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A master–slave game optimal scheduling strategy for park-integrated energy systems based on adjustable robust optimization

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As the bridge between power companies and users, the integrated energy system has become one of the carriers of energy reform, energy-saving, and emission reduction. Based on this, a master–slave game bilevel optimization model considering power company–park-integrated energy system (PIES)–user is established. In the upper game, the power company, as the leader, takes the maximization of its interests as the goal to consider and formulate the price of purchasing and selling electricity with the park. As a follower, combined with the fluctuation of electricity price and the electricity demand of its equipment, the park determines the relationship between purchasing and selling electricity with the power company. In the lower-level game, the park becomes the leader, taking into account the energy needs of users and formulating a reasonable price for selling energy. Users, as followers, intend to maximize consumer surplus and adjust their energy demand strategies to achieve the best energy consumption experience. Analyzing the properties of the game, it is verified that there is a unique Nash equilibrium solution in the game model. At the same time, the idea of solving the distribution of the model is adopted, and the equilibrium solution of the model is obtained by using limited information. In addition, the output uncertainty of renewable energy in the park is dealt with by adjustable robust optimization. Finally, aiming at achieving a win–win situation among all stakeholders, the proposed game model is verified to effectively solve the equilibrium strategy problem among the PIES, the power company, and users through simulation analysis of an example.

KEYWORDS

adjustable robust optimization, bilevel optimization model, energy transaction, park-integrated energy system, master–slave game

1 Introduction

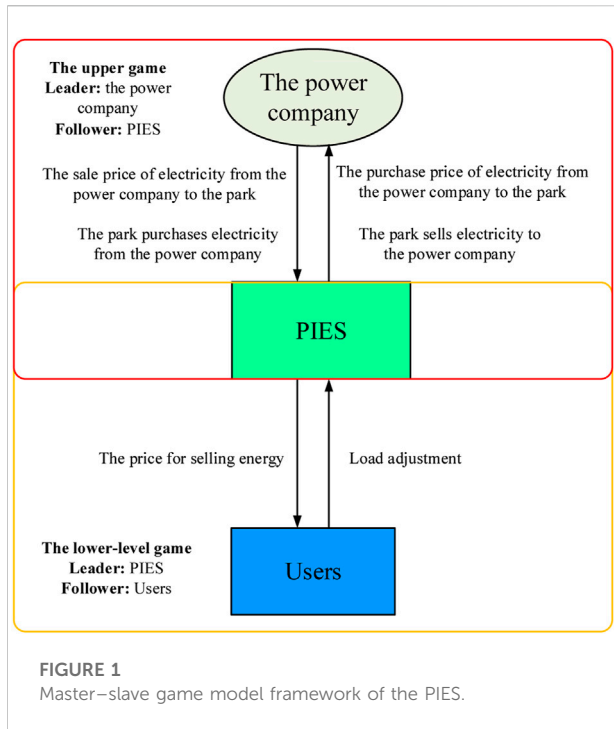
At present, with a series of problems such as energy exhaustion and environmental pollution becoming increasingly serious, the traditional energy distribution model has been unable to meet the production and living needs of the modern society. Therefore, it is urgent to accelerate the transformation of the energy development mode and solve the problem of sustainable supply of renewable energy. Based on this background, the park-integrated energy system (PIES), which combines cold, heat, electricity, and gas, came into being. It can improve the operating efficiency of the energy system and make full use of renewable energy (Xu et al., 2019). In the meantime, as the main platform for rational and efficient utilization of clean energy, the comprehensive energy system in the park helps to promote the complementary advantages of different types of energy and meet the diversified energy demand of users in the park (Tan et al., 2019). Therefore, it is of great significance to conduct an in-depth study on the connection and optimization scheduling between PIES and users of the power company (Yang et al., 2021).

With the further development of the integrated energy system and the gradual opening of the energy market, the fluctuation of energy prices will affect the energy demand of users. Through demand response, users are transformed from passive recipients of the scheduling results to participants, thus influencing the formulation of energy prices. In view of this conflict of interest, most scholars use the game theory method to deal with it. Huang et al. (2022) proposed a joint optimization scheduling model for the multi-park system and introduced a bargaining game mechanism to achieve win-win cooperation between parks. Fang et al. (2021) used game theory to solve the conflict between the overall optimal operation of the microgrid and the maximum profit of each investor and obtained the equilibrium solution to determine the optimal capacity allocation of the microgrid through the establishment of internal and external double-layer game iterative optimization. Wang et al. (2020) put forward a master-slave game optimization model of the community-integrated energy system. The authors constantly adjusted and optimized the pricing strategy of integrated energy vendors, generation arrangement of combined cooling and heat power (CCHP), and load demands of users and used an artificial intelligence algorithm to maximize the interests of each energy subject. Considering the distributed power generation-based sales companies and the participation of virtual power plants, Zhang et al. (2022) proposed the power transaction and optimal scheduling model based on the master-slave game optimization model. The establishment of the model made the main player get the maximum profit, while the secondary player represented by the virtual power plant (VPP) got the lowest internal scheduling cost. Taking into account the interests of all regions in the optimal dispatching of the comprehensive energy park, Chen et al. (2019) established a bilevel optimal dispatching model of the PIES based on the

non-cooperative game theory, with the minimum daily cost as the upper goal and the highest energy efficiency of the cogeneration system as the lower goal. Then the optimal operation strategy of each region was obtained through the game. Li et al. (2021c) proposed a hierarchical and partitioned coordinated operation method of the distributed integrated energy system (DIES) based on a master-slave game for the energy internet system containing multiple communities. The city-integrated energy system hierarchy structure was given; to consider interaction energy between different communities and interests, city managers and operators, as the game of the leader and followers, established the DIES of the master-slave game optimization model and used the mixed-integer linear programming method to solve the model. However, the current research focused on the game between PIES and the power company or electricity sellers as well as the game interaction between the park and users, without considering the bilevel game between the power company and users. In addition, when studying the interactive transaction of the integrated energy system, most literature emphasized the use of electricity price to play the game and seldom considered the influence of price fluctuation of other energy in the energy hub such as cold and heat on the game.

PIES, however, can boost the consumption of renewable energy such as wind power and photovoltaics. Units with uncertain output in the park will seriously affect the economy of system operation. At present, stochastic optimization (SO) (Mei et al., 2021; Wang et al., 2015) and robust optimization (RO) (Zhang et al., 2017; Shen et al., 2020) are popular optimization methods to solve uncertainty. However, both optimization methods have their own defects: the SO requires a large amount of data to generate the scene with a deterministic probability density function (PDF), so the accuracy of probability density is reduced due to the lack of data (Ioannou et al., 2019). However, because the optimization results are too conservative, RO adopts adjustable robust optimization (ARO) (Mejía-Giraldo and McCalley, 2014), which can adjust the conservative degree, so that the decision can flexibly balance economy and security.

In summary, the main contributions of this paper are summarized as follows: while considering the fluctuation of energy prices, a two-layer master-slave game interaction model based on PIES is constructed, and the uncertain output of wind power and photovoltaics in the park is optimized through ARO. In the upper game, the power company is the leader and the PIES is the follower. The two play the game through coordination and interaction, finally achieving the balance between electricity purchasing and selling. In the lower game, PIES is the leader and users are followers. PIES adjusts energy prices to maximize profits. Users adjust their load demand according to the price provided by PIES to maximize consumer surplus. Considering power flow and uncertain output of the power system in PIES, an adjustable robust optimal power flow model is constructed. Finally, the robust optimization model



is further transformed into a robust equivalence model by norm theory to eliminate the influence of uncertain forces on the optimal operation of the system.

2 The master-slave game model framework of PIES

The master-slave game model framework of PIES is shown in Figure 1. The power company is connected to a node in the power system, and the electricity price is adjusted according to the dispatching and distribution and actual operation to interact with PIES. By selling as much electricity as possible to maximize their profits, the PIES is directly connected with the power company through transmission lines. When the power supply of its equipment is insufficient, it can purchase power from the power company at a reasonable price to realize the normal operation of all equipment in the park and meet the load demand of users. Conversely, if the PIES produces excess electric energy, it can also be transmitted to the power company through the transmission line. Finally, as consumers, users can reasonably adjust the size of the energy consumption load to adapt to the energy selling price of the comprehensive energy system in the park and minimize the cost on the premise of meeting their energy consumption demands (Li et al., 2021b).

In brief, the upper-level game led by the power company is to realize the game with PIES through the transmission of electric power and the adjustment of the corresponding electricity price. The lower-level game is that PIES realizes game interaction with

users by meeting their demands for electricity, cooling, and heat load and adjusting the corresponding energy price.

