frontiers | Frontiers in Energy Research

TYPE Original Research
PUBLISHED 25 August 2022
DOI 10.3389/fenrg.2022.953873

OPEN ACCESS

EDITED BY
Xin Yao,
Xiamen University, China

REVIEWED BY
Kui Liu,
Shanghai University, China
Xiaolei Wang,
China University of Mining and Technology, China

*CORRESPONDENCE
Zhenhua Sun,
408398472@qq.com

SPECIALTY SECTION
This article was submitted to Sustainable Energy Systems and Policies, a section of the journal Frontiers in Energy Research

RECEIVED 26 May 2022
ACCEPTED 12 July 2022
PUBLISHED 25 August 2022

CITATION
Wang D, Lan F, Shen H, Liu M and Sun Z (2022), Optimal scheduling of power systems considering carbon markets: Based on blockchain theory and multi-objective particle swarm optimization algorithm.
Front. Energy Res. 10:953873.
doi: 10.3389/fenrg.2022.953873

Optimal scheduling of power systems considering carbon markets: Based on blockchain theory and multi-objective particle swarm optimization algorithm

Dongfa Wang[1], Fei Lan[1], Huaqiang Shen[1], Minghui Liu[1] and Zhenhua Sun[2]*

[1]State Grid Zhejiang Electric Power Co., Ltd., Hangzhou, China, [2]School of Economics and Management, Fuzhou University, Fuzhou, China

In the context of double carbon, it is an inevitable requirement for the low-carbon power industry to take economic efficiency and low carbon into consideration. This article introduces the carbon emission constraint into the economic dispatching of the power system. Then, combined with the blockchain theories, the methods of particle swarm optimization and multi-objective particle swarm optimization (MOPSO) are employed to simulate the economic and environmental scheduling of a power generation system based on six thermal power units. Research shows that the constraint processing approach is practical and effective, and it can firmly adhere to equality requirements, which is superior to other algorithms' constraint processing methods; the algorithm is stable, and the global optimal solution can be determined under different initial solutions. In the process of multi-objective optimization, the solutions of POF obtained by using the slope method are evenly distributed.

KEYWORDS

"dual carbon" strategy, optimal scheduling of power systems, environmental and economic dispatching, simulations analyse, multi-objective particle swarm optimization

1 Introduction

The energy crisis in the 1970s made all countries realize the importance of new energy development. Under the background of the global energy transition, it is the general trend to promote the diversified development of efficient and clean energy. On 22 September 2020, at the general debate of the 75th session of the United Nations General Assembly, Chinese President Xi Jinping officially stated that China aims to achieve a peak in carbon dioxide emissions by 2030 and achieve carbon neutrality by 2060. Since then, President Xi Jinping has stressed the significance of achieving carbon peak and carbon neutrality (referred to as the dual-carbon target) in many important speeches and held a series of important discussions on the principles and path for China to achieve the dual-carbon target. Achieving carbon peak and carbon neutrality is a broad and profound economic and social transformation. It is a necessary requirement for ecological progress and an urgent need for building a community with a shared future for mankind. The energy industry is the largest source of carbon emissions. To achieve the dual-carbon goal, policy forces are needed to guide the energy industry to steadily achieve low-carbon transformation. The carbon emission trading market, also known as the carbon market, is an important policy tool to achieve carbon emission reduction targets. Since October 2011, China has carried out local pilot projects for carbon emission trading in Beijing, Tianjin, Shanghai, Chongqing, Hubei, Guangdong, Shenzhen, and Fujian. On 16 July 2021, the national carbon market officially launched trading, and the power generation industry became the first industry to be included in the national carbon market. A total of 2,162 key emitters in the power generation industry were included in the first implementation cycle, covering annual CO_2 emissions of more than 4.5 billion tons. China's carbon market has become the world's largest in terms of greenhouse gas emissions. Global experience shows that carbon markets can promote energy sector optimization and carbon reduction.

Developing a low-carbon economy, accelerating the adjustment of energy structure, and realizing the cleanness, high efficiency, and low carbon of energy system have become the consensus of all countries in the world (Lin et al., 2021). Of the whole energy activities, the carbon emission of the power industry accounts for about 41%. As the main force of energy transformation and the pioneer of realizing the dual-carbon goal, the power system is facing huge pressure of emission reduction (Du et al., 2021). China's coal-dominated energy structure leads to pollutant emissions accounting for more than 80% of the country's total emissions. The coal-dominated power structure of the power industry leads to its CO_2 emissions accounting for 49.1% of China's carbon emissions and 32.1% of the world's carbon emissions (Musa et al., 2018). Facing the severe pressure of carbon emission reduction, realizing the green development of the power sector is crucial to the green transformation of the whole energy sector.

The premise of economic dispatching of power systems is to meet the safety operation of the power grid and provide high-quality electric energy for users. On this premise, energy and power generation equipment can be rationally utilized, and the system operation economy is considered, that is, continuous power supply for users at the lowest power generation cost Vansia and Dhodiya, (2021). Power system economic scheduling is a multi-constrained, nonlinear, non-convex, and multi-dimensional hybrid optimization problem. The traditional economic dispatching of a power system needs to consider the expected output power and constraints of the power system and use the optimal dispatching strategy to allocate the output power of the generator set with the goal of minimizing the generation cost or fuel cost. Due to the particularity of the electric power system, electric energy production will cause environmental problems, which in turn bring new challenges to economic dispatching. Therefore, in the process of power system operation, both energy and environmental issues should be considered. It is an important challenge for economic dispatching to effectively ensure environmental quality while satisfying economic dispatching, that is, to take environmental index and economic cost as the dual objectives of optimal dispatching. How to establish an effective model for the dynamic nature of environmental economic dispatching, adopt a reasonable algorithm to solve the model, improve the convergence speed and operation efficiency of the algorithm, and get better scheduling optimization results are the key points of innovation and improvement of dynamic environmental economic dispatching in power system. The essence of the power system environmental economic scheduling problem is to optimize a multi-objective optimization problem that includes both equality and inequality constraints. In the case of a new energy grid connection, the optimal environmental economic scheduling problem becomes more complex, which is manifested as a multi-objective optimization problem in multi-dimensional space and multi-variables. It is difficult to obtain the global optimal solution of a multi-objective optimization model in the process of optimizing an objective function.

