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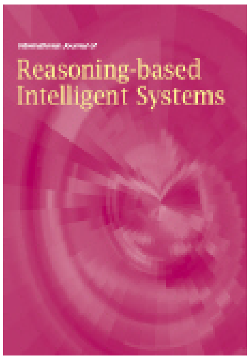

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Lei Yao

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Optimisation of operation algorithms based on artificial intelligence in power system control

Lei Yao

School of Information Engineering,
Nanning College of Technology,
Guilin 541006, China
Email: ylnnct202501@163.com

Abstract: The implementation of the dual carbon policy has introduced increased complexity in power system control and operation, owing to the interdependent nature of diverse generation units. To resolve the limitation in current research where power generation costs and environmental benefits cannot be optimised concurrently, this article first offers a multi-strategy adaptive particle swarm optimisation (PSO) approach (MAPSO) in light of a reward mechanism. Then, a dual-objective optimisation framework was established, simultaneously addressing power generation costs and gaseous pollutant emissions, while satisfying all necessary system constraints. Finally, by integrating external archiving technology, a multi-objective MAPSO (MOMAPSO) was proposed to compute dominated solutions for multiple objectives, thereby achieving overall operational optimisation. Simulation outcome indicate that the offered algorithm reduces fuel costs for power generation by at least \$294.6863/h and reduces pollutant emissions by at least 0.0101 t/h, achieving both economic and environmental benefits.

Keywords: power system control; operation algorithm optimisation; particle swarm optimisation algorithm; reward mechanism; external archiving technology.

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Biographical notes: Lei Yao received his Bachelor's degree from Beijing University of Chemical Technology in June 2011. He is currently working in Nanning College of Technology. His research interests include machine learning, electrical automation, motors and power electronics.

1 Introduction

As the global energy transition accelerates and the dual carbon objectives advance progressively, the power system is undergoing a historic transformation from a traditional fossil fuel-dominated vertical centralised architecture to a new power system dominated by new energy sources (Ardeshiri et al., 2021). The operation and control of power systems face two challenges: on the one hand, they must meet the stringent requirements of high-proportion renewable energy consumption for dispatch flexibility; on the other hand, they must cope with the new challenges to safety and stability posed by dynamic changes in grid topology. Traditional control algorithms based on mathematical modelling (such as optimal power flow and model predictive control) are constrained by parameter uncertainty, computational complexity, and real-time bottlenecks, making it difficult to efficiently handle multi-objective optimisation problems in new power systems (Ahmad et al., 2021). Heuristic optimisation algorithms in artificial intelligence (AI) technology provide a revolutionary approach to solving the above challenges. By simulating natural phenomena, they offer solutions with strong global search capabilities and high robustness for complex optimisation problems in power systems (Özlü et al., 2021).

Bogdan et al. (2007) fully considered the characteristics of air pollutants and carbon emissions from cement plants and their demand response capabilities in the control optimisation of power systems with wind power, achieving green and low-carbon operation of power systems through source-load coordination. Lotfy et al. (2017) considered factors such as system rotation reserves and network losses, and established a multi-objective dynamic environmental economic control optimisation model for wind-solar hybrid power systems. Panda and Das (2021) proposed the equal incremental rate method, which does not consider the constraints of each unit when optimising the output power of the units, resulting in the obtained unit output being too different from the actual production and unable to meet the actual operation requirements. Subsequently, people used mathematical methods to solve such problems, such as the gradient method (Souza et al., 2022) and Newton's method (Li et al., 2020), but these methods all have certain shortcomings. Heuristic algorithms, as an important branch of AI technology (Sangaiah et al., 2023), thereby improving the chance of discovering the globally optimal solution.

Mostafa et al. (2012) offered a novel combined AI-based optimisation technique based on particle swarm optimisation (PSO), in light of an unified control and performance optimisation approach, to minimise power consumption. Hasanien (2018) addressed the growing impact of photovoltaic uncertainty on power grids and proposed an economic control method for power systems that considers demand response based on the whale optimisation algorithm (WOA). Al-Shamma'a and Addoweesh (2014) proposed a decomposition-based multi-objective genetic algorithm (GA). Bai et al. (2021) proposed a Gaussian Cauchy difference evolution approach to address the economic environmental control optimisation issue in power systems, improving the algorithm in terms of solution accuracy and stability. Torkan et al. (2022) considered valve point effects, power transmission losses, and the feasible operating region of the system, and proposed a new GA based on collective information to solve the optimal control problem of multi-fuel cogeneration.

In addition to constraining the economic costs of power operation, multiple constraints must also be set in light of the characteristics in the power system. Karmellos and Mavrotas (2019) established a new multi-objective optimisation model. Pure thermal units, pure fire units, and cogeneration units were taken as the objectives, and the valve point effect of fire units was incorporated into the objective function. Mayer et al. (2020) used a Monte Carlo simulation GA to address a multi-objective optimisation model for power control. This method can more accurately simulate the actual operation of microgrid systems, while the optimisation search capabilities of GA also make the optimisation results more accurate and reliable. Hassan et al. (2024) used the white shark optimisation (WSO) algorithm to solve the power grid control model, taking into account the output characteristics of each power generation unit and the optimisation model. Parvin et al. (2023) offered a multi-objective PSO to address multi-objective improvement issues in power system control, which can effectively reduce system operating costs.

