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Research on dynamic pricing and operation optimization strategy of integrated energy system based on Stackelberg game

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ABSTRACT

Integrated energy system (IES) brings new solutions to promote energy coupling and improve energy efficiency. However, with the transformation of energy market from traditional vertical integrated structure to interactive competitive structure, traditional optimization methods are difficult to reveal the game pattern among IESs. In this paper, a Stackelberg game model of integrated energy system operator (IESO) and integrated energy system (IES) is established to study the IESO dynamic pricing behavior and the IES operation optimization strategy. Firstly, this paper takes the IESO as the leader and each IES as the follower to construct the Stackelberg operation framework. Secondly, the Stackelberg game model between the IESO and the IESs is constructed and solved by the double mutation differential evolution algorithm, and the existence and uniqueness of the game equilibrium solution is proved. Finally, an integrated energy system park is taken as an example to demonstrate the rationality and effectiveness of the model established in this paper. The results show that, for IES, the method can achieve economic benefits while taking into account the environmental cost; and for IESO, it can achieve the IESs optimal energy efficiency while taking into account its own benefits. This paper can provide guarantee and theoretical basis for the IES operation optimization and the interaction between IESs and IESO in terms of algorithm and transaction mode.

1. Introduction

Forming an energy supply system dominated by a high proportion of renewable energy has become the consensus of the international community, and it has become an inevitable trend for new energy to shift from supplementary power sources to main power sources [1–2]. *The 2020 world energy outlook* [3] released by the International Energy Agency points out that 80% of the increment of global power demand in the next 10 years will be met by renewable energy. The energy system is facing the pressure of ensuring energy security, improving energy efficiency and promoting the new energy consumption. With energy demand as the core, the integrated energy system (IES) integrates regional solar energy, wind energy, geothermal energy and fossil energy through digitization and informatization, which brings new solutions to promote energy coupling and improve energy efficiency. IES has become one of the main directions of energy system development [4–5]. At the same time, the power system reform provides an opportunity for user-side resources to participate in power transaction. The IES with distributed renewable energy can participate in power transaction according to its own needs and maximize economic benefits. However, the IES has flexible regulation ability, and there is an interaction between the transaction price and the system operation scheme. Moreover, the IES has the complex characteristics of multi-objective and multi-scene, which increases the difficulty of model construction and optimization. The traditional operation optimization method is difficult to describe the interaction between the IESs. Therefore, it is necessary to introduce the idea of game theory into the IES operation optimization.

(1) Study on IES operation optimization.

Current research on IES operation optimization has achieved some results in load characteristics, user-side demand response, equipment characteristics and energy storage cooperative operation.

Literature [6] proposes a hybrid multi-energy load forecasting method for regional integrated energy systems (RIES) considering temporal dynamic and coupling characteristics. Literature [7] expands the demand response (DR) concept to the RIES and presents an optimal operation model of RIES considering the DR mechanism on the energy price. Literature [8] proposes an environmental economic dispatch model for the coordinated operation of an integrated regional energy

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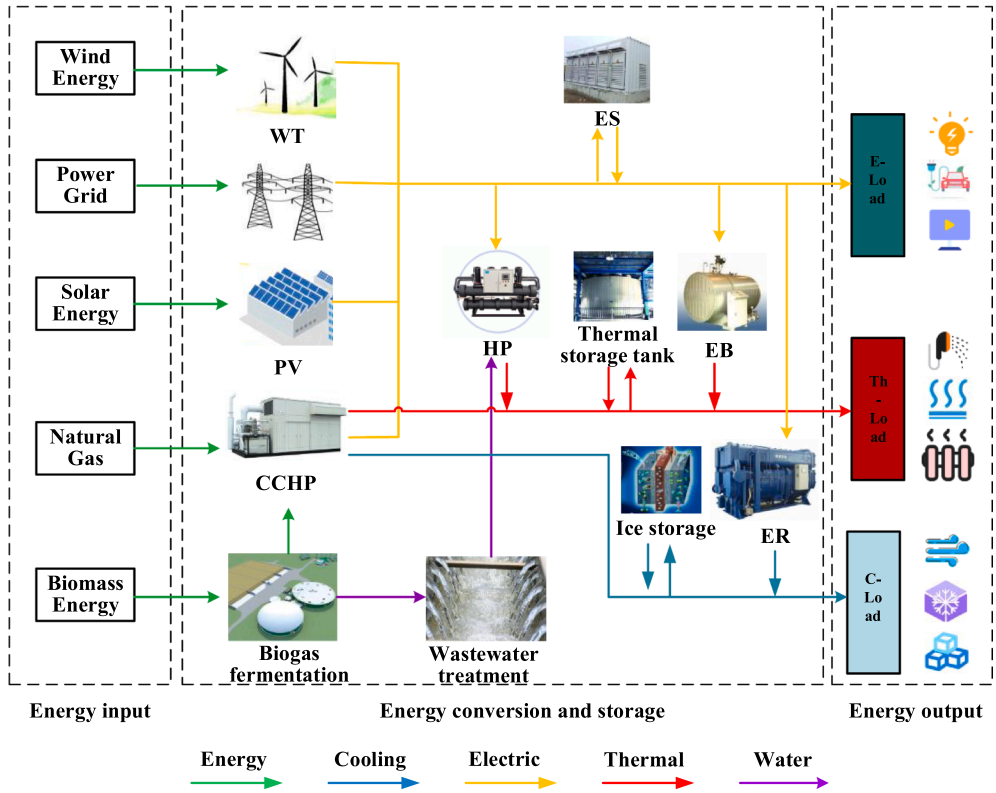
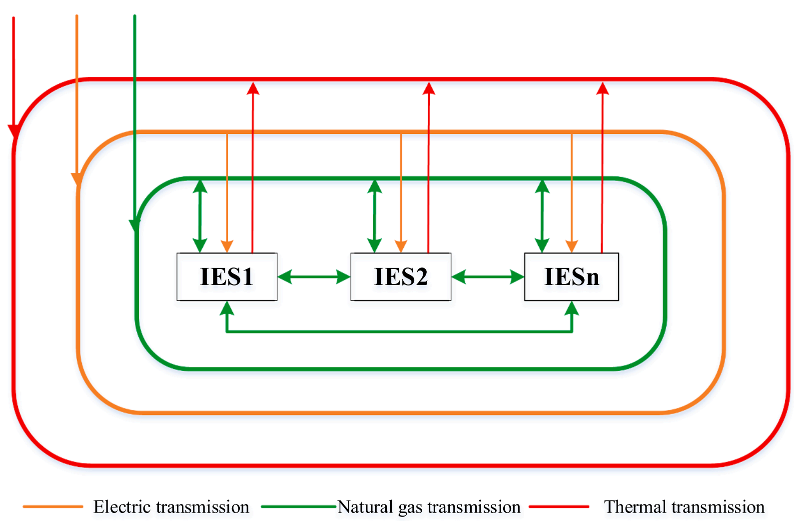