A blockchain, as the name implies, is a chain consisting of many partitions. Different partitions store different amounts of information and form a chain according to the chronological order of information generation. All the servers available in the system contain all the information in this chain, and for the blockchain to be secure, just one server in the entire system needs to be able to function properly. In the blockchain system, these servers are also called nodes, and their role is to provide enough memory and computing power to support the entire blockchain system run. Two prerequisites must be met to modify the information contained in the blockchain. First, there should be more than half of the nodes agreeing to the modification operation. Second, this modification must also overwrite the same information in all nodes to maintain consistency. However, these nodes are generally controlled and held by different subjects, so it is not an easy task to tamper with the information in the blockchain. Two core features of blockchain, namely, that data are not easily tampered with and that they are decentralized, set it apart from traditional networks. The information recorded by blockchain is more reliable, helping to solve the problem of trust in human interaction.

The main structure of this article is as follows:

(1) Section 3 sets the problem formulation of the environmental and economic dispatching and introduces the Pareto optimal solution of multi-objective optimization.
(2) Section 4 shows the particle swarm algorithm, namely, the basic particle swarm optimization and multi-objective particle swarm optimization.
(3) Section 5 uses simulation data to perform economic and environmental scheduling for the system; the single-objective PSO and the multi-objective particle swarm optimization algorithms are utilized, and the Pareto optimum frontier boundary solutions are obtained, namely, the solution with the lowest fuel cost and the lowest pollutant gas emissions.

2 Literature review

It is the key to the sustainable development of the power industry that how to reasonably consider the constraints of carbon emission in power generation dispatching and realize low carbon on the basis of taking into account the economy, and it is also an important starting point for China to achieve carbon peak and carbon neutralization (Kwakwa, 2021). Therefore, in the case of electric energy system scheduling, the economic cost and environmental impact should be considered at the same time from the single target economy to the multi-target environment economy scheduling change.

Environmental and economic dispatching (EED) optimization problem is a non-convex, nonlinear, high-dimensional, and multi-objective optimization problem with multiple constraints (Liu et al., 2018; Cheng and Yao, 2021). Traditional mathematical methods are slow and prone to infeasible solutions. On the contrary, an intelligent optimization algorithm has certain advantages in multi-objective, nonlinear, and high-dimensional optimization problems (Farag et al., 1995; Kennedy, 2003) and is widely used in environmental/economic scheduling problems (Sinha et al., 2003). Singh et al. (2018) proposed a chaotic differential evolutionary and Powell's pattern search (CDEPS) algorithm to solve the multi-objective thermal power load dispatch (MTPLD) problem.

The information security risk of power system economic dispatching is very serious, and its data security under network attack is also very important. In order to ensure the data security of distributed economic scheduling under network attack, blockchain technology is one of the research directions. Blockchain is the core supporting technology of digital cryptocurrency (Liu and Chen, 2021), with five characteristics of decentralized storage, immutable, traceable, secure, and programmable (Bao et al., 2020), which contributes to the establishment of a data protection framework for the communication network of the power system (Liang et al., 2019). As an emerging technology, scholars have carried out relevant studies on various aspects of power systems based on the characteristics of blockchain technology, such as power transaction blocking (Su et al., 2022), control of distributed energy under demand response (Claudia et al., 2018), distributed energy storage control (Baza et al., 2019), energy management of virtual power plants, consumer point-to-point transaction (Paudel et al., 2019), and electric vehicle energy transaction (Wang et al., 2019). It can be seen that the application of blockchain technology in power systems mainly focuses on power transactions, and the application of blockchain technology in power system economic dispatching data security has not caused enough attention. However, it is worth noting that with the rapid development of distributed control systems, network attacks lead to frequent physical information accidents. As a distributed, safe, and reliable database, blockchain technology has better practical significance for the safe and stable operation of smart grids in the future. Liang et al. (2019) proposed a management framework that uses the elliptic curve encryption algorithm in blockchain technology to ensure the reliability of energy dispatch data, so as to strengthen the information security of the power system. Claudia et al. (2018) studied the application of blockchain in distributed energy consumption for demand response in smart grids. A distributed ledger based on blockchain collects energy consumption information from smart devices in a way that is difficult to tamper with and balances energy demand through smart contracts. The results show that the distributed demand-side management system based on blockchain has high tracking precision for demand response signals. Qu et al. (2021) designed a data protection framework based on an alliance chain, which uses distributed storage, traceability, and hard-to-tamper characteristics of blockchain technology to solve the problem that artificial intelligence is vulnerable to network attacks and privacy disclosure, thus increasing the security and credibility of data. Many practical problems often have multiple nonlinear objective functions. In the process of objective optimization, these objective functions need to be processed at the same time, that is, the solution should satisfy multiple objective functions at the same time. However, these objective functions are often in conflict with each other. This kind of problem is called a multi-objective optimization problem. Multi-objective optimization problems can be solved by different algorithms. Vansia and Dhodiya (2021) presented an evolutionary approach-based solution to solve the multi-objective transportation-p-facility location problem by using a genetic algorithm (GA), non-dominated sorting genetic algorithm (NSGA-II and NSGA-III), and modified self-adaptive multi-population elitism Jaya algorithm (SAMPE JA). Xu et al. (2021) use a multi-objective learning backtracking search algorithm (MOLBSA) to solve the environmental/economic dispatch (EED) problem.