Most of the above studies establish multi-objective functions based on economic costs or operating costs, with few studies considering environmental benefits in power system operation control. Therefore, this paper optimises the power system control operation algorithm based on an improved PSO algorithm to reduce power generation costs and pollutant emissions. The innovative work of this algorithm can be summarised in the following four aspects.

1 To address the issue of traditional PSO easily falling into local optima, the multi-strategy adaptive particle swarm optimisation (MAPSO) algorithm is proposed, which employs a fitness-distance ratio-based particle displacement method to enhance population diversity. For the inertial weight and learning factor of particles, we propose a variation strategy based on a reward mechanism, which allows parameters to adaptively change during iteration to accelerate convergence speed.

2 The primary optimisation aims of the algorithm are centred around achieving the lowest possible aggregate power generation cost and the utmost reduction in pollutant emissions, for which a multi-objective function is established. To address these objectives, constraints for example system power balance, heat balance, and output capacity limits are proposed.

3 By integrating external archive technology, MOMAPSO was proposed to evaluate the density distribution of non-dominated solutions in the archive. Subsequently, select the Pareto-optimal and extreme solutions with highest crowding distance from the external archive to compose the global optimal set. With respect to each target particle, arbitrarily retrieve a solution from the updated global optimal solution set, and utilise it as the optimal solution for achieving compromise.

4 Simulation results demonstrate MOMAPSO's enhanced solution space exploration capability, achieving significantly broader coverage compared to baseline methods, quickly finding a set of optimal solutions with the best possible distribution. Applying this algorithm to power system control operations, comparative analysis shows that the algorithm can effectively balance power generation costs and environmental benefits, demonstrating high efficiency and robustness.

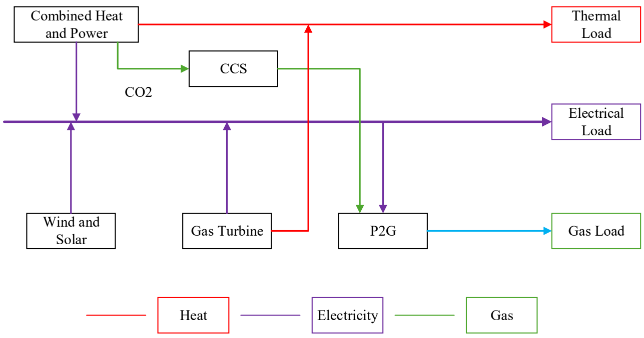
2 Relevant technologies

2.1 Power system control theory

The power control system is the core technology system that ensures the secure, stable, and cost-effective power system operation. It is mainly used for monitoring, regulating, and improving the entire process of power generation, distribution, and consumption. In the context of the extensive integration of renewable energy into large-scale power grids and the advancement of smart grid technologies, modern power control systems are evolving towards intelligence, adaptability, and high reliability. The power system has functions such as power generation, transmission, and distribution (Mohammad-Alikhani et al., 2022), mainly including distributed renewable energy, energy storage, and load. Traditional power grids only handle power supply, but new grids often need to handle heating and cooling too. The coupling of multiple energy flows, like electricity, heat, and cold, also makes it harder to optimise power system operations.

Figure 1 is a typical power control system, including energy input, energy conversion and storage, and energy consumption. The power grid contains various forms of energy, including cold, heat, electricity, and gas. Under specific conditions, different forms of energy can be converted into one another, with the ultimate goal of meeting the three types of load demands within the power grid: cold, heat, and electricity. The main power supply equipment for power control systems includes generator sets, switch control equipment, energy storage systems, etc. (Hossain et al., 2023).

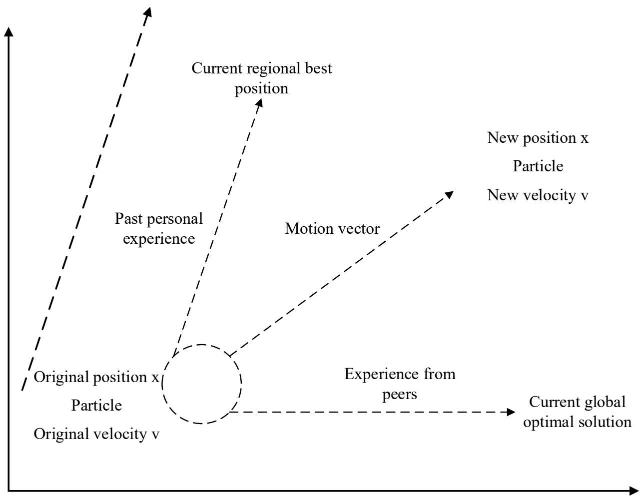
Figure 1 New power control system (see online version for colours)



2.2 PSO algorithm

PSO locates the optimal solution by means of collaborative efforts and the exchange of information among the individuals within a group (Gad, 2022). In comparison to alternative classical heuristic optimisation approaches, the PSO algorithm has the advantages of being easy to operate and implement, while requiring only a few control variables to be adjusted. It is currently widely used in AI algorithm-related application fields. The optimisation process of a single particle in PSO is shown in Figure 2.