a. Energy conversion coupling relationship in IES



b. Multi-IESs topology

Fig.1. Structure of IES.

system, which considering the carbon trading scheme and different air pollutant control technologies. Literature [9] presents a multi-follower bilevel programming approach to solve the 24-h decision-making problem faced by a combined heat and power (CHP) based micro-grid (MG). Literature [10] takes the interactive response characteristics analysis of multiple energy loads into account to establish a stochastic robust optimal operation model of community integrated energy system based on integrated demand response. Literature [11] constructs a micro-Gas Turbine operation optimization model to provide a theoretical basis for the selection of microgrid power supply equipment. Literature [12] develops dynamic models of the hybrid natural gas and electricity system for the analysis of their interactions. Literature [13] presents an optimal operation model of an integrated energy system considering the response of energy price. Literature [14] constructs an energy storage operation optimization model considering wind turbine power prediction, so as to stabilize the instability of wind power output. Literature [15] constructs a large-scale energy storage system efficiency mathematical model, combining the structure of the large-scale vanadium redox battery energy storage system and the power–efficiency coupling relationship.

To sum up, most of the research on the IES optimization focuses on the exploration of load forecasting methods, the selection of key factors affecting demand response, the operating efficiency calculation of multiple types equipment, and the application of energy storage to stabilize renewable energy output fluctuations. The current research is not enough to support the demand for the overall IES optimization considering the benefits from power purchase and selling.

(2) Application of game theory in energy system.

As for the research on the Stackelberg game, scholars have made some achievements in the energy management model and the market transaction mode of microgrid.

Literature [16] proposes a multiparty energy management framework with electricity and heat demand response for the CHP-MG, and the trading process is designed as a Stackelberg game. Literature [17] proposes a multiparty energy management framework for joint operation of CHP and photovoltaic prosumers with the internal price-based demand response, and designs an optimization model based on Stackelberg game. Literature [18] constructs an energy interaction model based on Stackelberg game in order to explore energy interaction modes between distributed energy and users. Literature [19] introduces a hierarchical system model that captures the decision making processes involved in a network of multiple providers and a large number of consumers in the smart grid, and establishes a Stackelberg game between providers and end users. Literature [20] proposes a novel incentive-based demand response model from the view of a grid operator to enable system-level dispatch of demand response resources, and proposes a two-loop Stackelberg game is to capture interactions between different actors. Literature [21] proposes a novel game model based on the hierarchical Stackelberg game for analyzing the multiple energies trading problem in integrated energy systems. Literature [22] proposes a novel Stackelberg game-based optimization framework for the optimal scheduling of integrated demand response-enabled integrated energy systems with uncertain renewable generations. Literature [23] investigates the energy scheduling for a three-level integrated energy system by applying the hierarchical Stackelberg game approach. Literature [24] models the energy transaction interaction among producers and consumers in virtual microgrids as a Stackelberg game in which producers lead and consumers follow, so as to optimize the interests of consumers.

To sum up, the current research mostly focus on the transaction of power with multiple types of microgrid. In addition, the current research still lacks the active and responsive mining of energy consumption side participating in power market transactions.

Aiming at the power transaction between IESO and IESs, this paper introduces the non-cooperative complete information dynamic game theory [25] and constructs a non-cooperative Stackelberg game model. Among them, the IESO is the game leader, and the IESs are the game follower, and the game optimization problem is equivalent to a two-tier optimization model. This paper can provide a guarantee and theoretical basis for the IES operation optimization and the interaction between IESs in terms of algorithm and transaction mode, which is of great significance to improve the IES operation efficiency and marketization level. The innovations of this paper are as follows:

1) Firstly, based on the non-cooperative complete information dynamic game theory, this paper constructs the Stackelberg game operation framework with the IESO as the leader and IESs as the follower, and puts forward the transaction mode of IES, IESO and regional power grid.