2.1 The power company model

2.1.1 The objective function

The objective function of the power company consists of transmission line power cost, equipment maintenance cost, generating cost, and benefits from electricity selling. The expressions are as follows:

$$\max F_d = E_{sell} - C_{gen} - C_p - C_{CW} \quad (1)$$

$$E_{sell} = \sum_{t=1}^T (c_{d,s}^t \cdot P_s^t - c_{d,b}^t \cdot P_b^t) \quad (2)$$

$$C_{gen} = \sum_{t=1}^T [a(P_s^t)^2 + bP_s^t + c] \quad (3)$$

$$C_p = \sum_{t=1}^T (p_{eq} \cdot (P_s^t + P_b^t)) \quad (4)$$

$$C_{CW} = \sum_{t=1}^T \left(\frac{c_{d,b}^t + c_{d,s}^t}{2} P_{GD-EX}^t \right) \quad (5)$$

where T is the total number of periods. In this study, it is 24 h. E_{sell} represents the benefits from electricity selling of the power company; P_s^t is the amount of electricity the power company sold to PIES at time t ; P_b^t is the amount of electricity the power company bought from PIES at time t ; $c_{d,s}^t$ and $c_{d,b}^t$ represent the price of electricity sold to PIES and the price of electricity purchased from PIES by the power company at time t , respectively; C_{gen} is the operating and maintenance cost of the power company's equipment; a , b , and c represent the consumption characteristic parameters of the generator set; C_p is the equipment operation and maintenance cost of the power company (Chen et al., 2021); p_{eq} is the coefficient of equipment maintenance cost; C_{CW} is the cost of transmission line between PIES; and P_{GD-EX}^t is the transmission line power.

2.1.2 Constraints of the power company

1) Electricity price constraints

$$0 \leq c_{d,s}^t \leq \bar{c}_{d,s,max} \quad (6)$$

$$0 \leq c_{d,b}^t \leq \bar{c}_{d,b,max} \quad (7)$$

where $\bar{c}_{d,s,max}$ and $\bar{c}_{d,b,max}$, respectively, represent the maximum price limit of electricity selling and the maximum price limit of electricity purchasing by the power company.

2) Transmission line power constraint

$$P_{GD-EX,min}^t \leq |P_{GD-EX}^t| \leq P_{GD-EX,max}^t \quad (8)$$

$P_{GD-EX,min}^t/P_{GD-EX,max}^t$ are the upper/lower limits of transmission line power, respectively.

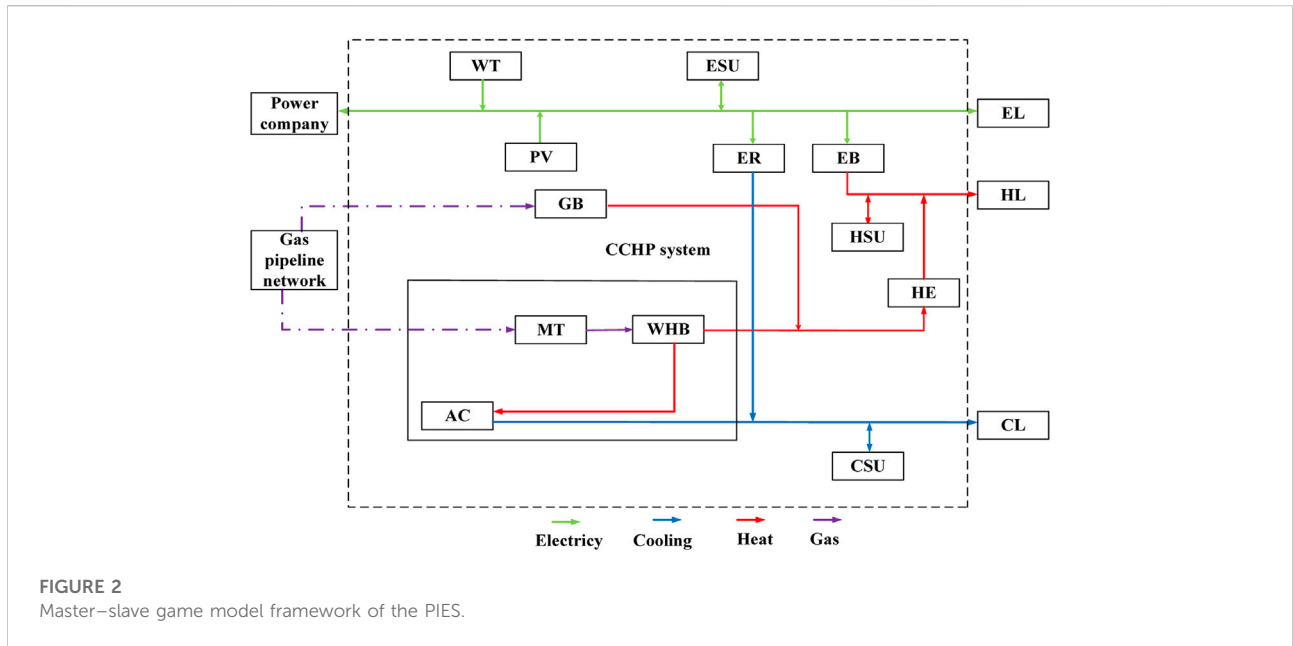


TABLE 1 Symbol definition of equipment in PIES.

Nomenclature	Abbreviations	Nomenclature	Abbreviations
Micro-turbine	MT	Heat exchange	HE
Photovoltaics	PV	Absorption cooling	AC
Wind turbine	WT	Electricity storage unit	ESU
Gas boiler	GB	Cooling storage unit	CSU
Waste heat boiler	WHB	Heat storage unit	HSU
Electric refrigeration	ER	Electricity load	EL
Electric boiler	EB	Cooling/heat load	CL/HL

2.2 PIES model

The structure of the PIES (Gu et al., 2021) is shown in Figure 2. The abbreviations for specific components are shown in Table 1. PIES contains a range of renewable energy units such as wind power and photovoltaics as well as gas boilers, micro-turbines, and absorption cooling and energy storage units to meet the needs of all loads. Modeling is conducted for different energy sources to ensure that energy balance and their respective operating constraints are met at each moment (Tan et al., 2020).

2.2.1 The objective function

PIES takes the maximization of the park's income as the objective function, where the objective function F_p includes gas acquisition cost, unit operation and maintenance cost, punishment cost, interaction cost with the power company,

and user-side energy supply income. The specific function expressions are as follows:

$$\max F_p = P_{sell} - C_{gas} - C_{OM} - C_{pc} - C_{grid} \quad (9)$$

$$P_{sell} = \sum_{n=1}^N \sum_{t=1}^T (y_n^t \cdot P_n^t) \quad (10)$$

$$C_{gas} = \sum_{t=1}^T \frac{R_{gas}^t}{H_{gas}^t} \left[\frac{P_{MT}^t}{\eta_{MT}} + \frac{P_{GB}^t}{\eta_{GB}} \right] \quad (11)$$

$$C_{OM} = \sum_{t=1}^T (C_{PV-OM}^t + C_{WT-OM}^t + C_{MT-OM}^t + C_{ES}^t) \\ = \sum_{t=1}^T [c_{PV} P_{PV}^t + c_{WT} P_{WT}^t + c_{MT} P_{MT}^t + \\ c_{EES} (P_{EES-C}^t + P_{EES-D}^t) + c_{CES} (P_{CES-D}^t + P_{CES-C}^t) + \\ c_{TES} (P_{TES-D}^t + P_{TES-C}^t)] \quad (12)$$

$$C_{pc} = \theta \sum_{t=1}^T (P_{DL}^t - P_{PV}^t - P_{WT}^t) \quad (13)$$

$$C_{grid} = \max(P_{DL}^t - P_{DS}^t, 0)c_{ds}^t + \min(P_{DL}^t - P_{DS}^t, 0)c_{db}^t \quad (14)$$

where P_{sell} is the income from selling energy to users of PIES, n represents the n -th energy, N is the set of energy, γ_n^t represents the real-time price of energy n at time t , and P_n^t represents the real-time power of energy n at time t . C_{gas} represents the cost of natural gas acquisition; R_{gas}^t is the unit price of purchasing gas ($\text{¥}/\text{m}^3$); H_{gas}^t is the calorific value of natural gas (kWh/m^3); and η_{MT} and η_{GB} are the efficiencies of the micro-turbine gas boiler turning gas to electric. C_{OM} is the operating and maintenance cost of the park. $C_{PV-OM}^{i,t}$, $C_{WT-OM}^{i,t}$, $C_{MT-OM}^{i,t}$, $C_{ES}^{i,t}$, and $C_{GD-EX}^{i,t}$ represent the operating and maintenance cost of photovoltaics, wind power, micro-turbines, energy storage, and interconnected line power, respectively. c_{MT}^t , c_{PV} , c_{WT} , and $c_{EES/CES/TES}$ represent the cost coefficient of micro-turbines, photovoltaics, wind power, and energy storage, respectively. C_{PC} is the punishment cost, representing the penalty of the difference between the output of renewable energy and the actual electric demand at time t . θ is the penalty price coefficient of unit electric power. C_{grid} is the interaction cost with the power company. When $C_{grid} > 0$, the park purchases electricity from the power company; otherwise, the park sells electricity to the power company. P_{DL}^t and P_{DS}^t represent the electricity load and output electrical power at time t , respectively.