Particle swarm optimization (PSO) algorithm has been used in reactive power optimization, photoelectric grid connection, load prediction, and other fields due to its advantages of fewer

10.3389/fenrg.2022.953873

parameter settings, fast convergence, and simple implementation (Kennedy J., 2003; Zhang et al., 2019). On this basis, a cross-particle swarm algorithm is proposed, which improves the crossover probability of parameter adaptive control, and its convergence speed is better than other algorithms (Zhou et al., 2020). Goudarzi et al. (2020) proposed a hybrid algorithm grounded on an improved genetic algorithm and an improved PSO algorithm to solve the optimization problem.

Abido (2009) and Niknam and Doagou-Mojarrad (2012) applied the MOPSO algorithm to schedule power system environmental and economic elements. The MOPSO method must redefine the population's global optimal solution and individual ideal solution. Different literature studies have given different definition methods, but there is no unified definition method at present. Many practical application problems can be attributed to multi-objective optimization problems. At present, the research on the algorithm for this kind of problem is mainly divided into Pareto dominance relation, decomposition strategy (Liu et al., 2014; Li and Zhang, 2015; Li et al., 2018a), performance evaluation index (Schutze et al., 2012; Brockhoff et al., 2015; Díaz-Manríquez et al., 2016; Li et al., 2018b), reference point (Deb and Jain, 2014; Cheng et al., 2016; Figueiredo et al., 2016; Liu et al., 2017), reduction of the number of targets (Bandyopadhyay and Mukherjee, 2015; Guo et al., 2016; Yuan et al., 2018), and coevolution strategy (Zhan et al., 2013; Chen et al., 2019; Zhou et al., 2020). The high-dimensional multi-objective optimization algorithm based on the Pareto dominance relation can reduce the Pareto frontier area by combining preference information in the search process (Li et al., 2018c; Qi et al., 2018). The selection pressure of the algorithm can be enhanced through the relaxed Pareto dominance relation so that the advantages and disadvantages of some non-dominant individuals can be compared and the search ability of the algorithm can be enhanced, such as γ-domination (Singh et al., 2018), ε-domination (Hernandez-Diaz et al., 2007), α-domination (Yuan et al., 2016), fuzzy domination (He et al., 2014), and lattice domination (Yang et al., 2013).

According to the connotation of a low-carbon energy system, the carbon constraint based on particle swarm optimization is introduced into the economic dispatching of the power system in this article, so as to fully explore how to give consideration to the economy and low carbon of power systems under the dual-carbon goal and promote the low-carbon development of energy system. Based on this model, the power generation system of six thermal power units is simulated. When solving with the multi-objective algorithm, the balance between the two objectives is coordinated to make all objective functions as optimal as possible, and the slope algorithm is used to find the optimal POF.

3 Problem formulation and the pareto optimal solution

The economic dispatching of power system is to solve the dispatching scheme to minimize the cost of power generation or fuel under the condition of satisfying the balance of power supply and demand and the upper and lower limits of unit output.

However, in the process of power generation, the thermal power unit inevitably emits pollution gases such as sulfur oxide, nitrogen oxide, dioxygen, and carbureted carbon into the atmosphere. With the enhancement of people's awareness of environmental protection, it has become an important goal of the power system to limit the emission of polluting gases. Power system from the original single objective economic dispatching to multi-objective environment/economic dispatching. Compared with other mitigation measures, EED is favored by researchers because of its low investment and quick results. Environmental and economic dispatching is a scheduling technique that concurrently optimizes the two objective functions of fuel cost and pollutant gas emission while maintaining power supply and demand balance and the unit output limit. The mathematical expression of environmental/economic dispatching is as follows.

3.1 The objective function

3.1.1 Economic dispatch function

Fuel cost is the objective function of the economic dispatching model. The fuel cost curve for each generator set is often described as a polynomial function, and the system's overall fuel cost can be expressed as follows:

$$TC(Q) = \sum_{i=1}^{N} \left(a_i Q_i^2 + b_i Q_i + c_i\right), \tag{1}$$

where N indicates the quantity of thermal power unit and a_i, b_i, and c_i denote a set of thermal power unit i's cost coefficients. Also, the actual total output of the thermal power unit i is denoted as Q_i, and Q denotes the active output vector of the system thermal power unit, which can be expressed as follows:

$$Q = [Q_1, Q_2, \ldots, Q_N]. \tag{2}$$

3.1.2 Environment dispatch function

The objective function of the environmental scheduling function is the emission of pollutant gas. Consider power generation units, which produce a variety of polluting gases throughout the power generation process, and each polluting gas's emission may be individually created to have a functional relationship with the thermal power unit's active power output. However, for the convenience of calculation, we adopted the comprehensive emission model of pollutant gases, and the total emission of pollutant gases in the system is as follows (Peng and Sun, 2009; Said et al., 2010):

$$G(Q) = \sum_{i=1}^{N} [10^{-2} (d_i Q_i^2 + e_i Q_i + f_i) + g_i e^{r_i Q_i}, \tag{3}$$

where d_i, e_i, f_i, g_i, and r_i are a set of polluting-gas-emission coefficients of the thermal power unit i.

3.2 The constraint function

3.2.1 Output constraint of thermal power unit

$$Q_{i\,\min} \le Q_i \le Q_{i\,\max}, \tag{4}$$

where $Q_{i\,\min}$ and $Q_{i\,\max}$ represent the lowest and highest active output levels of the thermal power unit i, respectively.