2) Secondly, considering the different interest needs of IESO and IESs, IESO dynamic pricing model and IES multi-objective operation optimization model based on Stackelberg game are established, in which the iterative calculation between IESO price strategy and IES operation optimization is carried out to achieve Nash equilibrium and optimize their utility function. According to the interaction between IESO and IESs, the equilibrium solution problem is transformed into a two-level optimization problem, which is solved by double mutation differential evolution algorithm.

The structure of this paper is as follows: Section 2 defines the framework of the integrated energy system studied in this paper; Section 3 establishes the non-cooperative Stackelberg game model of IESO and IESs, and the double mutation differential evolution algorithm is used to solve it; Section 4 takes an integrated energy system park for example to verify the effectiveness and scientificity of the model constructed in this paper; Section 5 establishes two operation scenarios to demonstrate the advantages of game optimization from the aspects of economic benefits and environmental costs; Section 6 summarizes the full text.

2. Research on IES operation optimization

2.1. IES architecture and equipment output model

The IES established in this paper is shown in Fig. 1. According to the energy flow path, the IES can be divided into three parts: energy input side, energy conversion and storage side and energy output side. On the energy input side, the main components include power grid, gas grid and thermal grid. On the energy conversion and storage side, it includes equipment such as wind turbine (WT), photovoltaic (PV), heat pump (HP), combined cooling heating and power (CCHP), energy storage(ES), electric refrigerator (ER) and electric boiler(EB),etc. On the energy output side, it mainly refers to the load demand of electric, thermal and cooling.

(1) Energy production equipment.

1) Wind Turbine (WT).

The WT output piecewise function constructed in this paper is shown as Formula (1):

$$P_t^{WT} = \begin{cases} 0, 0 < v_t < v_t^{inp}, v_t > v_t^{out} \\ \dfrac{\left(v_t^{inp}\right)^3 + k{v_t}^3}{\left(v_t^{rat}\right)^3 - \left(v_t^{inp}\right)^3} P^{WT,rat}, \quad v_t^{inp} < v_t < v_t^{rat} \\ P^{WT,rat}, v_t^{rat} < v_t < v_t^{out} \end{cases} \tag{1}$$

where P_t^{WT} represents the power generation output of WT (kW). v_t represents real-time wind speed (m/s). v_t^{inp} represents cut-in wind speed (m/s). v_t^{out} represents cut-out wind speed (m/s). v_t^{rat} represents rated wind speed (m/s). k represents the fitting parameter. $P^{WT,rat}$ represents rated power (kW).

2) Photovoltaic (PV).

The calculation of PV output power is shown as Formula (2):

$$P^{PV} = P_{STC}\frac{G}{G_{STC}}(1 + \kappa(T_C - T_{STC})) \tag{2}$$

where P^{PV} represents the actual output power of PV (kW). P_{STC} represents the rated output power of PV (kW). G represents the actual solar irradiation intensity(W/m^2). G_{STC} represents the solar irradiation intensity under standard conditions, usually takes 1000 W/m^2. κ represents the temperature coefficient of PV output device power, usually takes $-0.35/{}^\circ$C. T_C represents the temperature of PV device (°C). T_{STC} represents the temperature of the PV cell module under standard conditions, usually takes 25°C.

3) Heat Pump(HP).

HP can be used for heating in winter and cooling in summer, with high energy conversion efficiency. The output model of HP constructed in this paper is shown as Formula (3).

$$\begin{cases} P^{DHP,c} = P^{DHP,e}COP_c\tau \\ P^{DHP,h} = P^{DHP,e}COP_h(1-\tau) \end{cases} \tag{3}$$

where $P^{DHP,c}$ and $P^{DHP,h}$ respectively represent the cooling power and heating power of the HP (kW). $P^{DHP,e}$ represents the power consumption of HP operation (kW). COP_c and COP_h respectively represent the energy efficiency ratio curve of cooling and heating of the HP. τ represents the operating condition of the HP, when $\tau = 1$, it indicates that the HP is in cooling condition; when $\tau = 0$, it indicates that the HP is in heating

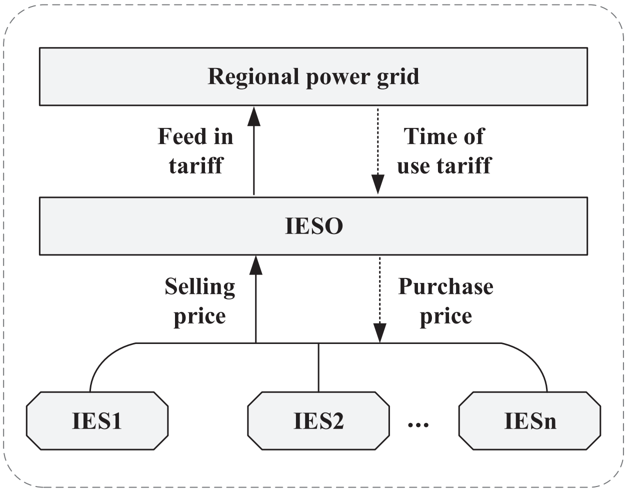


Fig. 2. Transaction flow chart.

condition.

(2) Energy conversion equipment.

1) Combined Cooling Heating and Power (CCHP).