2.2.2 The constraints of PIES

The busbar balance of each energy and safe operation constraints of each equipment should be considered when PIES operates. The second-order cone programming (SOCP) (Alizadeh and Goldfarb, 2003) is used to formulate the constraints on AC power flow in the power system. The detailed constraints are as follows:

1) Power balance constraints

$$P_{i,t}^g - P_{i,t}^d = G_{ii}c_{ii} + \sum_{\substack{j=1 \\ j \neq i}}^k [G_{ij}c_{ij} - B_{ij}s_{ij}] \quad (15)$$

$$Q_{i,t}^g - Q_{i,t}^d = -B_{ii}c_{ii} + \sum_{\substack{j=1 \\ j \neq i}}^k [-B_{ij}c_{ij} - G_{ij}s_{ij}] \quad (16)$$

where k is the total number of power systems; $P_{i,t}^g$ and $P_{i,t}^d$ are the active power and the load of bus i , respectively; $Q_{i,t}^g$ and $Q_{i,t}^d$ are the reactive power and load of bus i , respectively; G_{ij} and B_{ij} are the conductance and susceptance of line $i - j$; and c_{ij} and s_{ij} are variables.

2) Line security constraints

$$P_i^{g, \min} \leq P_i^g \leq P_i^{g, \max} \quad (17)$$

$$Q_i^{g, \min} \leq Q_i^g \leq Q_i^{g, \max} \quad (18)$$

$$\left| (c_{ii} - c_{ij})G_{ij} + s_{ij}B_{ij} \right| \leq P_{ij}^{\max} \quad (19)$$

$$c_{ij} = c_{ji} \quad (20)$$

$$s_{ij} = -s_{ji} \quad (21)$$

$$c_{ij}^2 + s_{ij}^2 + \left(\frac{c_{ii} - c_{jj}}{2} \right)^2 \leq \left(\frac{c_{ii} + c_{jj}}{2} \right)^2 \quad (22)$$

$$(V_i^{\min})^2 \leq c_{ii} \leq (V_i^{\max})^2 \quad (23)$$

$P_i^{g, \max}/P_i^{g, \min}$ represent the maximum active power and minimum active power of generator i , respectively, $Q_i^{g, \max}/Q_i^{g, \min}$ represent the maximum reactive power and minimum reactive power of generator i , respectively, V_i^{\max}/V_i^{\min} are the upper and lower limits of voltage amplitude i , respectively, and P_{ij}^{\max} is the maximum transmission power of line $i - j$.

3) Cooling balance constraints

$$P_{ER-EX}^t + P_{AC-EX}^t + P_{CES-D}^t = P_{CES-C}^t + P_{CL}^t \quad (24)$$

where P_{CL}^t is the cooling load of PIES

4) Thermal power balance

$$P_{EB-EX}^t + P_{HE-EX}^t + P_{TES-D}^t = P_{TES-C}^t + P_{HL}^t \quad (25)$$

where P_{HL}^t is the heat load of PIES.

5) Gas node balance constraints

$$P_{REC-EX}^t \cdot (1 - \mu) + P_{GB-EX}^t = P_{HE}^t \quad (26)$$

where P_{HE}^t is the heat consumed by the heat exchanger and μ is the proportion coefficient of flue gas distribution.

6) Energy conversion constraints

Electric refrigerating unit:

$$P_{ER}^t \cdot COP_{ER} = P_{ER-EX}^t \quad (27)$$

Absorption cooling:

$$\begin{aligned} P_{AC}^t &= P_{REC-EX}^t \cdot \mu \\ P_{AC-EX}^t &= P_{AC}^t \cdot \eta_{AC} \end{aligned} \quad (28)$$

Electric boiler:

$$P_{EB}^t \cdot COP_{EB} = P_{EB-EX}^t \quad (29)$$

Heat converter:

$$P_{REC}^t \cdot \eta_{REC} = P_{REC-EX}^t \quad (30)$$

Heat recovery steam generator:

$$P_{REC}^t \cdot \eta_{REC} = P_{REC-EX}^t \quad (31)$$

Gas boiler:

$$P_{GB}^t \cdot \eta_{GB} = P_{GB-EX}^t \quad (32)$$

where COP_{ER} represents the energy efficiency coefficient of the electric refrigerating unit, COP_{EB} represents the energy efficiency coefficient of the electric heat unit, and η is the efficiency of energy conversion.

7) Energy storage unit constraints

$$W_{EES}^{t+1} = W_{EES}^t (1 - \sigma_{EES}) + \left(P_{EES-C}^t \cdot \rho_{EES-C} - \frac{P_{EES-D}^t}{\rho_{EES-D}} \right) \cdot \Delta t \tag{33}$$

$$W_{CES}^{t+1} = W_{CES}^t (1 - \sigma_{CES}) + \left(P_{CES-C}^t \cdot \rho_{CES-C} - \frac{P_{CES-D}^t}{\rho_{CES-D}} \right) \cdot \Delta t \tag{34}$$

$$W_{TES}^{t+1} = W_{TES}^t (1 - \sigma_{TES}) + \left(P_{TES-C}^t \cdot \rho_{TES-C} - \frac{P_{TES-D}^t}{\rho_{TES-D}} \right) \cdot \Delta t \tag{35}$$

where ρ_{EES-C} , ρ_{CES-C} , and ρ_{TES-C} represent the charging efficiency; ρ_{EES-D} , ρ_{CES-D} , and ρ_{TES-D} represent the discharging efficiency; and σ_{BT} , σ_{CD} , and σ_{HC} represent the self-discharge efficiency.

8) Energy storage capacity constraints

$$0 \leq P_{EES/CES/TES-C}^t \leq Cap_{EES/CES/TES}^t \cdot \sigma_{EES/CES/TES-C} \tag{36}$$

$$0 \leq P_{EES/CES/TES-D}^t \leq Cap_{EES/CES/TES}^t \cdot \sigma_{EES/CES/TES-D} \tag{37}$$

$$W_{EES/CES/TES-D, \min}^t \leq W_{EES/CES/TES}^t \leq W_{EES/CES/TES-D, \max}^t \tag{38}$$

where $Cap_{EES/CES/TES}^t$ is the rated capacity of electric/cooling/heat storage and $\sigma_{EES/CES/TES-C}/\sigma_{EES/CES/TES-D}$ is the maximum rate of charge/discharge. The maximum and minimum capacities of energy storage in Eq. 38 take 0.92 and 0.2 times the rated capacity, respectively.

9) Energy price constraints

$$0 \leq \gamma_{DL}^t \leq \bar{\gamma}_{DL, \max}^t, 0 \leq \gamma_{CL}^t \leq \bar{\gamma}_{CL, \max}^t, 0 \leq \gamma_{HL}^t \leq \bar{\gamma}_{HL, \max}^t \tag{39}$$

where $\bar{\gamma}_{DL, \max}^t$, $\bar{\gamma}_{CL, \max}^t$, and $\bar{\gamma}_{HL, \max}^t$ represent the maximum selling price of electricity, cooling, and heat, respectively.

10) Heat recovery steam generator and gas boiler constraints

$$P_{REC, \min}^t \leq P_{REC}^t \leq P_{REC, \max}^t \tag{40}$$

$$P_{GB, \min}^t \leq P_{GB}^t \leq P_{GB, \max}^t \tag{41}$$

where $P_{REC, \max}^t/P_{REC, \min}^t$ are the upper and lower limits of heat recovery steam generator output, respectively, and $P_{GB, \max}^t/P_{GB, \min}^t$ are the upper and lower limits of gas boiler output, respectively.