3.2.2 Power balance constraint

$$\sum_{i=1}^{N} Q_i - Q_D = 0, \tag{5}$$

Where Q_D denotes the system's total load requirements.

3.3 Pareto optimal solution of multi-objective optimization

Since multi-objective optimization is a multi-objective optimization problem, the objectives are prone to collision, making the solution non-unique, that is, no solution can satisfy all constraints and allow all objectives to reach their optimal values at the same time. Therefore, in multi-objective optimization problems, only non-inferior solutions are generally solved. The efficient or Pareto optimal solution of a multi-objective optimization problem is also known as the Pareto optimal solution, and the set containing all Pareto optimal solutions is called a Pareto optimal boundary (POF).

TABLE 1 Data of the six generators.

Thermal power unit	a_i	b_i	c_i	$Q_{i\ max}$	$Q_{i\ min}$
1	0.05	10	10	150	5
2	0.06	7.5	10	150	5
3	0.02	9	20	150	5
4	0.03	5	10	150	5
5	0.02	9	20	150	5
6	0.05	7.5	10	150	5
Thermal power unit	d_i	e_i	f_i	g_i	r_i
1	0.003245	−0.2777	20.455	0.001	0.02857
2	0.002819	−0.30235	12.715	0.0025	0.03333
3	0.002293	−0.2547	21.29	0.000005	0.08
4	0.00169	−0.1775	26.63	0.01	0.02
5	0.002293	−0.2547	21.29	0.000005	0.08
6	0.002576	−0.27775	30.655	0.00005	0.06667

4 Particle swarm algorithm

4.1 Basic particle swarm optimization

The particle swarm optimization (PSO) algorithm is a stochastic optimization algorithm based on cluster intelligence, which was first proposed by Kennedy and Eberhart in the 1990s. Particle swarm optimization (PSO) is a heuristic method that mimics bird foraging behavior. It leverages particle collaboration and competition for intelligent guiding optimization. The idea is that each solution to the basic optimization problem is called a particle. A fit function is defined to measure the superiority of each particle solution. Each particle travels in groups according to the "flight experience" of itself and other particles, thus achieving the purpose of searching for the optimal solution from the whole space. The particle swarm optimization algorithm is a new evolutionary technology based on swarm intelligence that shows strong advantages in solving non-continuous, non-differentiable, nonlinear, ill-conditioned optimization problems and combinatorial optimization problems that are difficult to solve by classical optimization algorithms, resulting in widespread attention from the international academic and engineering communities.

Assume there are m particles in a population, each with an n-dimensional variable, accordingly, the location and movement speed of the particle i in the iteration k are $X_i^k = [x_{i,1}^k, x_{i,2}^k, \ldots, x_{i,n}^k]$ and $V_i^k = [v_{i,1}^k, v_{i,2}^k, \ldots, v_{i,n}^k]$. By calculating the optimum value of the objective function, the best position of each particle is determined to be $P_i^k = [p_{i,1}^k, p_{i,2}^k, \ldots, p_{i,n}^k]$, and the optimal location of the population is $G_i^k = [g_{i,1}^k, g_{i,2}^k, \ldots, g_{i,n}^k]$. the velocity and position of the particle i in the next iteration will be determined as follows:

$$\begin{aligned} v_{i,j}^{k+1} &= \omega v_{i,j}^k + c_1 r_1 \cdot \left(p_{i,j}^k - x_{i,j}^k\right) + c_2 r_2 \cdot \left(g_{i,j}^k - x_{i,j}^k\right), \\ x_{i,j}^{k+1} &= x_{i,j}^k + v_{i,j}^{k+1}, j = 1, 2, \ldots, n, \end{aligned} \tag{6}$$

where r_1 and r_2 are random numbers that obey uniform distribution in the interval [0,1]. Both c_1 and c_2 are learning parameters and are constants. The inertial weight, ω, is employed to find a balance between the particle's global and local optimization capabilities.

The value of ω is calculated as follows:

$$\omega = \omega_{\max} - \frac{\omega_{\max} - \omega_{\min}}{K} k, \tag{7}$$

TABLE 2 Economic and environmental scheduling results with single-objective PSO algorithm.

Thermal power unit	Economic dispatch			Environmental dispatch		
	Q*	Fuel cost	Pollutant emission	Q*	Fuel cost	Pollutant emission
1	10.88	124.72	0.18	40.51	497.15	0.15
2	29.77	286.45	0.07	45.70	478.06	0.06
3	52.28	545.18	0.14	53.67	560.64	0.14
4	102.04	832.56	0.34	38.73	248.65	0.24
5	52.79	550.85	0.14	54.09	565.32	0.14
6	36.24	347.47	0.24	51.29	526.21	0.23
Summation	284.00	2,687.23	1.11	283.99	2,876.03	0.97

where K is the maximum number of iterations and k is the current iteration number.

The velocity of the particle i in all dimensions should satisfy $-v_{j\max} \le v_{i,j} \le v_{j\max}$, and $v_{j\max}$ is the maximum flight speed of the particle i in dimension space j. Generally, v takes 10%–20% of the j-dimensional variable search space (Goldberg, 1989; Hemamalini and Simon, 2008).

One of the most important aspects of using the PSO algorithm to address constraint optimization problems is how to cope with the constraints. The PSO algorithm's approaches for coping with restrictions can be classified into two categories, namely, the penalty function method and design-specific constraint correction factors (Zhang et al., 2019; Zhang and Lu, 2019; Xin-gang et al., 2020).