Figure 2 The optimisation process of a single particle in PSO



The PSO commences with a collection of randomly initialised particles, and subsequently locates the optimal solution through an iterative process. At every epoch, particle tracking is performed to obtain the update based on the polarity value global polarity *Gbest* and individual polarity *Pbest*. After obtaining the individual and global extremes, the particle determines its position and velocity vectors again by using equation (1) and equation (2), respectively, and continues the next iteration until the optimal solution is found.

$$V_i^{k+1} = \omega V_i^k + c_1 r_1 \left(Pbest_i^k - X_i^k\right) + c_2 r_2 \left(Gbest^k - X_i^k\right) \quad (1)$$

$$X_i^{k+1} = X_i^k + V_i^{k+1} \quad (2)$$

where $i = 1,2,\ldots,N$, N are the total amount of particles in the group; X_i is the existing location of the particle; V_i is the particle's existing velocity; *Pbest* and *Gbest* represent the personal extremum and the global extremum respectively, w is the inertia coefficient; r_1 and r_2 are arbitrary values; c_1 and c_2 are studying elements.

3 Multi-strategy adaptive particle swarm algorithm based on reward mechanism

The traditional PSO approach only moves toward the individual's historical optimal location and the global optimal location, which leads to a decrease in population diversity. Thus, this article suggests a MAPSO algorithm in light of a reward mechanism. The algorithm is based on a multi-sample learning mechanism of fitness distance ratio. By calculating the fitness distance ratio, particles that are farther from the current particle position but have similar fitness values can be found. These particles often represent another local extreme point, which effectively avoids falling into a local optimum while increasing the population's diversity.

First, standardise the current position of the particles as shown in equation (3), where m^d and s^d are the mean and standard deviation in dimension d. Calculate the distance between other particles and the current particle using equation (4), and then calculate the fitness and distance ratio of the particles using equation (5), where X_i is the current position of the particle, $\bar{X}_i^d$ is the average value of the particle at the current position, F_i and F_j are the fitness of the particle, and RFD_j is the distance ratio of the particle.

$$\bar{X}_i^d = \frac{X_i^d - m^d}{s^d} \quad (3)$$

$$DG_j = \sum_{d=1}^{D} \sqrt{\left(\bar{X}_i^d - X_j^d\right)^2} \quad (4)$$

$$RFD_j = \frac{F_j - F_i}{DG_j} \quad (5)$$

Find the minimum value in matrix RFD_j, and use the particle corresponding to the minimum value as an additional sample RFD_{best}. Equation (6) gives the new particle velocity update equation, where $V_i^d(t+1)$ is the latest particle position, $V_i^d(t)$ is the particle position at the previous moment, $\omega(t)$ is the current weight, *pbest* is the individual extreme value, *gbest* is the global extreme value, c_1, c_2, c_3 are the learning factor, r_1, r_2, r_3 are the random number.

$$V_i^d(t+1) = \omega(t)\cdot V_i^d(t) + c_1 r_1\left(pbest_i^d(t) - X_i^d(t)\right) + c_2 r_2\left(gbest^d(t) - X_i^d(t)\right) + c_3 r_3\left(RFDbest^d(t) - X_i^d(t)\right) \tag{6}$$

In traditional PSO algorithms, inertia weights and learning factors are the key parameters that control the search behaviour of particles. The inertia weights mainly control the contribution of the particle's current speed to the next move, balancing global exploration and local exploitation. The learning factor regulates the attraction of the particle toward the individual historical optimum and the group historical optimum, respectively. In summary, the reason why particles cannot jump out of the local optimum is mainly related to the fixed settings of inertia weights and learning factors. When a particle becomes stuck in a local optimum during an iteration, this prevents the particles from effectively escaping the local optimum. Therefore, a parameter self-adaptive change strategy based on a reward mechanism is proposed. First, the particles obtain the reward value for the next iteration based on the fitness value after iteration using equation (7).

$$reward_i(t) = \begin{cases} 2, & f(X_i) < f(gbest) \\ 1, & f(X_i) < f(pbest) \\ 0, & otherwise \end{cases} \tag{7}$$

After obtaining the reward value, the particle obtains the adjustment parameters through equation (8), and then calculates the values of the inertial weight and learning factors to be employed in the subsequent iteration, which are determined based on the adjusted parameters. The formulas for the inertial weight and learning factor are shown in equation (9) and equation (10), respectively. Through this adaptive reward mechanism, each particle obtains parameters suitable for the current iteration process in each iteration, thereby improving the convergence, diversity, and ability of the population to escape local optima, where $reward_i(t)$ is the reward function, $f(X)$ is the fitness function, $AC_i(t)$ is the adjustment function, and $f(gbest)$ is the fitness function for global extremes.