11) The output of energy conversion constraints

$$P_{ER-EX, \min}^t \leq P_{ER-EX}^t \leq P_{ER-EX, \max}^t \tag{42}$$

$$P_{EB-EX, \min}^t \leq P_{EB-EX}^t \leq P_{EB-EX, \max}^t \tag{43}$$

$$P_{AC-EX, \min}^t \leq P_{AC-EX}^t \leq P_{AC-EX, \max}^t \tag{44}$$

$$P_{HE-EX, \min}^t \leq P_{HE-EX}^t \leq P_{HE-EX, \max}^t \tag{45}$$

where P_{ER-EX}^t is the output of the electric refrigerating unit, limited by the upper and lower limits $P_{ER-EX, \max}^t/P_{ER-EX, \min}^t$; P_{EB-EX}^t is the output of the electric boiler; $P_{EB-EX, \max}^t/P_{EB-EX, \min}^t$ are the corresponding upper and lower limits; P_{AC-EX}^t is the output power of the lithium bromide refrigeration unit using waste heat flue gas; $P_{AC-EX, \max}^t/P_{AC-EX, \min}^t$ are its upper and lower limits, respectively; and P_{HE-EX}^t is the output of heat conversion equipment, limited by the upper and lower limits $P_{HE-EX, \max}^t/P_{HE-EX, \min}^t$.

2.3 The load model of users

Based on the known selling price of electricity, cooling, heat from PIES, and user satisfaction with energy, users adjust energy demands. The two points form users' objective function, which is different between the utility function and energy cost of users (Li et al., 2021a).

$$\max F_u = \sum_{t=1}^T [f_u^t - P_{sell}] \tag{46}$$

where f_u^t is the utility function of users, which is a measure of user satisfaction. This paper uses a commonly used expression of a quadratic function form to describe it (Maharjan et al., 2013; Chai et al., 2014):

$$f_u^t = \sum_{n=1}^N [\alpha_n P_n^t - \beta_n (P_n^t)^2] \tag{47}$$

where α_n and β_n are energy preference parameters of users. α_n is approximately twice as large as β_n . The change of preference parameters will directly affect the variation of user satisfaction, and the change of user satisfaction will further affect the user demand for energy.

The electricity load of the user side is divided into fixed electricity load and shifting electricity load (Huang et al., 2019), which can be expressed as

$$P_{DL}^t = P_{fDL}^t + P_{aDL}^t \tag{48}$$

where P_{fDL}^t is the fixed electricity load at time t . Its consumption time is relatively specific to ensure the demand of normal life and work. P_{aDL}^t is the shifting electricity load at time t . Users adjust their electricity demand according to the price from PIES and follow the constraints:

$$P_{aDL, \min}^t \leq |P_{aDL}^t| \leq P_{aDL, \max}^t \tag{49}$$

where $P_{aDL, \max}^t$ and $P_{aDL, \min}^t$ are the maximum and minimum of shifting electricity load at time t , respectively.

Moreover, the heat load can be divided as fixed heat load and reducing heat load, which can be expressed as

$$Q_{HL}^t = Q_{fHL}^t - Q_{aHL}^t \quad (50)$$

where Q_{fHL}^t is the fixed heat load at time t and Q_{aHL}^t is the reducing heat load at time t . It can be reduced in a certain proportion according to the users' actual use of energy and comfort. The reducing heat load should satisfy

$$Q_{aHL, \min}^t \leq |Q_{aHL}^t| \leq Q_{aHL, \max}^t \quad (51)$$

where $Q_{aHL, \max}^t$ and $Q_{aHL, \min}^t$ are the upper and lower limits of reducing heat load at time t , respectively.

The cooling load is also composed of fixed cooling load and reducing cooling load, which can be expressed as

$$Q_{CL}^t = Q_{fCL}^t - Q_{aCL}^t \quad (52)$$

where Q_{fCL}^t is the fixed cooling load at time t and Q_{aCL}^t is the reducing cooling load at time t , which can adjust reasonably according to the park's sufficient degree of energy supply and its demand. The reducing cooling load should satisfy the following constraints:

$$Q_{aCL, \min}^t \leq |Q_{aCL}^t| \leq Q_{aCL, \max}^t \quad (53)$$

where $Q_{aCL, \max}^t$ and $Q_{aCL, \min}^t$ are the upper and lower limits of reducing cooling load at time t , respectively.

Summarily, although the model of the power company is a nonlinear model with nonlinear constraints, it is still a convex programming problem. Similarly, the PIES model and load model of users are both convex programming problems, and the global optimal solution can be obtained by selecting appropriate solution methods.

3 Model analysis and solution methodology

3.1 Game interaction and equilibrium

3.1.1 Analysis of game interaction

In the process of energy trading, variation in the real-time purchase and sale prices of power companies will affect the purchase and sale strategies of PIES. At the same time, PIES adjusts the selling price to users based on the output of each piece of equipment in the park. Affected by the fluctuation of energy price, users will adjust part reducing and interruptible loads and develop new energy purchasing strategies. These factors will trigger the interaction among participants, and participants constantly adjust their strategies to coordinate the interests of each other and finally maximize the interest of each subject to obtain the equilibrium solution of the game.

In this game model, PIES serves as a bridge between the power company and users in a bilevel game. As the power company, PIES, and users have their interests, and there is no agreement among them. However, there is a sequence of decisions among the three; the game model is as follows:

$$G = \langle P; \delta; U \rangle \quad (54)$$

Eq. 54 contains the three elements of the master-slave game, participants P , strategies δ , and utility U , specifically as follows:

- 1) Participants: The participants in the game are the power company, PIES, and users.
- 2) Strategies: In the upper game, the strategy set of the leading power company is the selling and purchasing prices of PIES at each moment $\{c_{d,s}^t, c_{d,b}^t\}$. The strategy set of the following PIES is the sale and purchase of electricity $\{P_b^t, P_s^t\}$ to power companies at each moment. In the lower game, the strategy set of the leading PIES is the sale price $\{y_{DL}^t, y_{CL}^t, y_{HL}^t\}$. The strategy set of the following users is the transferable load $\{P_{aDL}^t, Q_{aHL}^t, Q_{aCL}^t\}$.
- 3) Utility: The utility of each participant is the objective function of the subject, which has been shown in the previous section.

3.1.2 The proof of game equilibrium

When all followers make the optimal response according to the strategy given by the leaders and the leader also accepts the response, the game reaches equilibrium, and the optimal solution is called Nash equilibrium.

Only when the master-slave game model satisfies the following three conditions can there be a unique master-slave game equilibrium solution (Liang and Su, 2018; Xiang et al., 2021):

- 1) In the game process, both the leader and follower's strategy sets are non-empty sets and also satisfy to be closed and bounded;
- 2) In the game, if the leader determines the strategy, as a follower, there is only one optimal strategy;
- 3) In the game process, if the follower determines the strategy, the leader also has only one optimal strategy.

Then, we verify whether the above three conditions are satisfied from the lower game model.

- a) Condition 1) is satisfied because the strategy sets of power companies, PIES, and users are all non-empty, closed, and bounded convex sets in Euclidean space.
- b) Verify that the follower has a unique optimal strategy after the leader gives a strategy. Taking the following layer game as an example, the first-order partial derivative of the users'

objective function against the energy consumption load can be obtained:

$$\frac{\partial F_u}{\partial P_n^t} = \frac{\partial (f_u^t - P_{sell}^t)}{\partial P_n^t} = \alpha_n - 2\beta_n P_n^t - \gamma_n \quad (55)$$

Let the first-order partial derivative of the above equation equal 0. The optimal value of available energy consumption load is

$$P_n^t = \frac{\alpha_n - \gamma_n}{2\beta_n} \quad (56)$$

Then take the second-order partial derivative of Eq. 56 concerning P_{DL}^t , P_{CL}^t , and P_{HL}^t , respectively,

$$\begin{cases} \frac{\partial^2 F_u}{\partial (P_{DL}^t)^2} = -2\beta_{DL} \\ \frac{\partial^2 F_u}{\partial (P_{CL}^t)^2} = -2\beta_{CL} \\ \frac{\partial^2 F_u}{\partial (P_{HL}^t)^2} = -2\beta_{HL} \end{cases} \quad (57)$$

Since the user energy preference parameters are generally positive, the second-order partial derivatives here are all less than 0, so Eq. 56 is the maximum value of the users' objective function. As the sale energy price of PIES changes, the extreme value may be located on the boundary of the load, but no matter how the sale energy price changes, the unique optimal load solution can be obtained.

c) Verify that the leader has a unique optimal strategy when the followers of the game are given a strategy. Substitute the optimal energy consumption load Eq. 56 into the PIES objective function Eq. 9 and take the second-order partial derivatives of γ_{DL} , γ_{CL} , and γ_{HL} , respectively,

$$\begin{cases} \frac{\partial^2 F_p}{\partial (\gamma_{DL})^2} = -\frac{1}{\beta_{DL}} \\ \frac{\partial^2 F_p}{\partial (\gamma_{CL})^2} = -\frac{1}{\beta_{CL}} \gamma_{HL} \\ \frac{\partial^2 F_p}{\partial (\gamma_{HL})^2} = -\frac{1}{\beta_{HL}} \end{cases} \quad (58)$$

According to Eq. 58, the second-order partial derivatives are all less than 0, and there is a maximum value. Therefore, when the energy consumption load is determined by the user, there is a unique optimal solution for the sale price of PIES.