The output model of CCHP system is shown as Formula (4):

$$\begin{cases} P_t^{MT} = \dfrac{V_t^{MT} \iota_t^{MT} LHV_{ng}}{\Delta t} \\ Q_t^{MT} = \dfrac{P_t^{MT}(1-\iota_t^{MT}-\iota_d)}{\iota_t^{MT}} \iota_{re} BC_h \end{cases} \tag{4}$$

where P_t^{MT} represents the power generation output of CCHP. V_t^{MT} represents the consumption of natural gas per unit time (m^3/h). LHV_{ng} represents the calorific value of natural gas, taking 9.78 kWh/m^3. ι_t^{MT} represents the power generation efficiency of CCHP. ι_d represents the heat dissipation loss rate. ι_{re} represents waste heat recovery efficiency ; BC_h represents the heating coefficient of lithium bromide refrigerator.

2) Electric Refrigerator (ER).

The equipment model of the ER is shown as Formula (5):

$$P_t^{ER} = P_t^{ER,E} COP_t \tag{5}$$

where P_t^{ER} represents the ER cooling power in operation. COP_t represents the ER cooling power. $P_t^{ER,E}$ represents the electric power consumed by ER.

3) Electric Boiler(EB).

The equipment model of the EB is shown as Formula (6):

$$P_t^{EB} = P_t^{EB,E} \lambda_{EB} \tag{6}$$

where P_t^{EB} represents the EB heating power (kW). $P_t^{EB,E}$ represents the EB electric input power(kW). λ_{EB} represents the EB operating efficiency.

(3) Energy storage equipment.

1) Electrical energy storage (ES).

The equipment model of the ES is shown as Formula (7):

$$P_t^{ES} = (1-\delta)P_{t_0}^{ES} + (P_t^{ES,ch} \times \vartheta_{ch} - \frac{P_t^{ES,dis}}{\vartheta_{dis}})\Delta t \tag{7}$$

where P_t^{ES} and $P_{t_0}^{ES}$ respectively represent the remaining power of the ES at time t and t_0. δ represents self-discharge rate of the ES. $P_t^{ES,ch}$ and $P_t^{ES,dis}$ respectively represent the charge and discharge power of the ES. ϑ_{ch} and ϑ_{dis} respectively represent the charge and discharge efficiency of the ES.

2.2. Construction of IES operation framework based on non-cooperative Stackelberg game

Game Theory is a mathematical theory that uses rigorous mathematical models to analyze whether there is the most reasonable behavior decision when the behavior of decision-makers interacts and how to find the optimal behavior decision [26]. The three elements of game theory include participants, strategies and benefits. Participants are all individuals with decision-making power in a Game.

The Stackelberg game model is a kind of non-cooperative complete information dynamic game in which multiple independent decision makers make decisions in response to leaders [27], and the participants in the game do not have the same market position, so there are time series in decision-making behavior. The first actor refers to his own factors to make decision-making behavior, and the latter actor obtains the decision information of the first actor and then combines his own factors to make decisions. Therefore, the Stackelberg game model can be adopted to solve the following problems:

(1) The actors participating in the game are independent and have their own decision-making basis;

(2) The decision-making behavior of participants affects the benefits obtained by at least one other participant;

(3) In the process of participating in the game, the decision-making behavior of the participants has obvious timing. The first actor takes decision-making behavior to maximize his own interests, and based on the first-mover advantage, the latter actor will be constrained to a certain extent. The actions taken by the latter actors also affect the decision-making behavior of the first actor.

(4) The final decision-making behavior of participants should be acceptable to all participants.

The transaction process constructed in this section mainly includes three types of participants: power grid, IESO and IES. Among them, the power grid receives the power provided by the IESO at feed in tariff, and provides power support in time-of-use (TOU) tariff when the IESO has power demand. IESO is responsible for the power dispatch optimization of multi-IESs, purchasing power from the power grid when the system power is insufficient and selling power to the power grid when the system power is sufficient. The IES interacts with the IESO on the basis of meeting its own needs. The transaction mechanism among the three is shown in Fig. 2.

In the actual optimization environment, IESO and IES have all the strategic information of each other. IESO plays a leading role in decision-making by formulating pricing strategies, and IES responds accordingly to price information. There is a sequence in the game process between the two, which is in line with the dynamic game situation of the master–slave hierarchical structure. Therefore, the Stackelberg game model should be used to analyze the interaction between the subjects.

Aiming at the sequence of IESO and IESs in the transaction process and the process of information exchange, this paper takes IESO and IESs as participants in the game, and conducts a IESO-IESs non-cooperative Stackelberg game framework, as shown in Fig. 3.

As shown in Fig. 3, IESO as the leader summarizes the power information of the follower IESs in the game process. In combination with the interaction price with the power grid, IESO sets the purchase and selling price for IESs over the next 24 h, with its own benefits maximization as the objective function. IESs act as follower to optimize the dispatch of multi-type equipment output within the system, guided by price signals developed by the IESO, with the objective function set to the lowest operation cost and the lowest environmental cost to determine the electric quantity traded with the IESO. IESO and IESs have a sequence and influence with each other, the two play games until they reach equilibrium.