$$AC_i(t) = \frac{1}{reward_i(t) + e^{f(X) - f(gbest)}} \tag{8}$$

$$\omega_i(t+1) = \omega(t+1) * \left(AC_i(t) + 0.5\right) \tag{9}$$

$$c_i(t+1) = \begin{cases} c_i(t+1) * \left(AC_i(t) + 0.3\right), & f(X_i) < f(gbest) \\ c_i(t+1) * \left(AC_i(t) + 0.7\right), & otherwise \end{cases} \tag{10}$$

The traditional PSO algorithm typically updates positions based on the previous iteration's position and current velocity. This position update method lacks a process for conducting a detailed search around the global optimum solution. Therefore, a spiral search mechanism is introduced in the subsequent stages of the approach iteration to enhance local search capabilities. The new position update formula is as below.

$$X_i^d(t+1) = \begin{cases} \left|gbest^d(t) - X_i^d(t)\right| \cdot \beta + gbest^d(t), \\ rand > Pf \\ X_i^d(t) + V_i^d(t+1), \quad otherwise \end{cases} \tag{11}$$

$$\beta = \exp(bl)\cdot\cos(2\pi b) \tag{12}$$

$$Pf = 1.3 - \frac{t}{maxgen} \tag{13}$$

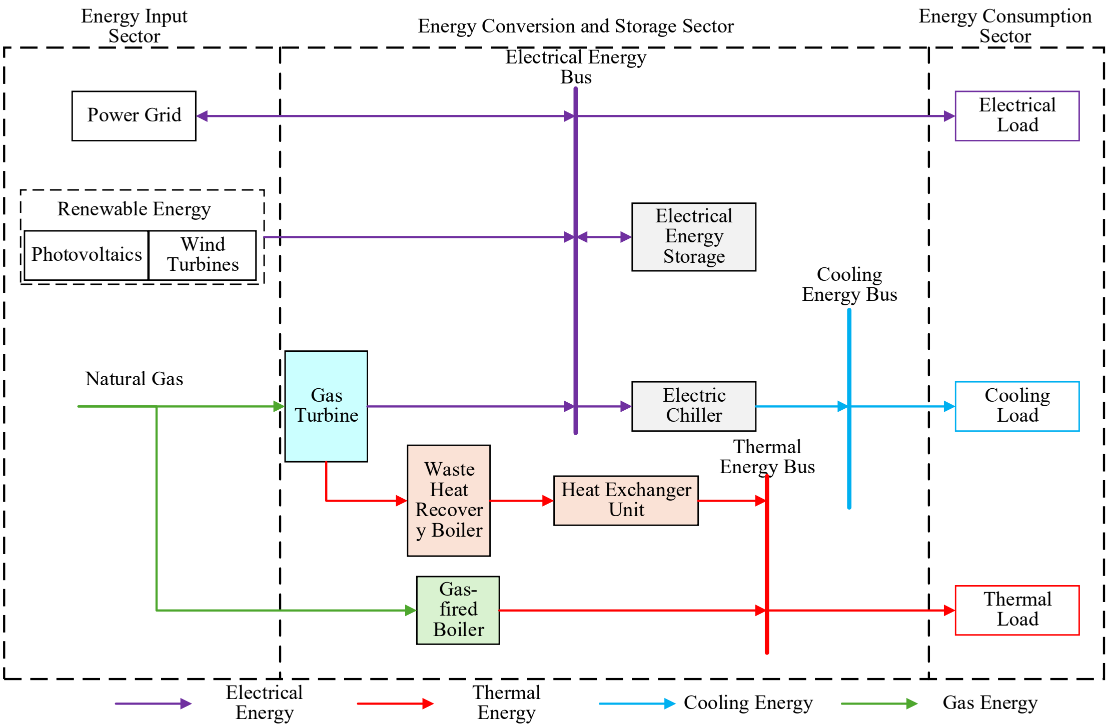
where b is an arbitrary value among –1 and 1, and Pf is the probability of performing a spiral search. To further avoid getting stuck in a local optimum, the number of times the global optimum solution has not been updated is represented by the number of stagnations *stag*. When the amount of stagnations achieves the set threshold, the global optimum solution *gbest* is perturbed using the Cauchy perturbation (Haklı and Uğuz, 2014).

4 Establishment of objective functions and constraints for power system control optimisation

4.1 Design of objective function for power system control optimisation

The fundamental goal of power system operation is to satisfy electricity demand while minimising generation fuel expenditures, without considering the environmental impact. However, under the dual carbon context, energy conservation and emission mitigation have emerged as a pivotal control target within the domain of power systems, requiring the lowest possible generation costs while ensuring minimal harm to the environment. Therefore, to address the current research limitation of not being able to balance economic and environmental benefits in power system control, a multi-objective optimisation function for power system control is designed. Constraints related to economic and environmental factors are jointly optimised through a composite objective function. The multi-objective MAPSO developed in subsequent chapters is adopted to optimise the multi-objective problem. The flow of the suggested power system control optimisation algorithm is shown in Figure 3.