The proof process of the upper game is similar to that of the lower, which is not described here. Since the upper and lower of the game are interrelated and affect each other, it is proved that both the upper and lower game models have a unique Nash equilibrium solution, which indirectly proves that the two-level

master-slave game model proposed in this section has a unique Nash equilibrium solution.

3.2 Adjustable robust optimal power flow model

ARO (Mejia Giraldo and Mccalley, 2014) is used to process wind power and photovoltaics with large fluctuation. The feature of robust optimization is that it makes decisions in the worst case to minimize the influence of decision parameters, but it also has the disadvantage of being too conservative. The emergence of ARO improves this disadvantage, and it can make a better choice between conservatism and robustness according to its own needs.

ARO controls the size of the uncertain set by introducing uncertainty. Suppose uncertain parameter $\tilde{P}_{i,t}^{PV} \in [P_{i,t}^{PV} - \Delta P_{i,t}^{PV}, P_{i,t}^{PV} + \Delta P_{i,t}^{PV}]$, $\tilde{P}_{i,t}^{WT} \in [P_{i,t}^{WT} - \Delta P_{i,t}^{WT}, P_{i,t}^{WT} + \Delta P_{i,t}^{WT}]$. $P_{i,t}^{PV}$ is the predicted photovoltaic active power output, and $\tilde{P}_{i,t}^{PV}$ is the actual photovoltaic active power output. $P_{i,t}^{WT}$ is the predicted active wind power, and $\tilde{P}_{i,t}^{WT}$ is the actual active wind power. Because the maximum or minimum value in the uncertain set is covered, if the uncertain set is directly adopted, it will bring absolute conservatism and uneconomy to the system. Therefore, ARO is used to process the set to reduce the conservatism of the model.

The uncertain sets of photovoltaics and wind power are defined as follows:

$$U_{PV}(\Gamma^{PV}, P_{i,t}^{PV}) = \{ \tilde{P}_{i,t}^{PV} \in [P_{i,t}^{PV} - \zeta_i \Delta P_{i,t}^{PV}, P_{i,t}^{PV} + \zeta_i \Delta P_{i,t}^{PV}] \} \quad (59)$$

$$\|\zeta_i\|_{\infty} \leq \Gamma^{PV}, i \in N_{PV} \quad (60)$$

$$U_{WT}(\Gamma^{WT}, P_{i,t}^{WT}) = \{ \tilde{P}_{i,t}^{WT} \in [P_{i,t}^{WT} - \tau_i \Delta P_{i,t}^{WT}, P_{i,t}^{WT} + \tau_i \Delta P_{i,t}^{WT}] \} \quad (61)$$

$$\|\tau_i\|_{\infty} \leq \Gamma^{WT}, i \in N_{WT} \quad (62)$$

where N_{PV} and N_{WT} are the sets of photovoltaic and wind power nodes, respectively. Γ^{PV} and Γ^{WT} represent photovoltaic and wind power uncertainty levels, respectively, which are 1 by default. When $\zeta_i = 0$ and $\tau_i = 0$, it means that the output errors of photovoltaics and wind power are both 0, and the model becomes a deterministic model with the worst system robustness. With the increase of ζ_i and τ_i , the uncertainty prediction error becomes larger, and the robustness and anti-interference ability are enhanced.

Therefore, based on the optimal power flow of the PIES deterministic power system introduced above, wind power and photovoltaics with uncertain output are considered to build an adjustable robust optimal power flow model.

1) Power balance constraints

$$P_{i,t}^g + P_{i,t}^{WT} + P_{i,t}^{PV} - P_{i,t}^d = G_{ii}c_{ii} + \sum_{\substack{j=1 \\ j \neq i}}^k [G_{ij}c_{ij} - B_{ij}s_{ij}] \quad (63)$$

$$Q_{i,t}^g + Q_{i,t}^{WT} + Q_{i,t}^{PV} - Q_{i,t}^d = -B_{ii}c_{ii} + \sum_{\substack{j=1 \\ j \neq i}}^k [-B_{ij}c_{ij} - G_{ij}s_{ij}] \quad (64)$$

2) Line security operation constraints

$$P_i^{g,\min} \leq P_{i,t}^g + \left(\sum_{i \in N_{WT}} \Delta P_i^{WT} \zeta_i + \sum_{i \in N_{PV}} \Delta P_i^{PV} \tau_i \right) \leq P_i^{g,\max} \quad (65)$$

$$\|\zeta_i\|_{\infty} \leq \Gamma^{PV}, i \in N_{PV} \quad (66)$$

$$\|\tau_i\|_{\infty} \leq \Gamma^{WT}, i \in N_{WT} \quad (67)$$

$$|(c_{ii} - c_{ij})G_{ij} + s_{ij}B_{ij}| \leq P_{ij}^{\max} \quad (68)$$

$$c_{ij} = c_{ji} \quad (69)$$

$$s_{ij} = -s_{ji} \quad (70)$$

$$c_{ij}^2 + s_{ij}^2 + \left(\frac{c_{ii} - c_{jj}}{2} \right)^2 \leq \left(\frac{c_{ii} + c_{jj}}{2} \right)^2 \quad (71)$$

$$(V_i^{\min})^2 \leq c_{ii} \leq (V_i^{\max})^2 \quad (72)$$

In the above adjustable robust optimal power flow model, there are constraints with uncertain parameters, so the model cannot be solved directly. In this paper, the dual norm theory is used to transform the original model into a robust equivalence model. The constraints with uncertain parameters in the original model are Eqs 65–67. According to the dual norm theory, $\max_{\|\zeta_i\|_{\infty} \leq 1} \sum_{i \in N_{WT}} \Delta P_i^{WT} \zeta_i$ is the dual norm of $\|\sum_{i \in N_{WT}} \Delta P_i^{WT}\|_1$. Similarly, $\max_{\|\tau_i\|_{\infty} \leq 1} \sum_{i \in N_{PV}} \Delta P_i^{PV} \tau_i$ is the dual norm of $\|\sum_{i \in N_{PV}} \Delta P_i^{PV}\|_1$. Therefore, the original constraint can be expressed as

$$P_i^{g,\min} \leq P_{i,t}^g + \left\| \sum_{i \in N_{WT}} \Delta P_i^{WT} \right\|_1 + \left\| \sum_{i \in N_{PV}} \Delta P_i^{PV} \right\|_1 \leq P_i^{g,\max} \quad (73)$$

Obviously, the constraint Eq. 73 no longer contains the constraint of uncertain parameters, and the model is transformed into a convex model that can be solved directly, which is convenient for a subsequent solution.

3.3 The idea of a distributed solution

In the process of the real transaction and game, transaction subjects do not want other participants to know their objective function and strategy (Lin et al., 2019). To better protect the information of each participant, the distributed solution of the game equilibrium of the power company, the PIES, and users is provided. In this way, the independent decision of each participant can be realized without disclosing the objective function information of both parties.