4.2 Multi-objective particle swarm optimization

4.2.1 Basic principle of multi-objective particle swarm optimization

The multi-objective particle swarm optimization algorithm can solve the problem of multiple conflicting objectives of granularity distribution, and then obtain a set of Pareto optimal solutions. In order to continuously update the Pareto optimal solutions generated in the iteration, this study uses archiving technology to set the previous Pareto optimum solution and the global Pareto optimal solution set in the iteration process. Pareto solutions that are globally optimal are supposed to contain all Pareto optimal solutions created during the current iteration.

4.2.2 Main algorithm

The following is the MOPSO algorithm.

1 Set up the population POP:
(a) for $i = 0$ to MAX (MAX represent the number of particles*)
(b) initialize $POP[i]$.
2 Set each particle's initial speed:
(a) for $i = 0$ to MAX
(b) $VEL[i] = 0$.
3 Calculate the value of each particle in POP.
4 Keep track of where non-dominant vector particles are in the repository REP.
5 Create hypercubes from the previously searched search space and arrange the particles into coordinate systems, with each particle's coordinates defined by the goal function's value.
6 Initialize the memory of each particle:
(a) for $i = 0$ to MAX
(b) $PBESTS[i] = POP[i]$.
7 While the maximum number of cycles has not yet been attained, we take the following steps.
(a)Calculate the speed of each particle:

$$VEL[i] = W \times VEL[i] + R_1 \times (PBESTS[i] - POP[i]) + R_2 \times (REP[h] - POP[i]), \quad (8)$$

where W equals 0.4; R_1 and R_2 are random numbers from 0 to 1; $REP[h]$ is a value retrieved from the repository; $PBESTS[i]$ represents the particle i's optimal position; $REP[h]$ is a value retrieved from the repository. The index h is chosen based on the following: we give hypercubes with more than one particle a fitness, which is obtained by dividing any number $x > 1$ by the number of particles they contain. We then use these fitness values to apply a roulette wheel selection to select the corresponding particle for the hypercube. Then, a random hypercube particle after selecting the hypercube. $POP[i]$ is the current value of the particle i.

(b) Calculate the new particle positions by adding the speed from the previous step:

$$POP[i] = POP[i] + VEL[i]. \quad (9)$$

(c) Keep particles within the search space and prevent them from escaping (avoid generating solution space that is not based on a valid search). When a decision variable exceeds its bounds, we

TABLE 3 Boundary solution of POF.

Thermal power unit	Economic dispatch	Environmental dispatch
1	11.1649	41.1786
2	30.2682	46.4108
3	52.0618	53.4319
4	101.7981	38.6051
5	53.2231	48.4839
6	35.4839	50.9397
Fuel costs	2,687.25	2,879.261
Pollutant emission	1.110992	0.97101

force it to take its corresponding value bounds (upper or lower bounds) and velocity times (−1) in the other direction.

(d) Count each particle in *POP*.

(e) In terms of particle positions in the hypercube, update the contents of *REP*. All current non-dominant locations will be inserted into the repository as part of this release. In this process, every dominant position in the repository is eliminated. Because the memory's size is limited, we use a previously prepared second criterion. Since the size of memory is finite, when memory is filled, we use the second rule we have prepared previously, that is, particles in the target space's less populous areas take precedence over particles in the more inhabited places (Coello et al., 2004).

(f) When the particle's current location is better than the one stored in memory, the particle's location is updated.

$$PBESTS[i] = POP[i]. \tag{10}$$

Pareto dominance is applied to formulate the standard, which determines what position to keep from memory. This means that if the current location is controlled by a location in memory, that location will remain in memory. Otherwise, the present location takes the place of the memory location. Also, if any two of them are unaffected by each other, we will pick one at random.

(g) Increment cycle counter.

8 End while.

5 Case analysis

The simulation is done in MATLAB, and network loss in the electric energy balancing constraint is not taken into account. There are six generating sets. The system's overall load is 284 MW. Table 1 provides the power maximum and lower limitations, fuel cost coefficient, and pollutant emission coefficient for each generator set.

5.1 Single-objective optimization

In order to carry out economic and environmental scheduling of the system, the single-objective PSO algorithm was adopted to obtain two Pareto optimal boundary solutions, namely, the solution with the lowest fuel cost and the solution with the lowest pollution gas emissions, so as to judge whether the MOPSO algorithm has excellent distribution characteristics for POF solutions (Zhang et al., 2019).

The population *POP* is set to 60 in the single-objective PSO, and the learning elements c_1 and c_2 are both equal to 2. The maximum number of iterations is 100. Table 2 shows the best solution.

By comparing the economic and environmental scheduling results in Table 2, there is little difference between the optimal fuel cost and pollutant emissions, and there is almost no network damage, which proves that the algorithm proposed in this article has good global search ability.

5.2 Multi-objective optimal scheduling

The multi-objective optimization uses 60 particles per generation, 1,000 iterations, and 30 solutions on the Pareto optimal front. The case was optimized with MOPSO to obtain 30 populations. The slope method is used to obtain the boundary solution of POF as shown in Table 3. The two boundary points of POF correspond to the optimal values of economic and environmental scheduling, respectively.

By comparing the results in Table 3 with the single-objective optimization results in Table 2, it can be seen that there is little difference, indicating that the multi-objective algorithm proposed in this article can find better boundary solutions under various conditions, and the obtained POF has a wide distribution range.

6 Conclusion

This article introduces multi-objective particle swarm optimization and applies it to environmental economic power system scheduling. Using MATLAB software, the MOPSO algorithm was used to simulate the economic and environmental scheduling difficulties of a thermal power system, and the following results were obtained.