The Stackelberg game model between IESO and IESs constructed in this paper includes the following parts:

1) Participants. IESO and IES form a non-cooperative Stackelberg

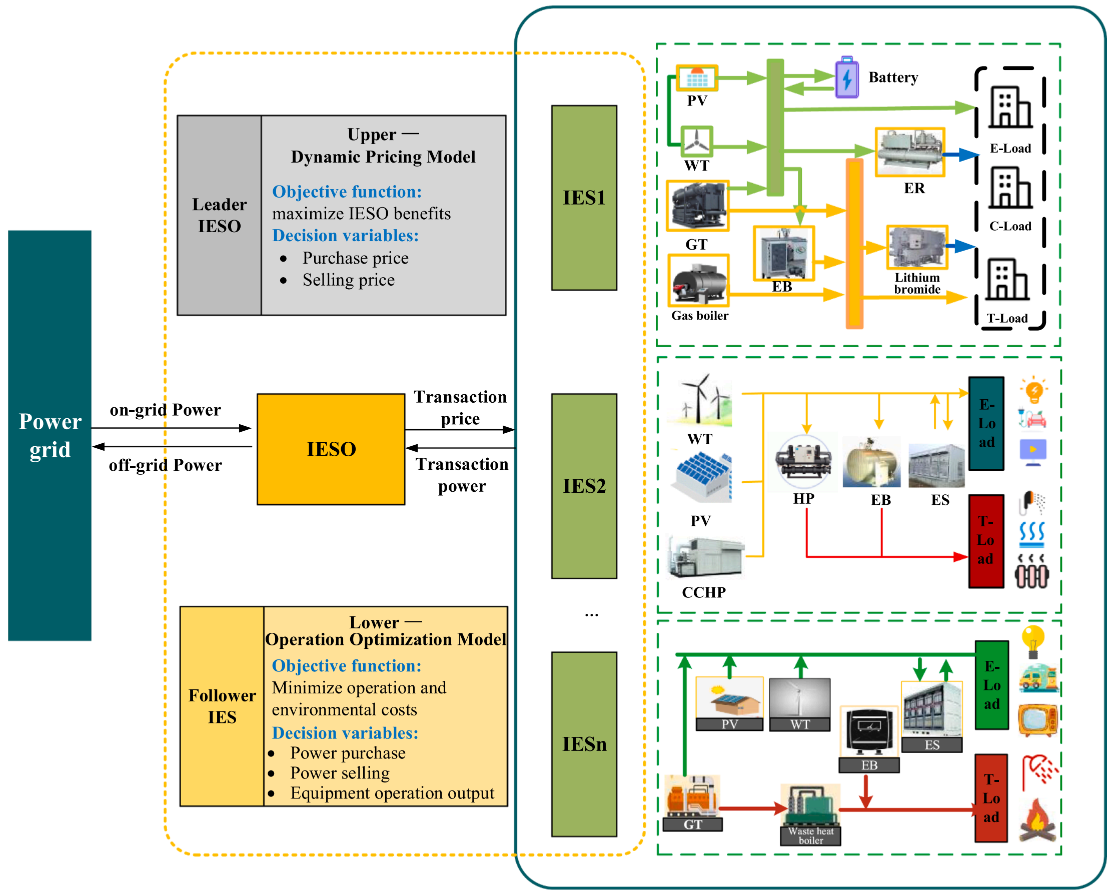


Fig.3. Framework of non-cooperative Stackelberg game model.

game as leaders and followers respectively.

2) Strategies. In the game, IESO takes the purchase and selling price as a competitive strategy. IES takes purchase and selling power and equipment output as its competitive strategy.

3) Utility function. IESO aims to maximize its own economic benefits, so the utility function is set as benefit maximization. IES takes environmental benefits into account while pursuing economic benefits, so it takes minimizing operation cost and environmental cost as the utility function.

3. Construction and solution of multi-IES Stackelberg game model

3.1. System mathematical model construction

3.1.1. Leader IESO dynamic pricing game model

(1) Strategies.

The IESO game strategy is to formulate the purchase price $p_t^{IES,b}$ and selling price $p_t^{IES,s}$ for IESs at time t, denoted as $p_t^{IES,b} = (p_1^{IES,b}, p_2^{IES,b}, \cdots, p_T^{IES,b})$ and $p_t^{IES,s} = (p_1^{IES,s}, p_2^{IES,s}, \cdots, p_T^{IES,s})$.

(2) Utility function.

IESO sets the utility function as the highest economic benefit, in which the economic benefit mainly covers the power purchase cost and power selling income for the interaction between the IESs and the power grid. As shown in Formula (8):

$$maxR^{IESO} = \sum_{t=1}^{T} \left\{ p_t^{IESO,s} q_t^{IESO,s} - p_t^{IESO,b} q_t^{IESO,b} + p_t^{IES,b} \sum_{i=1}^{N} q_{i,t}^{IES,b} - p_t^{IES,s} \times \sum_{i=1}^{N} q_{i,t}^{IES,s} \right\} \tag{8}$$

where $p_t^{IESO,s}$ and $p_t^{IESO,b}$ respectively represent the feed-in tariff and power purchase price traded between IESO and power grid at time t;$q_t^{IESO,s}$ and $q_t^{IESO,b}$ respectively represent the power sold and purchased by IESO to power grid at time t. $p_t^{IES,s}$ and $p_t^{IES,b}$ respectively represent the selling price and purchase price between IESs and IESO at time t. $q_{i,t}^{IES,s}$ and $q_{i,t}^{IES,b}$ respectively represent the power sold and purchased by IESs to IESO at time t. N represents the total number of IES.