Figure 3 Multi-objective MAPSO-based power system control optimisation process (see online version for colours)



The process of optimising power system control constitutes a non-convex, nonlinear, high-dimensional, multi-objective optimisation issue that is subject to a multitude of constraints. Its objective function includes economic and environmental aspects, and there exists a mutually conflicting correlation between the power generation cost function and the pollutant emission function. In other words, when power generation costs are lowest, environmental pollution is more severe. Conversely, when pollutant emissions are lowest, economic benefits are low. Therefore, it is necessary to seek a compromise solution that maximises the benefits of both the economy and the environment.

1 Power generation costs of generator sets. The principal aim of power dispatch is to achieve the minimisation of the aggregate generation cost across all power-producing units within the power system. The target function expression for the total generation cost of a quadratic function which is employed to represent the power generation units within the technical framework, as indicated in equation (14). This objective does not consider the valve point effect of the generator set, so the target function for the aggregate cost of power generation is shown in equation (15).

$$C(P) = \sum_{i=1}^{N} \left\{ a_i P_i^2 + b_i P_i + c_i + \left| d_i \sin\left[e_i \left(P_i^{\min} - P_i \right) \right] \right| \right\} \quad (14)$$

$$C(P) = \sum_{i=1}^{N} a_i P_i^2 + b_i P_i + c_i \quad (15)$$

where $C(P)$ is the overall cost associated with the generation of electric power for the designated power-generation unit; $P_i^{\min}$ is the least allowable active power output magnitude for the i^{th} power generating component; N is the total number of power generation units in the power generation system; a_i, b_i, c_i, d_i, and e_i are the electricity generation cost coefficients for the i^{th} power generation unit; and P_i is the output power of the power generation unit.

2 Pollutant gas emissions from generator sets. When generator sets burn fossil fuels, they produce large amounts of polluting gases that cause serious harm to the environment. The dispatch objective is to minimise the full emissions of pollutants from power plant generating units. The emissions of each pollutant are linked to the real power introduced into the system by each individual entity and are all independent functions. By combining the pollutant emission targets of each power generation unit, a comprehensive function relationship was established, as shown below.

$$E(P) = \sum_{i=1}^{N} \left[10^{-2} \left(\mu_i + k_i P_i + \pi_i P_i^2 \right) + \sigma_i e^{(\theta_i P_i)} \right] \quad (16)$$

where $E(P)$ is the total pollutant gas emissions from conventional power generation units; μ_i, k_i, π_i, σ_i, θ_i is the pollutant gas emission coefficient of the i^{th} conventional power generation unit.

4.2 Establishment of constraints related to power system control optimisation

After establishing the objective functions for power generation costs and pollutant emissions, this paper proposes a set of constraints for these objective functions, including system power balance constraints, heat balance constraints, and output capacity limits, as shown below.

The constraint on system-level power equilibrium and the constraint on thermodynamic equilibrium within the power control system are shown in equation (17) and equation (18), respectively, where P_D is the total active power of the load, O_i is the output power of the generator set, H_D is the total heat demand of the power control system, N is the amount of generator sets, H_i is the heat generation power of the generator set, and T_i is the heat generation power of the pure heat generator set.

$$P_D = \sum_{i=1}^{N} \left(P_i + O_i \right) \tag{17}$$

$$H_D = \sum_{i=1}^{N} \left(H_i + T_i \right) \tag{18}$$

In power system control, every individual unit is subject to a distinct output capacity constraint. For generator units, due to their physical characteristics, the upper and lower constraints on output magnitude are presented as follows.

$$P_i^{\min} \le P_i^{\max} \tag{19}$$

where $i \in 1,2,\dots,N$ and $P_i^{\min}$ are the minimum thresholds for the active power output capacity of the generator assembly; $P_i^{\max}$ represents the maximum threshold for the active power output capacity of the generator assembly.

For power generation units, the output is first limited by upper and lower limits. Second, electrical power and thermal power are interrelated, with one type of output constraining the other, thus defining the operating range of the power generation unit. The upper and lower boundaries of thermal power output capacity are delineated in the manner set out below.

$$P_i^{\min}\left(H_i \right) \le P_i^{\max}\left(H_i \right) \tag{20}$$

$$H_i^{\min}\left(P_i \right) \le P_i \le H_i^{\max}\left(P_i \right) \tag{21}$$

where $P_i^{\min}(H_i)$ constitutes the minimum threshold for the active power output capacity of the generator assembly; $P_i^{\max}(H_i)$ functions as the maximum threshold for the active power output capacity of the generator assembly.