(1) The constraint processing approach is practicable and effective, and it can adhere to stringent equality restrictions, which is superior to other constraint processing methods.
(2) The method has good stability and can identify the global optimal solution under a certain range of start-up conditions. In the process of multi-objective optimization, the POF solutions generated by the slope method are evenly distributed.
(3) The Pareto optimal frontier can be quantitatively analyzed, and the algorithm can be applied to solve a series of complex grid-connected power system environmental and economic scheduling problems.
(4) By comparing the economic and environmental scheduling results, there is little difference in the optimal fuel costs and the pollutant emission, and there is almost no network damage, which shows the good global search capability of the algorithm proposed in this article.

In the process of power system dispatching, there may be some practical combination problems such as standby load and unit maintenance, which will greatly increase the difficulty of solving the model. Therefore, exploring a more effective and accurate algorithm is an important problem that needs to be solved further. In addition, another measure to achieve energy conservation and emission reduction is to vigorously develop clean energy. In view of this, the dynamic emission economic dispatch model considering the grid connection of renewable energy such as hydropower, wind power, and solar power is also a potential important research direction in the future.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material; further inquiries can be directed to the corresponding author.

Author contributions

DW: writing—original draft, formal analysis, methodology, and software. FL: writing—review and editing, investigation, and software; HS and ML: writing—original draft and conceptualization. ZS: writing—review and editing, supervision, methodology, and validation.

Funding

This study is supported by the Natural Science Foundation of Fujian Province (Grant No. 2020J05123) and the Project of Fuzhou University (Grant no. GXRC202005 and grant no. GXRC202104).

Conflict of interest

Authors DW, FL, HS and ML were employed by State Grid Zhejiang Electric Power Co., Ltd.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

References

Abido, M. A. (2009). Multiobjective particle swarm optimization for environmental/economic dispatch problem. *Electr. Power Syst. Res.* 79, 1105–1113. doi:10.1016/j.epsr.2009.02.005

Bandyopadhyay, S., and Mukherjee, A. (2015). An algorithm for many-objective optimization with reduced objective computations: A study in differential evolution. *IEEE Trans. Evol. Comput.* 19 (3), 400–413. doi:10.1109/TEVC.2014.2332878

Bao, Z., Wang, Q., Shi, W., Wang, L., Lei, H., and Chen, B. (2020). When blockchain meets SGX: An overview, challenges, and open issues. *IEEE Access* 8, 170404–170420. doi:10.1109/ACCESS.2020.3024254

Baza, M., Nabil, M., Ismail, M., Mahmoud, M., Serpedin, E., and Rahman, M. "Blockchain-based charging coordination mechanism for smart grid energy storage units[C]," in Proceedings of the 2019 IEEE International Conference on Blockchain (Blockchain), Atlanta, GA, USA, July 14 2019 to July 17 2019 (IEEE). doi:10.1109/Blockchain.2019.00076

Brockhoff, D., Wagner, T., and Trautmann, H. (2015). 2 indicator-based multiobjective search. *Evol. Comput.* 23 (3), 369–395. doi:10.1162/EVCO_a_00135

Chen, Z. G., Zhan, Z. H., Lin, Y., Gong, Y. J., Gu, T. L., Zhao, F., et al. (2019). Multiobjective cloud workflow scheduling: A multiple populations ant colony system Approach. *IEEE Trans. Cybern.* 48 (8), 2912–2926. doi:10.1109/TCYB.2018.2832640

Cheng, R., Jin, Y. C., Olhofer, M., and Sendhoff, B. (2016). A reference vector guided evolutionary algorithm for many-objective optimization. *IEEE Trans. Evol. Comput.* 20 (5), 773–791. doi:10.1109/TEVC.2016.2519378

Cheng, Y., and Yao, X. (2021). Carbon intensity reduction assessment of renewable energy technology innovation in China: A panel data model with cross-section dependence and slope heterogeneity. *Renew. Sustain. Energy Rev.* 135, 110157. doi:10.1016/j.rser.2020.110157

Claudia, P., Tudor, C., Marcel, A., Anghel, I., Salomie, I., and Bertoncini, M. (2018). Blockchain based decentralized management of demand response programs in smart energy grids. *Sensors* 18 (2), 162. doi:10.3390/s18010162

Coello, C. A. C., Pulido, G. T., and Lechuga, M. S. (2004). Handling multiple objectives with particle swarm optimization. *IEEE Trans. Evol. Comput.* 8, 256–279. doi:10.1109/TEVC.2004.826067

Deb, K., and Jain, H. (2014). An evolutionary many-objective optimization algorithm using reference-point-based nondominated sorting approach, Part I: Solving problems with box constraints. *IEEE Trans. Evol. Comput.* 18 (4), 577–601. doi:10.1109/tevc.2013.2281535

Díaz-Manríquez, A., Pulido, G. T., Barron-Zambrano, J. H., and Tello-Leal, E. (2016). R2-Based multi/many-objective particle swarm optimization [J]. *Comput. Intell. Neurosci.* 2016, 1–10. doi:10.1155/2016/1898527

Du, K., Cheng, Y., and Yao, X. (2021). Environmental regulation, green technology innovation, and industrial structure upgrading: The road to the green transformation of Chinese cities. *Energy Econ.* 98, 105247. doi:10.1016/j.eneco.2021.105247

Farag, A., Al-Baiyat, S., and Cheng, T. C. (1995). Economic load dispatch multiobjective optimization procedures using linear programming techniques. *IEEE Trans. Power Syst.* 10, 731–738. doi:10.1109/59.387910

Figueiredo, E. M. N., Ludermir, T. B., and Bastos-Filho, C. J. A. (2016). Many objective particle swarm optimization. *Inf. Sci.* 374, 115–134. doi:10.1016/j.ins.2016.09.026

Goldberg, D. E. (1989). *Genetic algorithms in search, optimization, and machine learning*. Massachusetts, United States: Addison-Wesley. Reading.