In order to ensure the supply–demand balance between IESs and IESO, $q_t^{IESO,s}$ and $q_t^{IESO,b}$ should meet Formula (9):

$$\begin{cases} q_t^{IESO} = \sum_{i=1}^{N} (q_{i,t}^{IES,b} - q_{i,t}^{IES,s}) \\ q_t^{IESO,b} = \begin{cases} q_t^{IESO}, q_t^{IESO} \geq 0 \\ 0, q_t^{IESO} < 0 \end{cases} \\ q_t^{IESO,s} = \begin{cases} -q_t^{IESO}, q_t^{IESO} < 0 \\ 0, q_t^{IESO} \geq 0 \end{cases} \end{cases} \tag{9}$$

where q_t^{IESO} represents the electric quantity that the IESO interacts with the power grid after collecting the information of each IES. When $q_t^{IESO} > 0$, it indicates that the system power consumption is tight, and IESO need to purchase power from the power grid. When $q_t^{IESO} < 0$, it indicates that the system power supply is loose, and IESO can sell power to the power grid for benefits.

(3) Strategy space.

In the process of power transaction, the settlement between IESO and power grid is carried out according to TOU tariff $p_t^{IESO,b}$ and feed in tariff $p_t^{IESO,s}$. The settlement between IESO and IESs is based on the selling price $p_t^{IES,s}$ and purchase price $p_t^{IES,b}$. In order to mobilize IESs to participate in the power transaction, the internal purchase and selling price should be better than the transaction price between the power grid, that is:

$$p_t^{IESO,s} \leq p_t^{IES,s} \leq p_t^{IES,b} \leq p_t^{IESO,b} \tag{10}$$

The strategy space of IESO is determined by Formula (10) and denoted as Ω^{IESO}.

3.1.2. Follower IES operation optimization game model

(1) Strategies.

Multiple types equipment output and power interaction between IESs and IESO belong to IES game strategy. Specifically expressed as: electric quantity sold $q_t^{IES,s}$ and electric quantity purchased $q_t^{IES,b}$ by IESs to IESO. WT output power $P_{i,t}^{WT}$ at time t, PV output power $P_{i,t}^{PV}$ at time t, MT output power $P_{i,t}^{MT}$ at time t, ES output power $P_{i,t}^{ES}$ at time t, Adjustable Load (AL) interruption power P_t^{AL} at time t, denoted as $P_i = (q_t^{IES,s}, q_t^{IES,b}, P_{i,t}^{MT}, P_{i,t}^{ES}, P_{i,t}^{AL}), i \in M$. M refers to multi types equipment in IES.

(2) Utility function.

IES takes the economic benefit maximization as the utility function and the lowest operation cost F_1 and environmental cost F_2 as the objective function of economic benefit. The operation of MT is an important factor affecting the environmental cost. In order to ensure that the game has an equilibrium solution, the operation cost and environmental cost are combined. The IES utility function includes: energy transaction cost $C_{EE,t}$, ES operating cost $C_{ES,t}$, AL compensation cost $C_{AL,t}$, distributed generation cost $C_{DG,t}$, equipment maintenance cost $C_{OM,t}$, environmental cost $C_{E,t}$. Among them, distributed generation equipment includes WT, PV, CHP or CCHP system. The power generation cost of WT and PV is converted to $C_{OM,t}$. $C_{DG,t}$ mainly lies in the natural gas consumption of gas turbine in CHP or CCHP. The main carbon emission source of $C_{E,t}$ comes from the operation of gas turbine in CHP or CCHP system.

Considering the application of game strategy in utility function, various cost calculation formulas can be expressed as Formulas (11–17):

$$minC^{IES} = F_1 + F_2 = C_{EE,t} + C_{ES,t} + C_{AL,t} + C_{DG,t} + C_{OM,t} + C_{E,t} \tag{11}$$

$$C_{EE,t} = \sum_{t=1}^{T} (p_t^{IES,b} q_{i,t}^{IES,b} - p_t^{IES,s} q_{i,t}^{IES,s}) \tag{12}$$

$$C_{DG,t} = \sum_{i \in M} \sum_{t=1}^{T} (a_n \left(P_{i,t}^{MT}\right)^2 + b_n P_{i,t}^{MT} + c_n) \tag{13}$$

$$C_{ES,t} = \sum_{i \in M} \sum_{t=1}^{T} (a_m \left(P_{i,t}^{ES}\right)^2 + b_m P_{i,t}^{ES} + c_m) \tag{14}$$

$$C_{AL,t} = \sum_{t=1}^{T} \gamma_t P_{i,t}^{AL} \tag{15}$$

$$C_{OM,t} = \sum_{t=1}^{T} \zeta_t (P_{i,t}^{WT} + P_{i,t}^{PV}) \tag{16}$$

$$C_{E,t} = \sum_{i \in M} \sum_{t=1}^{T} \varpi_i P_{i,t}^{MT} \tau_i + \mu \tag{17}$$

where, a_n, b_n, c_n represents the cost factor of MT operation; a_m, b_m, c_m represents the cost factor of ES operation; γ_t represents the AL compensation price coefficient at time$t$. ζ_t represents the maintenance cost of equipment per unit power. ϖ_i、τ_i and μ respectively represent emission coefficient, unit cost and emission penalty cost.

(3) Strategy space.