5 Optimisation of operating algorithms in power system control based on multi-objective MAPSO method

The multi-objective optimisation function established in the previous section reflects a fundamental difference between multi-objective and single-objective algorithms: rather than yielding a unique global optimal solution, the outcome transforms into a set of solutions. The optimisation results constitute a group of Pareto optimal solutions (Han et al., 2023). Yet, in the offered MAPSO algorithm, the individual optimal solution and the global optimal solution are given equal weights, despite the fact that different search stages necessitate varying weight settings. This significant discrepancy leads to the algorithm's failure to satisfy the search performance criteria at different stages. Consequently, the present paper puts forward a multi-objective optimisation algorithm, MOMAPSO, and applies it to power system control to determine the optimal solution which leads to the least fuel expenditure for power generation and the smallest amount of pollutant discharges as the objective function, thereby achieving overall operational optimisation.

Currently, the main method for updating *gbest* in multi-objective PSO is to randomly select from an external archive that stores a predetermined number of Pareto-efficient solutions. Under this particular approach, each particle employs an uniform *gbest* parameter throughout every epoch step. In the event that *gbest* is identified as a local optimum, every particle will gravitate toward it, which will hamper the exploration of the solution space, i.e., getting stuck in a local optimum.

External archiving technology is still used in MOMAPSO. However, *gbest* is not chosen arbitrarily from the comprehensive collection of the external archive. First, two extreme solutions were identified, corresponding to the minimal fuel expenditure associated with power generation and the minimum levels of pollutant gas discharges. Second, determine the crowding distance metric for every Pareto-optimal solution within the outer archive. Then, extract the top five Pareto – optimal solutions with the highest crowding distances and the two extreme solutions from the external archive. Meanwhile, aggregate them to form a new set of global optimal solutions for further processing. Finally, concerning every target particle, arbitrarily extract a solution from the novelly established set of global optimal solutions, and utilise this extracted solution as the optimal solution for the objective particle. This enhanced strategy diminishes the probability of *gbest* being equivalent to *pbest*, thereby guaranteeing that particles will not stay in a dormant state.

With the escalation of the iteration count, the quantity of Pareto-optimal solutions within the external archive progressively rises. Once it surpasses the pre-specified value, certain solutions must be eliminated. In general, the slope is calculated as follows to delete redundant solutions.

$$k_{i,i+1} = \frac{\left(f_{2,i} - f_{2,i+1}\right) / \left(f_{2,\max} - f_{2,\min}\right)}{\left(f_{1,i} - f_{1,i+1}\right) / \left(f_{1,\max} - f_{1,\min}\right)} \tag{22}$$

$$k_{i-1,i+1} = \frac{\left(f_{2,i-1} - f_{2,i+1}\right) / \left(f_{2,\max} - f_{2,\min}\right)}{\left(f_{1,i-1} - f_{1,i+1}\right) / \left(f_{1,\max} - f_{1,\min}\right)} \tag{23}$$

where $k_{i,i+1}$ represents the standardised gradient between the i^{th} and $(i+1)^{\text{th}}$ Pareto-optimal solutions. $k_{i-1,i+1}$ constitutes the standardised gradient between the $(i-1)^{\text{th}}$ and $(i+1)^{\text{th}}$ Pareto-optimal solutions. If $k_{i,i+1} \leq k_{i-1,i+1}$, delete the i^{th} Pareto optimal solution.

MOMAPSO is based on multi-objective technology, where particles in the population cooperate with each other to identify a collection of Pareto-optimal solutions with the best approximation, breadth, and uniformity. The power system control optimisation approach in light of the MOMAPSO method is as below.

1 Derive the upper and lower bounds of the output data corresponding to each generator within a multi-generator power system, the coefficient data for the fuel consumption function, the coefficient data for the harmful gas emission function, the total system load, and the power generation cost data, and establish a mathematical optimisation model for power system control.

2 Randomly initialise a population of N particles and their corresponding fitness values. For a multi-objective problem with N objectives, divide the population into N subpopulations, and initialise the speed, maximum iteration count, *pbest* and *gbest* of all particles, as well as $N_{\max}$ for each subpopulation and the external archive set.

3 Update the velocity of all particles in the population using equation (6). Compute the target of the novel particles' fitness values, determine whether they can dominate the non-dominated solutions in the external archive, and if so, generate a reward learning factor; otherwise, generate a penalty learning factor. Update *pbest*, *gbest*, and $N_{\max}$ separately.

4 Update the external archive set, determine whether the external archive size exceeds the population size, and if so, use the crowding distance to update the external archive. Increase the number of iterations and ascertain whether the termination requirement of the algorithm is fulfilled. If so, proceed to step (5); otherwise, proceed to step (3).

5 Output the Pareto optimal frontier. Use the determined final solution as instructions and send them through the automatic power generation control device to the automatic control and regulation devices of the relevant power plants or units to achieve control of the power generation capacity of the units, the algorithm ends.

6 Experimental results and analyses

This study validates the feasibility of the NSMFO-BERT optimisation method using the IEEE 118-bus power system. All experiments were conducted in MATLAB 2024a on a computer equipped with an AMD R7-8845HS 3.8GHz CPU and 32.0GB RAM. The decision variable in this research is the electrical power output from generating units, including thermal power, wind power, photovoltaic power, nuclear power, biomass power, tidal power, pumped storage power, and virtual power generation units. The coefficients pertaining to power generation cost and carbon emission are derived from relevant references (Güven and Samy, 2022). In the experiment, the maximum amount of epochs was 200, the population size was 100, and the learning rate was 0.01. The experimental parameters are set as shown in Table 1.