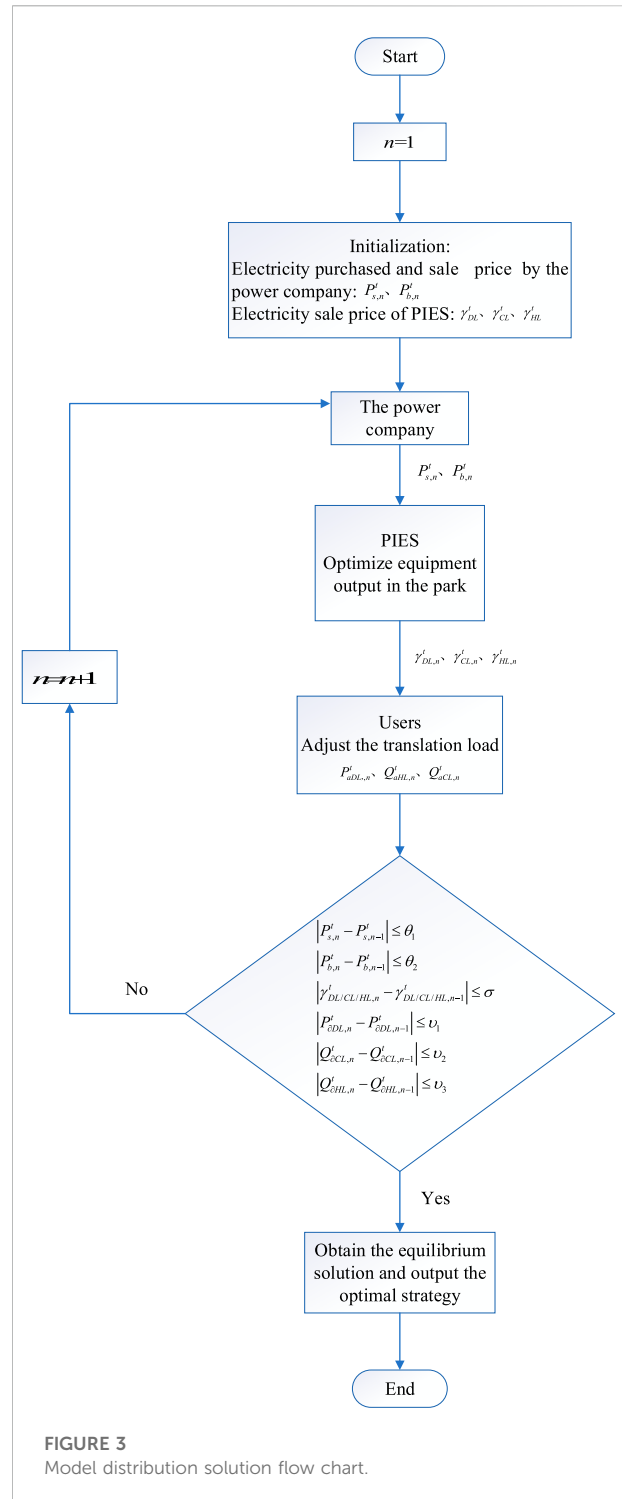


FIGURE 3 Model distribution solution flow chart.

The idea of a distributed solution is as follows:

It is assumed that there is a control center in the middle of each participant, which is responsible for summarizing the real-time information provided by the participant, allowing other participants to obtain the information and

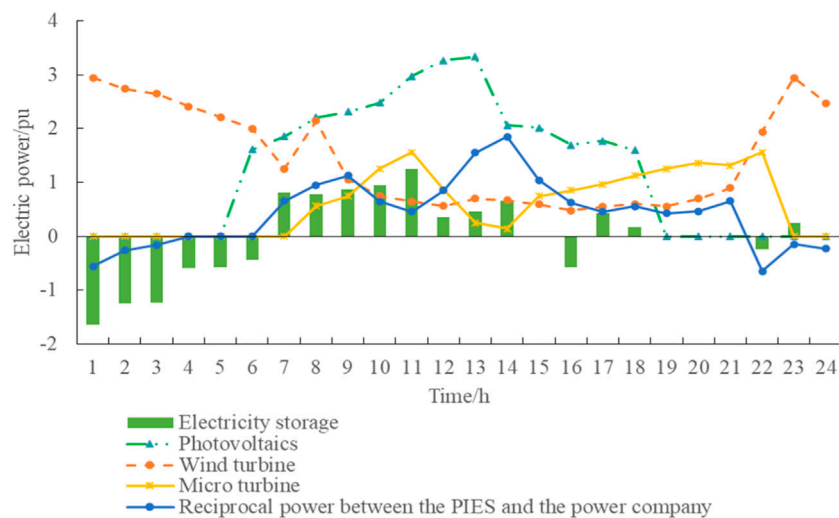


FIGURE 4
Optimization results of electricity output.

accept their feedback decision information, and realizing the coordinated solution of game equilibrium through continuous iteration. The specific flow chart is shown in Figure 3.

In the upper game, the power company initializes the unit purchase and sale prices, satisfies the purchasing and selling price constraints, and informs the control center of the initial price information. After obtaining the corresponding price from the control center, PIES determines the purchasing and selling relationship with the power company by taking into account the output of the equipment in the park.

In the lower game, PIES determines a reasonable initial selling price based on users' energy usage and passes this information to the control center. After users obtain the energy price from the control center, they make an adjustment based on their actual situation and feedback the information to the control center. The park then makes new energy prices according to the strategy feedback from users from the control center and meets the energy price constraints. PIES achieves the Nash equilibrium by constantly updating the pricing strategy and purchasing and selling strategy, feeding back to the customer and the power company.

4 Simulation example

4.1 Analysis of the result of a calculation example

In this chapter, simulation results verify the rationality and economy of the proposed power company-PIES-user master-slave game model.

The simulation is carried out using Matlab 2021a combined with the Yalmip optimization toolbox (Lofberg, 2005) on a standard personal computer with an Intel Core i7-7700 CPU running at 16 GB RAM, and the Gurobi solver (Optimization, 2014) is used to solve the master-slave game model. In this section, the PIES uses an IEEE 30-bus system for example analysis. The simulation results are presented in the form of standard identity data, and the power reference value is 100 kW. The optimization results of electrical output, cooling output, and thermal output within PIES are shown in Figures 4–6, respectively. The comparison of user demand before and after the game of various loads is shown in Figures 7–9.

As shown in Figure 4, the PIES stores the excess electrical energy in the electrical energy storage unit and transfers it to the electrical power because the wind power output is high in the early morning and late night, and the users' electricity loads are low. During the peak power consumption period from 7:00 to 11:00 in the daytime, the output of photovoltaic and micro-combustion units gradually increases, while the output of wind power gradually decreases, and energy storage units release energy to further meet the load demand. Nevertheless, the equipment in the park still fails to meet the load power demand of users, so the part of power shortage needs to be purchased from power.

As shown in Figure 5, the output of absorption cooling will be limited by the waste heat power, so the output gradually increases to the peak value during daytime working hours, and the output is less at night. The output of electric refrigeration changes with the fluctuation of cooling load demand. When the load demand is large from 8:00 to 11:00 and from 16:00 to 17:00, the output of electric refrigeration will be large, and the energy storage unit will

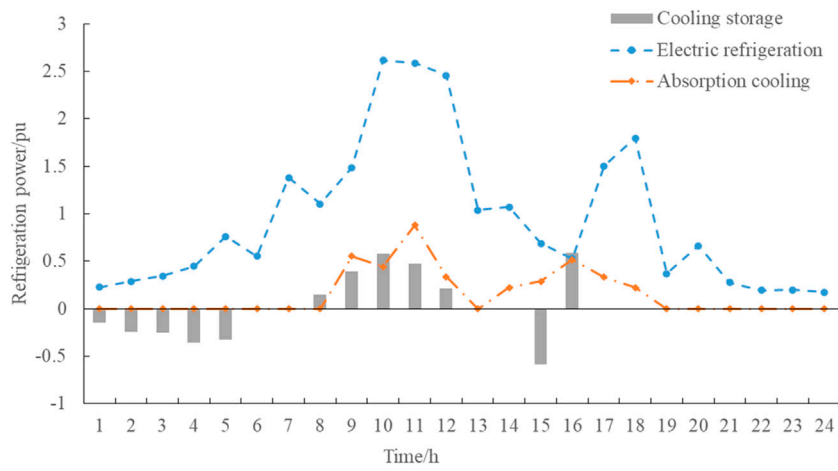


FIGURE 5
Optimization results of cooling output.

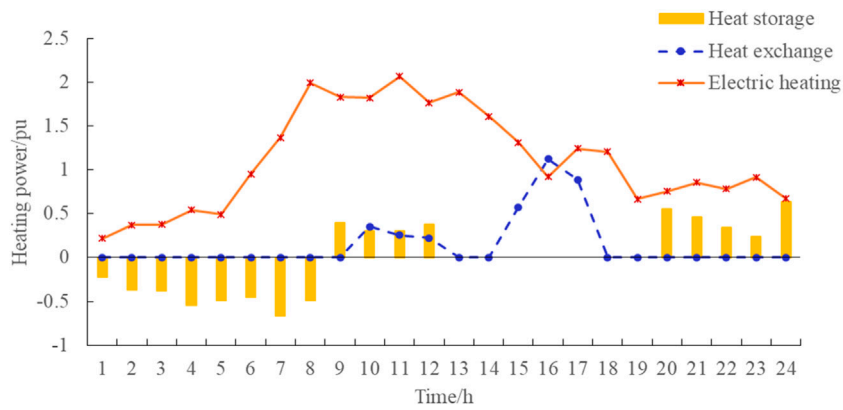


FIGURE 6
Optimization results of thermal output.