During the game, the strategy also needs to meet the constraints shown in Formulas (18–22):

$$\begin{cases} P_t^{IES} = q_t^{IES,b} - q_t^{IES,s} \\ P_t^{IES} + \sum_{i \in M} \left(P_{i,t}^{MT} + P_{i,t}^{WT} + P_{i,t}^{PV} + P_{i,t}^{ES} + P_t^{AL}\right) = \sum_{i \in M} P_{i,t}^{L} \end{cases} \tag{18}$$

$$\begin{cases} 0 \leq P_t^{IES,s} \leq \theta_t P_{t,max}^{IES} \\ 0 \leq P_t^{IES,b} \leq (1-\theta_t) P_{t,max}^{IES} \end{cases} \tag{19}$$

$$\begin{cases} 0 \leq P_{i,t}^{MT} \leq P_{i,max}^{MT} \\ P_{i,-R}^{MT} \leq P_{i,t}^{MT} - P_{i,t-1}^{MT} \leq P_{i,R}^{MT} \end{cases} \tag{20}$$

$$\begin{cases} P_{i,min}^{ES} \leq P_{i,t}^{ES} \leq P_{i,max}^{ES} \\ S_{i,t}^{ES} = S_{i,t-1}^{ES} - \dfrac{\Delta t}{S_{i,max}} P_{i,t}^{ES} \\ S_{i,min}^{ES} \leq S_{i,t}^{ES} \leq S_{i,max}^{ES} \\ S_{i,o}^{ES} = S_{i,T}^{ES} \end{cases} \tag{21}$$

$$\begin{cases} 0 \leq P_{i,t}^{AL} \leq P_{i,max}^{AL} \\ 0 \leq P_{i,t}^{WT} \leq P_{i,max}^{WT} \\ 0 \leq P_{i,t}^{PV} \leq P_{i,max}^{PV} \end{cases} \tag{22}$$

where $P_{i,t}^{L}$ represents the predicted value of load at time t, θ_t represents a Boolean variable. When $\theta_t = 1$, it indicates that the system power supply is loose at time t, and IESs can sell power to the IESO for benefits. When $\theta_t = 0$, it indicates that the system power consumption is tight at time t, and IESs need to purchase power from the IESO. $P_{t,max}^{IES}$ represents the maximum value of interaction power between IESs and IESO. $P_{i,max}^{MT}$ represents the maximum output power of MT, $P_{i,-R}^{MT}$ and $P_{i,R}^{MT}$ respectively represent the downward and upward climbing rates of MT. $S_{i,t}^{ES}$ represents the charged state of ES at time t.$S_{i,min}^{ES}$ and $S_{i,max}^{ES}$ respectively represents the upper and lower limits of the charge state. $P_{i,max}^{ES}$ and $P_{i,min}^{ES}$ respectively represents the upper and lower limits of ES charge and discharge power. $S_{i,max}^{ES}$ represents the maximum capacity of the ES. $P_{i,max}^{AL}$ represents the maximum acceptable interruption value of AL. The IES strategy space is determined by Formulas (18–22), denoted as Ω^{IES}.

3.1.3. Non-cooperative Stackelberg game optimization model

(1) Stackelberg game model.

From the follower strategy, for the arbitrarily determined internal price $p_t^{IES,b}$ and $p_t^{IES,s}$ in each period, the optimal power transaction between IESs and IESO can be expressed by Formula (23):

$$\{q_{i,t}^{IES,s^*}, q_{i,t}^{IES,b^*}\} == \underset{q_{i,t}^{IES,s}, q_{i,t}^{IES,b}}{\operatorname{argmin}} C^{IES}(p_t^{IES,b}, p_t^{IES,s}, P_i) \tag{23}$$

From the leader strategy, IESO encourages IESs to actively participate in power transactions to maximize IESO benefits by setting $p_t^{IESO,s}$ and $p_t^{IESO,b}$, and its optimal internal purchase and selling prices can be expressed by Formula (24):

$$\{p_t^{IESO,b^*}, p_t^{IESO,s^*}\} = \underset{p_t^{IESO,b}, p_t^{IESO,s}}{\operatorname{argmin}} (R^{IESO} q_t^{IESO,s}, q_t^{IESO,b}, \underset{q_{i,t}^{IES,s}, q_{i,t}^{IES,b}}{\operatorname{argmin}} C^{IES}(p_t^{IES,b}, p_t^{IES,s}, P_i) \tag{24}$$

The game solution between IESO and IESs can be equivalent to finding the internal optimal purchase and selling price and the IES optimal operation strategy. To maximize utility, IESO needs to consider the response of IESs to the internal purchase and selling price and find an equilibrium solution as the best strategy.

According to the above description, if strategy $(p_t^{IES,b^*}, p_t^{IES,s^*}, P_i^*)$ exists in the strategy space which satisfies Formula (25):

$$\begin{cases} R^{IESO}(p_t^{IES,b^*}, p_t^{IES,s^*}, P_i^*) \geq R^{IESO}(p_t^{IES,b^*}, p_t^{IES,s}, P_i^*) \\ R^{IESO}(p_t^{IES,b^*}, p_t^{IES,s^*}, P_i^*) \geq R^{IESO}(p_t^{IES,b}, p_t^{IES,s}, P_i^*) \\ C^{IES}(p_t^{IES,b^*}, p_t^{IES,s^*}, P_i^*) \leq C^{IES}(p_t^{IES,b^*}, p_t^{IES,s^*}, P_i) \end{cases} \tag{25}$$

Then this strategy $(p_t^{IES,b^*}, p_t^{IES,s^*}, P_i^*)$ is the Nash equilibrium solution of the Stackelberg game model. In this strategy, IESO is unable to unilaterally change the price strategy to achieve higher benefits, IES is unable to adjust equipment output to achieve minimum costs, and this strategy maximizes benefits for both subjects.

