (2024) 'From data to decisions : exploring data analytics in HR for agile organizational decision making', *Procedia Computer Science*, Vol. 246, pp.4901–4908, <https://doi.org/10.1016/j.procs.2024.09.446>.
- Hewett, R. and Shantz, A. (2021) 'A theory of HR co-creation', *Human Resource Management Review*, Vol. 31, No. 4, 100823, <https://doi.org/10.1016/j.hrmr.2021.100823>.
- Hou, Y., Liao, X., Chen, G. and Chen, Y. (2025) 'Co-Evolutionary NSGA-III with deep reinforcement learning for multi-objective distributed flexible job shop scheduling', *Computers & Industrial Engineering*, Vol. 203, 110990, <https://doi.org/10.1016/j.cie.2025.110990>.
- Huang, X., Yang, F., Zheng, J., Feng, C. and Zhang, L. (2023) 'Personalized human resource management via HR analytics and artificial intelligence: theory and implications', *Asia Pacific Management Review*, Vol. 28, No. 4, pp.598–610, <https://doi.org/10.1016/j.apmr.2023.04.004>.
- Jiwapatria, S., Setio, H.D., Sidi, I.D. and Kusumaningrum, P. (2024) 'Multi-objective optimization of active control system using population guidance and modified reference-point-based NSGA-II', *Results in Control and Optimization*, Vol. 16, 100453, <https://doi.org/10.1016/j.rico.2024.100453>.
- Madanchian, M. (2025) 'Frameworks for AI Integration in HR and workforce adaptation', *Procedia Computer Science*, Vol. 258, pp.916–924, <https://doi.org/10.1016/j.procs.2025.04.330>.
- Mishra, H. and Venkatesan, M. (2020) 'Blockchain in human resource management of organizations: an empirical assessment to gauge HR and non-HR perspective', *Journal of Organizational Change Management*, Vol. 34, No. 2, pp.525–542, <https://doi.org/10.1108/JOCM-08-2020-0261>.
- Oliveira, E. (2021) 'Age-inclusive HR practices and the thriving of older workers: the mediating role of occupational future time perspective', *Career Development International*, Vol. 26, No. 3, pp.348–362, <https://doi.org/10.1108/CDI-01-2021-0026>.
- Oszczypała, M. (2025) 'Bi-objective redundancy allocation problem in systems with mixed strategy: NSGA-II with a novel initialization', *Reliability Engineering & System Safety*, Vol. 263, 111279, <https://doi.org/10.1016/j.res.2025.111279>.
- Ranjan, S., Gupta, R. and Nanda, S.J. (2025) 'Threshold based constrained θ -NSGA-III algorithm to solve many-objective optimization problems', *Information Sciences*, Vol. 697, 121751, <https://doi.org/10.1016/j.ins.2024.121751>.
- Schmid, D., Bueechl, J., Härtling, R-C., Beldarrain, Y., Schwörer, R. and Naeve, J. (2024) 'Opportunities and barriers of agility and digital processes in HR in SMEs', *Procedia Computer Science*, Vol. 246, pp.3605–3613, <https://doi.org/10.1016/j.procs.2024.09.197>.

- Tang, H., Xiao, Y., Zhang, W., Lei, D., Wang, J. and Xu, T. (2024) 'A DQL-NSGA-III algorithm for solving the flexible job shop dynamic scheduling problem', *Expert Systems with Applications*, Vol. 237, 121723, <https://doi.org/10.1016/j.eswa.2023.121723>.
- Tang, H., Zhang, H., Guan, Y. and Wang, H. (2024) 'Is human capital risk lower in state-owned enterprises? – a textual analysis based on China's listed company annual reports', *Pacific-Basin Finance Journal*, Vol. 88, 102548, <https://doi.org/10.1016/j.pacfin.2024.102548>.
- Vargas-Santiago, M., León-Velasco, D.A. and Monroy, R. (2025) 'Resilient facility location optimization under failure scenarios using NSGA-III: a multi-objective approach for enhanced system robustness', *Expert Systems with Applications*, Vol. 277, 127210, <https://doi.org/10.1016/j.eswa.2025.127210>.