Table 1 Experimental parameter setting

Parameters	*Number of iterations*	*Number of populations*	*Learning rate*	*Learning factor*	*Inertia weight*
Value	200	100	0.01	0.5	0.5

MOMAPSO was compared with five heuristic optimisation algorithms, namely GA, ACO, PSO, ABC, and WOA. The convergence curves of various approaches are shown in Figure 4. As can be seen from Figure 4, the convergence speed of GA is significantly lower than that of the other five algorithms, while MOMAPSO can converge to an optimal target value within a short iteration time. This is because MOMAPSO finds particles that are farther away from the current particle position but have similar fitness values by calculating the fitness distance ratio. This increases population diversity while effectively avoiding getting stuck in local optima.

Figure 4 Convergence curves for different algorithms (see online version for colours)

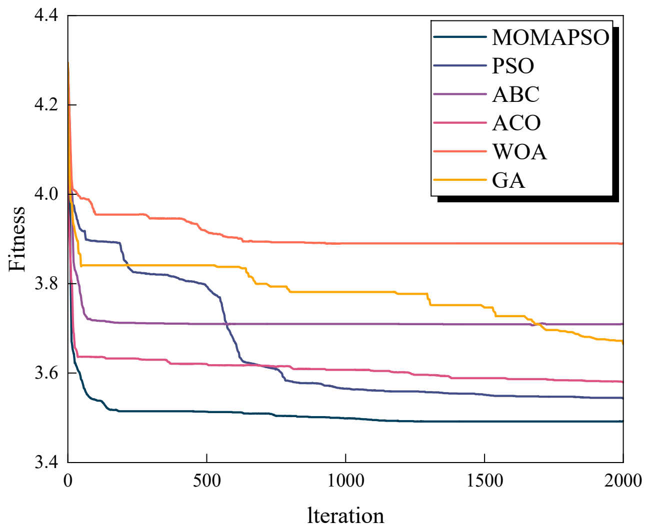


Figure 5 Pareto curve for 03:00-04:00 (see online version for colours)

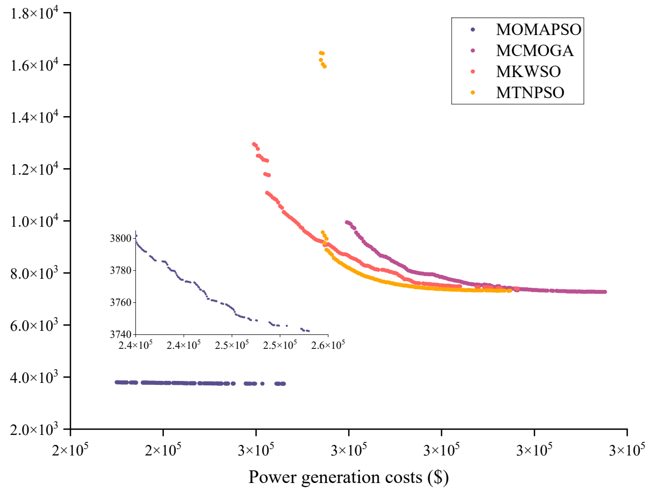
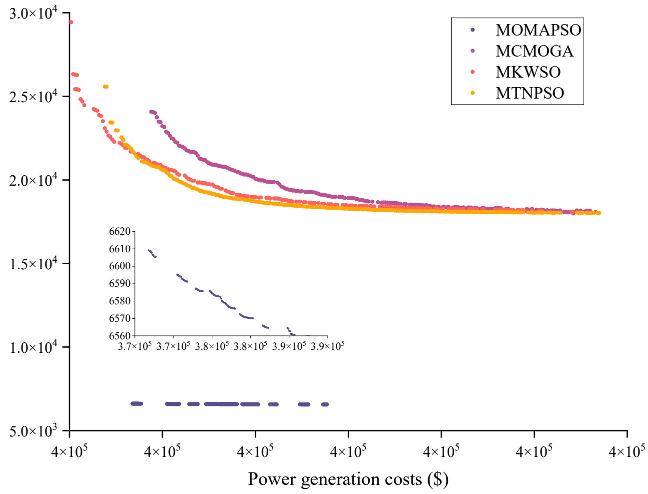


Figure 6 Pareto curve for 21:00-22:00 (see online version for colours)



This paper compares the proposed MOMAPSO method with the MCMOGA, MKWSO, and MTNPSO methods through experimental comparisons. The Pareto curves of different methods at 3:00–4:00 and 21:00–22:00 are shown in Figure 5 and Figure 6 respectively. The Pareto curves for these two time periods represent the overall optimisation results for the entire day. As shown in Figure 5, the Pareto curve obtained by MOMAPSO is generally located to the lower left of the curves obtained by other methods, indicating that the power generation costs and carbon emissions obtained by MOMAPSO are lower than those obtained by other comparison algorithms. This means that, with the same number of iterations, MOMAPSO can achieve lower power generation costs and carbon emissions, demonstrating its strong exploration capabilities and ability to effectively discover solution spaces that other algorithms have failed to explore. Figure 6 shows that MOMAPSO achieves significantly lower carbon emissions than other algorithms under the same power generation cost conditions. This indicates that MOMAPSO performs well in optimising carbon emission targets and can provide more environmentally beneficial solutions.