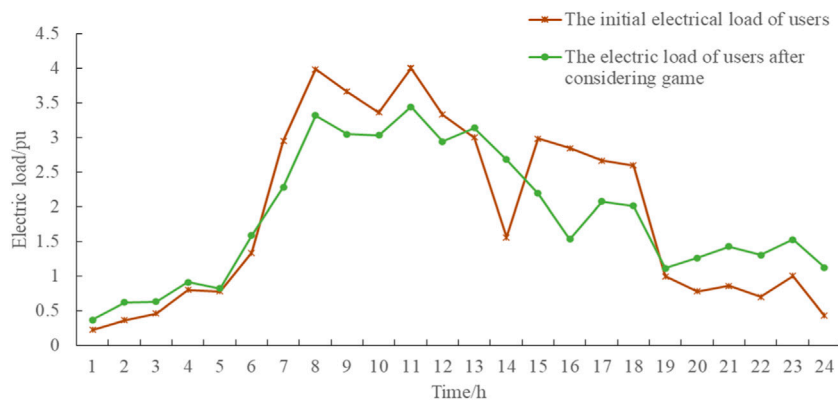


FIGURE 7
Comparison between the users' initial electricity load and the electricity load after considering the game.

also provide energy during this period to meet the energy demand.

In Figure 6, the electric heating device provides heat according to the users' demand, presenting a double-peak shape as a whole, reaching the peak value at 11:00 and 17:00, which matches the users' energy usage habits. Heat exchange is mainly affected by the gas boiler and waste heat boiler, and the output is not much throughout the day, reaching the peak at 16:00. The thermal energy storage unit as a whole presents the characteristics of internal charging when the load demand is small and provides energy when the load demand is large.

Figure 7 shows the comparison between the users' initial electricity load and the electricity load demand after considering the game. As can be seen from the figure, after considering the game, the electricity price for users in the park keeps rising during the peak periods of 7:00–12:00 and 15:00–18:00. At this point, the load is significantly optimized, and the fluctuation range of electricity load becomes smaller, which plays a good role in peak load cutting and valley filling. It relieves the power supply pressure of the park during peak hours and also reduces the power purchase cost of users so that the system can operate more safely and reliably.

Figure 8 shows the comparison between users' initial cooling load and cooling load demand after considering the game. As seen from the figure, to ensure users' energy consumption experience and comfort, the cooling load is reduced by a small amount, which is mainly reflected in the load reduction near the peak energy consumption and when the energy sale price is high. In the stage of low energy consumption and relatively cheap cooling prices in the park, the load demand should be appropriately increased.

Figure 9 shows the comparison between the users' initial heat load and the heat load demand after considering the game. As shown in the figure, after the game, the heat load is cut in the two stages of 8:00–12:00 and 15:00–17:00 to reduce the energy consumption cost and relieve the pressure on the equipment output of the comprehensive energy system in the park during the peak energy consumption period.

Figure 10 shows the price at which PIES buys and sells electricity to power companies. The dotted line in the figure represents the latest time-of-use price provided by electricity. As seen from the figure, PIES formulates the electricity purchase price strategy within the range of the dotted line. Compared with the time-of-use price, most of the periods are lower than the time-of-use price; that is, after considering the game, it has a better price advantage. At the same time, increasing the purchased and sale electricity price during peak electricity consumption encourages the equipment in the comprehensive energy system of the park to generate more electricity, therefore reducing the purchase of electricity from the power company to achieve the purpose of increasing the total income of the park.

Figure 11 shows the energy selling price of PIES to users. In order to maximize revenue, the energy selling price of each energy in the park is increased during peak energy consumption of users to obtain more excess revenue. In the low-energy-consumption period, the energy price of each energy in the park will be reduced to encourage users to increase energy consumption at this stage. Compared with the traditional time-of-use electricity price, it is smoother and easier to accept by users and ensures that the system runs more safely and stably.

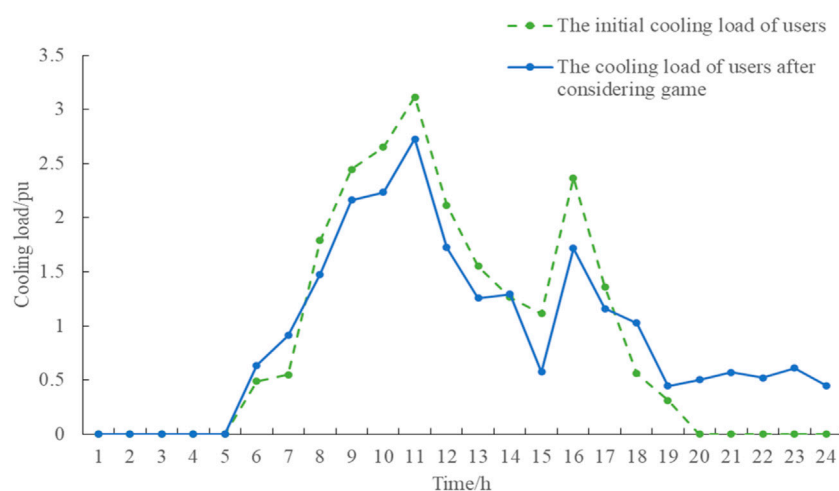


FIGURE 8

Comparison between users' initial cooling load and cooling load after considering the game.

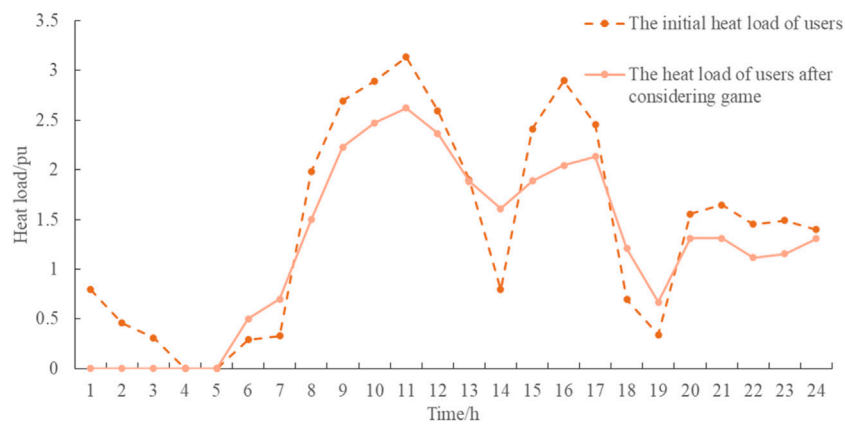


FIGURE 9 Comparison between users' initial heat load and heat load after considering the game.

TABLE 2 Income comparison of the integrated energy system of the distribution network and park under different scenarios.

Scenario	Earnings from electricity selling by the power company/¥	Interests in PIES/¥
Scenario 1	5443.3	1824.9
Scenario 2	5296.6	1021.5
Scenario 3	4627.4	1262.7
Scenario 4	4500.2	1207.8

4.2 Contrastive analysis

4.2.1 The influence of game interaction on the income of each subject

In order to better reflect the influence of game interaction on the income of each subject, the following scenarios are set up in this paper:

Scenario 1: Consider the electricity price game between the power company and the PIES and the energy price game between the PIES and the users.

Scenario 2: The price game between the power company and the PIES is considered, but the energy selling price between the PIES and the users is fixed.

Scenario 3: The price game between the PIES and the users is considered, but the energy selling price between the power company and the PIES is fixed.

Scenario 4: Regardless of any game, the upper and lower levels are trading at fixed prices.

The fixed prices in scenarios 2, 3, and 4 are taken from the average prices of the corresponding variables in scenario 1.

Table 2 shows the income comparison between the power company and the PIES in different scenarios. Scenarios 2 and 3 with the only a single-layer game have significantly higher benefits than the traditional scenario 4 without considering the game. For scenario 1 with two games, the benefits are obviously higher than those of scenarios 2 and 3 with only a single game. Under the guidance of the price game, a variety of energy shows a more reasonable optimal allocation after participating in the game, so the best benefits for both sides of the game are achieved. Therefore, the game model proposed in this paper has a better economy.

TABLE 3 Partial line power comparison.