Goudarzi, A., Li, Y., and Xiang, J. (2020). A hybrid non-linear time-varying double-weighted particle swarm optimization for solving non-convex combined environmental economic dispatch problem. *Appl. Soft Comput.* 86, 105894. doi:10.1016/j.asoc.2019.105894

Guo, X. F., Wang, Y. P., and Wang, X. L. (2016). An objective reduction algorithm using representative Pareto solution search for many-objective optimization problems. *Soft Comput.* 20 (12), 4881–4895. doi:10.1007/s00500-015-1776-4

He, Z., Yen, G. G., and Zhang, J. (2014). Fuzzy-based pareto optimality for many-objective evolutionary algorithms. *IEEE Trans. Evol. Comput.* 18 (2), 269–285. doi:10.1109/TEVC.2013.2258025

Hemamalini, S., and Simon, S. P. (2008). "Emission constrained economic dispatch with valve-point effect using particle swarm optimization," in Proceedings of the TENCON 2008 - 2008 IEEE Region 10 Conference. Presented at the TENCON 2008 - 2008 IEEE Region 10 Conference, Hyderabad, India, November 19–21, 2008, 1–6. doi:10.1109/TENCON.2008.4766473

Hernandez-Diaz, A. G., Santana-Quintero, L. V., Coello, C. A. C., and Molina, J. (2007). Pareto-adaptive ε-dominance. *Evol. Comput.* 15 (4), 493–517. doi:10.1162/evco.2007.15.4.493

Kennedy, J., 2003. Bare bones particle swarms, in: Proceedings of the 2003 IEEE Swarm Intelligence Symposium. Indianapolis, IN, USA. 26-26 April 2003. IEEE. SIS'03 (Cat. No.03EX706). , pp. 80–87. doi:10.1109/SIS.2003.1202251

Kwakwa, P. A. (2021). The carbon dioxide emissions effect of income growth, electricity consumption and electricity power crisis. *Manag. Environ. Qual. Int. J.* 32, 470–487. doi:10.1108/MEQ-11-2020-0264

Li, F., Cheng, R., Liu, J., and Jin, Y. (2018a). A two-stage R2 indicator based evolutionary algorithm for many-objective optimization. *Appl. Soft Comput.* 67, 245–260. doi:10.1016/j.asoc.2018.02.048

Li, K., Zhang, Q. F., and Kwong, S., (2015). An evolutionary many-objective optimization algorithm based on dominance and decomposition. *IEEE Trans. Evol. Comput.* 19 (5), 694–716. doi:10.1109/tevc.2014.2373386

Li, K., Deb, K., and Yao, X. (2018b). R-Metric: Evaluating the performance of preference-based evolutionary multiobjective optimization using reference points. *IEEE Trans. Evol. Comput.* 22 (6), 821–835. doi:10.1109/tevc.2017.2737781

Li, Z., Lin, K., Nouioua, M., and Jiang, S. (2018c). "A decomposition based evolutionary algorithm with angle penalty selection strategy for many-objective optimization [J] ICSI 2018, lecture notes in computer science 10941," in *Advances in swarm intelligence* (Cham: Springer), 561–571. doi:10.1007/978-3-319-93815-8_53

Liang, G., Weller, S. R., Luo, F., Zhao, J., and Dong, Z. Y. (2019). Distributed blockchain-based data protection framework for modern power systems against cyber attacks. *IEEE Trans. Smart Grid* 10 (3), 3162–3173. doi:10.1109/TSG.2018.2819663

Lin, Y., Huang, R., and Yao, X., 2021. Air pollution and environmental information disclosure: An empirical study based on heavy polluting industries. *J. Clean. Prod.* 278, 124313. doi:10.1016/j.jclepro.2020.124313

Liu, G., Zhu, Y. L., and Jiang, W. (2018). Dynamic environmental economic dispatch based on hybrid DE-PSO multi-objective algorithm[J]. *Electr. Power Autom. Equip.* 38 (08), 1–7. in Chinese.

Liu, H. L., Gu, F. Q., and Zhang, Q. F. (2014). Decomposition of a multiobjective optimization problem into a number of simple multiobjective subproblems. *IEEE Trans. Evol. Comput.* 18 (3), 450–455. doi:10.1109/tevc.2013.2281533

Liu, Hongling, and Chen, Yuqiang (2021). Using blockchain technology in IoT manufacture environment for intelligence prediction. *Soft Comput.* 22 (8), 2137–2155. doi:10.1007/s00500-021-06044-1

Liu, Y. P., Gong, D. W., Sun, X. Y., and Zhang, Y. (2017). Many-objective evolutionary optimization based on reference points. *Appl. Soft Comput.* 50 (1), 344–355. doi:10.1016/j.asoc.2016.11.009

Musa, S. D., Tang, Z., Ibrahimb, A. O., and Habib, M. (2018). China's energy status: A critical look at fossils and renewable options. *Renew. Sustain. Energy Rev.* 81 (1), 2281–2290. doi:10.1016/j.rser.2017.06.036

Niknam, T., and Doagou-Mojarrad, H. (2012). Multiobjective economic/emission dispatch by multiobjective thetas-particle swarm optimisation. *IET Generation, Transm. Distribution* 6 (14), 363–377. doi:10.1049/iet-gtd.2011.0698

Paudel, A., Chaudhari, K., Long, C., and Gooi, H. B. (2019). Peer-to-Peer energy trading in a prosumer-based community microgrid: A game-theoretic model. *IEEE Trans. Ind. Electron.* 66 (8), 6087–6097. doi:10.1109/TIE.2018.2874578