The optimisation results of different methods are compared in Table 2. For the optimal extreme value solution of power generation fuel costs, MOMAPSO obtained a value of $27,675.9198/h, with related pollutant gas emissions of 24.0591 t/h. In contrast to the remaining three algorithms, the fuel cost for power generation was reduced by at least $294.6863/h, and the related pollutant gas emissions were reduced by at least 0.0101 t/h. This also demonstrates that the MOMAPSO algorithm has strong search capabilities in finding extreme solutions for fuel cost and pollutant gas emissions. In addition, the runtime of the proposed algorithm is 10.69 ms, which is 2.38 ms, 2.15 ms, and 2.07 ms lower than MCMOGA, MKWSO, and MTNPSO, respectively, further demonstrating that the optimised algorithm has high runtime efficiency.

Table 2 Optimisation results of different algorithms

Optimisation goal	*Target*	*MCMOGA*	*MKWSO*	*MTNPSO*	*MOMAPSO*
Optimal power generation costs	Fuel cost	28,974.4235	28,110.8411	27,970.6061	27,675.9198
	Emission	25.0259	24.2348	24.1646	24.0591
Emission optimisation	Fuel cost	34,425.3596	34,228.7138	34,251.5266	34,070.1483
	Emission	2.3861	2.3759	2.3763	2.3658
	Running time	13.07	12.84	12.76	13.69

Table 3 Outcome of IGD indicators and Wilcoxon rank-sum test

Algorithm	*Mean value*	*Standard deviation*	*Maximum*	*Minimum value*	*Significance test*
MCMOGA	23.5529	2.3657	27.2274	17.5276	–
MKWSO	23.2547	2.6793	25.7296	17.7695	–
MTNPSO	21.2561	2.6258	24.1359	17.0238	–
MOMAPSO	16.3219	1.7331	18.6495	12.9942	

Upon conducting 100 separate and unbiased trials, the arithmetic mean and the measure of dispersion denoted by the standard deviation of the inverted generational distance (IGD) were obtained. In addition, this paper adopted the widely recognised Wilcoxon rank-sum test was employed to scrutinise the outcomes, with a predetermined significance threshold set at 0.05, where '+', '–', and '≈' imply that the comparison approach exhibits a markedly superior performance compared to MOMAPSO, the comparison approach under study performs considerably less effectively than MOMAPSO, and the comparison approach exhibits no statistically significant difference in comparison with MOMAPSO, respectively. The outcome of the IGD index and Wilcoxon rank-sum test are shown in Table 2. The IGD indices associated with MOMAPSO are uniformly lower than those pertaining to MCMOGA, MKWSO, and MTNPSO algorithms, implying that MOMAPSO significantly outperforms the other three algorithms with respect to the aspects of diversity and convergence. The test outcome indicates that the MOMAPSO algorithm demonstrates excellent operational performance in power system control.

6 Conclusions

With the rapid development of the global economy, environmental pollution and energy shortages have become increasingly serious issues. The growing number of power generation units being linked to the power grid has posed significant challenges for optimising the operation of power generation units. For this purpose, this paper optimises the control operation algorithm of power systems based on an improved PSO algorithm. First, to address the issue of slow convergence speed in PSO, the MAPSO algorithm is proposed. Based on a reward mechanism, the inertial weight and learning factor are optimised through a strategy of changing the reward mechanism, which is adapted during the iteration process to accelerate convergence speed. Second, establish a multi-objective function for the power generation costs and pollutant emissions of the generator set, and propose constraints for example system power balance constraints, heat balance constraints, and output capacity restrictions for these objective functions. Finally, MOMAPSO was proposed by integrating external archiving technology and applied to power system control to solve the optimal solution with lower power generation costs and fewer pollutant emissions as the target function, thereby achieving overall operational optimisation. Simulation results indicate that the proposed approach achieves a power generation cost of $27,675.9198/h and pollutant emissions of 24.0591 t/h. In comparison to alternative algorithms, the offered approach can achieve a higher-quality operation scheme with lower power generation costs and fewer pollutant emissions.

This paper only focuses on control optimisation on the power generation side and does not consider demand response. Demand response can improve the resource utilisation of system control through load reduction or transfer adjustments. Therefore, further research is needed on how to utilise demand response mechanisms to enable interaction between the power system and the demand side. Also in this paper, deployment challenges (e.g., regulatory frameworks, system data privacy) as well as environmental and economic tradeoffs in real systems will be thoroughly investigated to further enhance the operational performance of the model.

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Declarations

All authors declare that they have no conflicts of interest.

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