Scenario	Line power/ptu						
	1-2	2-4	3-4	4-6	8-28	16-17	19-20
0	0.8136	1.4171	0.7236	0.1252	1.5896	1.0127	0.0641
1	0.7598	0.7214	0.4263	0.1296	0.6841	0.7402	0.0527

TABLE 4 Benefits of the PIES under different adjustable uncertainty levels.

I^{PV}/I^{WT}	Interests in PIES/yuan
0	1824.9
0.1	1800.5
0.2	1769.5
0.3	1748.6
0.4	1739.5
0.5	1723.1
0.6	1708.6
0.7	1689.4
0.8	1682.6
0.9	1680.3
1.0	1677.5

4.2.2 Influence of network power flow on PIES

To study the influence of power network flow on PIES, we set the following two scenarios:

Scenario 0: PIES ignoring the power flow of the power system.

Scenario 1: PIES in this paper considers the optimal power flow of the power system.

As shown in Table 3, scenario 1 takes into account the power flow constraints of the power system and the power of each line is within a reasonable operating range. In contrast, in scenario 0, lines 2–4 and 8–28 appear as power overload (The power overload is indicated in bold) because the line safety operation constraints are not considered. If such an overload problem appears in the

actual system, it will bring unnecessary losses and make the scheduling plan not feasible. Therefore, PIES considering power system network flow is more feasible and stable.

4.2.3 The influence of uncertainty changes on model results

As shown in Table 4, when $I^{PV} = I^{WT} = 0$, the model is deterministic, the PIES benefit is the highest, but system robustness is the worst. As wind power and photovoltaics have a larger output range, the robustness and anti-interference ability of the system are enhanced and can achieve more secure and stable operation. When I^{DG} equals to 1, the system's economy is the worst for all uncertainties of renewable energy units in the system considered.

4.2.4 User preference analysis

The influence of user preference parameters on the game equilibrium solution, that is, the influence of parameter value changes on the game solution, is observed.

Taking the transaction situation at a random time as an example, the user energy preference parameters are gradually increased from 20 to 200 to observe the influence of energy preference parameters on the game results.

As shown in Figure 12, when the energy preference parameter is below 40, users have low requirements for energy consumption experience and can reduce large amounts of various loads, so users are more sensitive to energy consumption experience. When the user preference parameters increase to more than 40, the users' sensitivity to energy experience decreases obviously, and the users' actual energy load increases with the increase of the preference parameters.

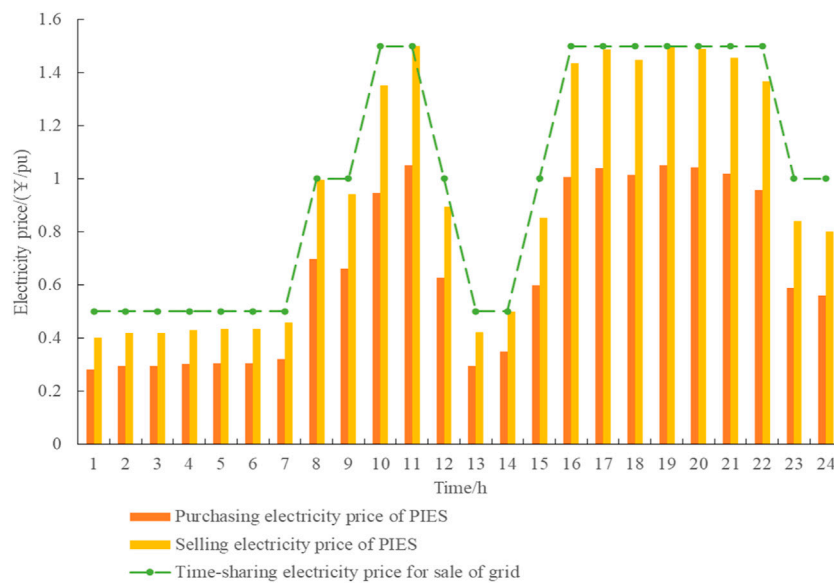


FIGURE 10 PIES purchases and sells electricity from the power grid.

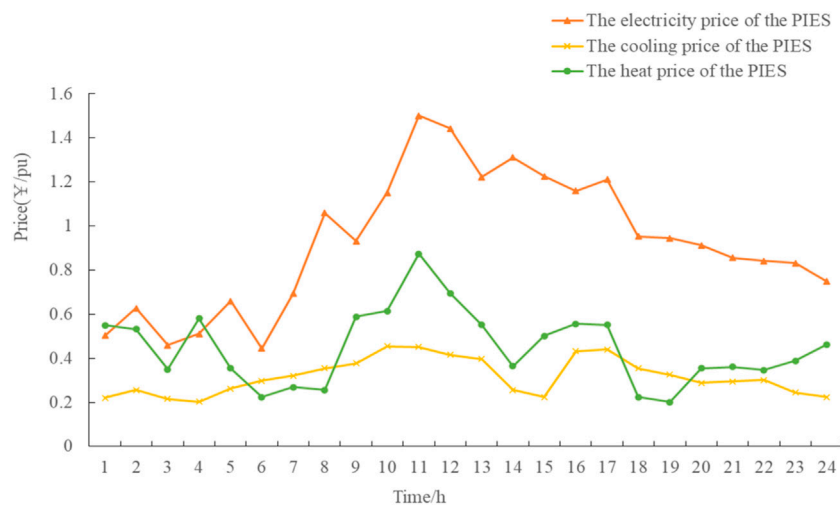


FIGURE 11 Price of PIES to users.

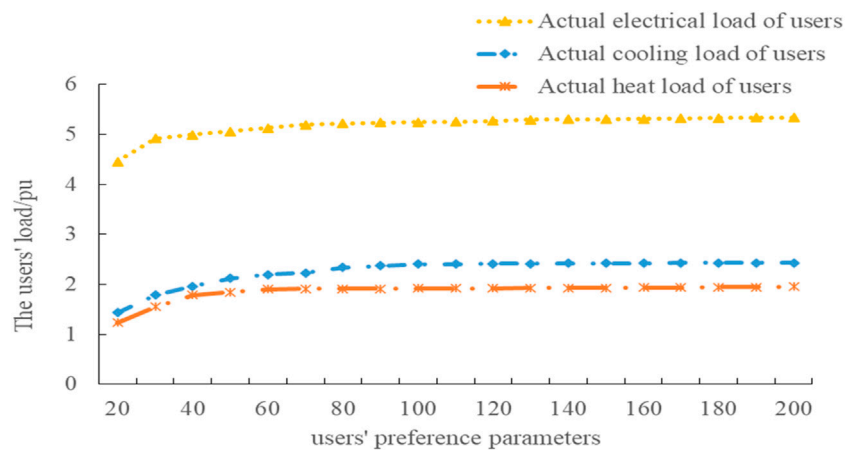


FIGURE 12 Influence of users' preference parameters on game results.

5 Conclusion

In this paper, a two-level master–slave game optimization model of the power company, PIES, and users is proposed, and a distributed algorithm solution to protect the privacy of each participant is provided to solve the model. Finally, the cooperative optimization of PIES and other subjects is realized, and the game balance is achieved. At the same time, considering the existing renewable energy units in the park, the method of ARO is considered to deal with the uncertain output. Finally, the following conclusions are drawn through the analysis of calculation examples:

- 1) It is proved that the two-level master–slave game interaction strategy constructed in this paper has a Nash equilibrium solution. In addition, the feasibility of this strategy is verified by the method of distribution solution, and the purpose of protecting the privacy of participants is realized.
- 2) By comparing the proposed game model with the traditional optimization model, both sides of the game have better economic performance after introducing the price game of the power company and the energy sale price game.
- 3) Considering the ARO model, the conservatism of the traditional robust model is improved, and the adjustable robust optimal power flow model is established. In

addition, this paper also studies the influence of user preference parameters on users. The difference in preference parameters will affect users' energy consumption and then affect the game equilibrium solution.

Future work will consider not only the electricity price game between the power company and the PIES but also the gas price game between the natural gas company and the PIES. In addition, the cooperative optimization operation of source-load-storage will be focused on, and the multi-energy free trade among multi-PIES is considered to optimize the energy utilization rate further (Li et al., 2021c).

Data availability statement

The raw data supporting the conclusion of this article will be made available by the authors, without undue reservation.

Author contributions

PW, TD, and XB contributed to the concept and design of the study. WPM wrote the first draft of the manuscript. TD, XB, LZ, and GL wrote parts of the manuscript. All authors participated in

revising the manuscript, reading, and approving the submitted version.

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Conflict of interest

The 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.

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