Peng, C., and Sun, H. (2009). Multi-objective optimization power dispatch based on non-dominated sorting differential evolution. *Proceedings of the CSEE* 29 (34), 71–76. (in Chinese). doi:10.13334/j.0258-8013.pcsee.2009.34.017

Qi, Y. T., Li, X. D., Yu, J. S., and Miao, Q. (2018). User-preference based decomposition in MOEA/D without using an ideal point. *Swarm Evol. Comput.* 44, 597–611. doi:10.1016/j.swevo.2018.08.002

Qu, Y., Pokhrel, S. R., Garg, S., Gao, L., and Xiang, Y. (2021). A blockchained federated learning framework for cognitive computing in industry 4.0 networks. *IEEE Trans. Ind. Inf.* 17 (4), 2964–2973. doi:10.1109/TII.2020.3007817

Said, L. B., Bechikh, S., and Ghedira, K. (2010). The r-dominance: A new dominance relation for interactive evolutionary multicriteria decision making. *IEEE Trans. Evol. Comput.* 14 (5), 801–818. doi:10.1109/TEVC.2010.2041060

Schutze, O., Esquivel, X., Lara, A., and Coello, C. A. C. (2012). Using the averaged hausdorff distance as a performance measure in evolutionary multiobjective optimization. *IEEE Trans. Evol. Comput.* 16 (4), 504–522. doi:10.1109/TEVC.2011.2161872

Singh, Nirbhow Jap, Dhillon, J. S., and Kothari, D. P. (2018). Multi-objective thermal power load dispatch using chaotic differential evolutionary algorithm and Powell's method. *Soft Comput.* 22 (7), 2159–2174. doi:10.1007/s00500-016-2473-7

Sinha, N., Chakrabarti, R., and Chattopadhyay, P. K. (2003). Evolutionary programming techniques for economic load dispatch. *IEEE Trans. Evol. Comput.* 7, 83–94. doi:10.1109/TEVC.2002.806788

Su, Hong, Guo, Bing, Lu, Jun Yu, and Suo, Xinhua (2022). Cross-chain exchange by transaction dependence with conditional transaction method. *Soft Comput.* 26 (3), 961–976. doi:10.1007/s00500-021-06577-5

Vansia, Dhruvrajsinh O., and Dhodiya, Jayesh M. (2021). Solution of multi-objective transportation-p-facility location problem with effect of variable carbon emission by evolutionary algorithms. *Soft Comput.* 25 (8), 9993–10005. doi:10.1007/s00500-021-05619-2

Wang, S., Taha, A. F., Wang, J. H., Kvaternik, K., and Hahn, A. (2019). Energy crowdsourcing and peer-to-peer energy trading in blockchain-enabled smart grids. *IEEE Trans. Syst. Man. Cybern. Syst.* 49 (8), 1612–1623. doi:10.1109/TSMC.2019.2916565

Xin-gang, Z., Ji, L., Jin, M., and Ying, Z. (2020). An improved quantum particle swarm optimization algorithm for environmental economic dispatch. *Expert Syst. Appl.* 152, 113370. doi:10.1016/j.eswa.2020.113370

Xu, X., Hu, Z., Su, Q., Xiong, Z., and Liu, M. (2021). Multi-objective learning backtracking search algorithm for economic emission dispatch problem. *Soft Comput.* 25 (10), 2433–2452. doi:10.1007/s00500-020-05312-w

Yang, S. X., Li, M. Q., Liu, X. H., and Zheng, J. (2013). A grid-based evolutionary algorithm for many-objective optimization. *IEEE Trans. Evol. Comput.* 17 (5), 721–736. doi:10.1109/TEVC.2012.2227145

Yuan, Y., Ong, Y. S., Gupta, A., and Xu, H. (2018). Objective reduction in many-objective optimization: Evolutionary multiobjective approaches and comprehensive Analysis. *IEEE Trans. Evol. Comput.* 22 (2), 189–210. doi:10.1109/TEVC.2017.2672668

Yuan, Y., Xu, H., Wang, B., and Yao, X. (2016). A new dominance relation-based evolutionary algorithm for many-objective optimization. *IEEE Trans. Evol. Comput.* 20 (1), 16–37. doi:10.1109/tevc.2015.2420112

Zhan, Z. H., Li, J. J., Cao, J., Zhang, J. N., Chung, H. S. H., and Shi, Y-H. (2013). Multiple populations for multiple objectives: A coevolutionary technique for solving multiobjective optimization problems. *IEEE Trans. Cybern.* 43 (2), 445–463. doi:10.1109/TSMCB.2012.2209115

Zhang, Y., Li, H.-G., Wang, Q., and Peng, C. (2019). A filter-based bare-bone particle swarm optimization algorithm for unsupervised feature selection. *Appl. Intell. (Dordr).* 49, 2889–2898. doi:10.1007/s10489-019-01420-9

Zhang, Z., and Lu, H. "Environmental/economic power dispatch based on multi-objective particle swarm algorithm," in Proceedings of the IEEE 3rd Conference on Energy Internet and Energy System Integration (EI2), Changsha, China, Friday, November 8 – Sunday, November 10, 2019, 2957–2961. doi:10.1109/EI247390.2019.9062078

Zhou, S. Z., Zhan, Z. H., Chen, Z. G., Kwong, S., and Zhang, J. (2020). A Multi-Objective ant colony system algorithm for airline crew rostering problem with fairness and satisfaction [J]. *IEEE Trans. Intelligent Transp. Syst.* 22 (11), 6784–6798. doi:10.1109/TITS.2020.2994779