(2) Existence of equilibrium.

In the Stackelberg model, if the following conditions are met, there is a equilibrium solution [28–30]:

1) The strategy space of leaders and followers in the model is a nonempty quasi-convex set.

2) After the upper leader strategy is determined, the lower follower has an optimal solution.

3) After the lower follower strategy is determined, the upper leader has an optimal solution.

Step1: Prove that the strategy space of leaders and followers is a nonempty quasi-convex set.

Firstly, the leader and follower are continuous functions of strategy space Ω^{IESO} and Ω^{IES} respectively. For the upper leaders, the strategy space Ω^{IESO} is determined by linear constraints, which is obviously a nonempty quasi-convex set. For the lower followers, the IES cost includes $C_{EE,t}$, $C_{ES,t}$, $C_{AL,t}$, $C_{DG,t}$, $C_{OM,t}$, $C_{E,t}$ and so on. Except for $C_{ES,t}$ and $C_{DG,t}$, the costs are linear functions and obviously quasi-convex functions. Since the actual cost function of ES and MT shows that the quadratic term coefficient is greater than 0, the ES and MT cost function is also classified as quasi-convex function. Therefore, based on the given transaction price, the strategy space of the lower follower is a nonempty quasi-convex set.

Step2: Prove that when the leader's strategy is given, all followers have a unique optimal solution.

Firstly, the objective function (11) of IES is calculated with respect to the first-order partial derivatives of $q_{i,t}^{IES,b}$, $q_{i,t}^{IES,s}$, $P_{i,t}^{MT}$, $P_{i,t}^{ES}$, $P_{i,t}^{AL}$, $P_{i,t}^{WT}$ and $P_{i,t}^{PV}$, and the Formula (26) is obtained:

$$\begin{cases} \dfrac{\partial C^{IES}}{\partial q_{i,t}^{IES,b}} = p_t^{IES,b} \\ \dfrac{\partial C^{IES}}{\partial q_{i,t}^{IES,s}} = -p_t^{IES,s} \\ \dfrac{\partial C^{IES}}{\partial P_{i,t}^{MT}} = 2a_n P_{i,t}^{MT} + b_n + \varpi_i \tau_i \\ \dfrac{\partial C^{IES}}{\partial P_{i,t}^{ES}} = 2a_m P_{i,t}^{ES} + b_m \\ \dfrac{\partial C^{IES}}{\partial P_{i,t}^{AL}} = \gamma_t \\ \dfrac{\partial C^{IES}}{\partial P_{i,t}^{WT}} = \zeta_t \\ \dfrac{\partial C^{IES}}{\partial P_{i,t}^{PV}} = \zeta_t \end{cases} \tag{26}$$

If the first-order partial derivative is 0, Formula (27) can be obtained:

$$\begin{cases} P_{i,t,0}^{MT} = -\dfrac{b_n + \varpi_i \tau_i}{2a_n} \\ P_{i,t,0}^{ES} = -\dfrac{b_m}{2a_m} \end{cases} \tag{27}$$

Secondly, take the second-order partial derivative of Formula (11), and the Formula (28) is obtained:

$$\begin{cases} \dfrac{\partial^2 C^{IES}}{\partial (P_{i,t}^{MT})^2} = 2a_n \\ \dfrac{\partial^2 C^{IES}}{\partial (P_{i,t}^{ES})^2} = 2a_m \end{cases} \tag{28}$$

Since the energy preference coefficient is generally positive, and the second-order partial derivatives are greater than 0, $P_{i,t,0}^{MT}$ and $P_{i,t,0}^{ES}$ are the minimum points of Formula (11), considering the interval constraint of optimization variables, the range of optimal solution can be expressed as Formulas (29–30):

$$P_{i,t,opt}^{MT} \in \left\{P_{i,t,0}^{MT}, 0, P_{i,max}^{MT}\right\} \tag{29}$$

$$P_{i,t,opt}^{ES} \in \left\{P_{i,t,0}^{ES}, 0, P_{i,max}^{ES}\right\} \tag{30}$$

Step3: Proved that when the follower's strategy is given, the leader has a unique optimal solution.

This section only discusses the cases of $q_t^{IESO} < 0$ and $q_t^{IES,b} < q_t^{IES,s}$, then the IESO benefits can be expressed as Formula (31):

$$R^{IESO} = \sum_{t=1}^{T} \left\{ p_t^{IESO,s} q_t^{IESO,s} + p_t^{IES,b} \sum_{i=1}^{N} q_{i,t}^{IES,b} - p_t^{IES,s} \sum_{i=1}^{N} q_{i,t}^{IES,s} \right\} \tag{31}$$

Substitute a set of optimization strategies $\left\{q_{t,0}^{IES,s}, q_{t,0}^{IES,b}, P_{i,t,0}^{MT}, P_{i,t,0}^{ES}, P_{i,t,0}^{WT}, P_{i,t,0}^{PV}, P_{i,t,0}^{AL}\right\}$ of the follower into Formula (31), and calculate the first-order partial derivatives of the leader's objective function (8) with respect to $p_t^{IESO,s}$, $p_t^{IESO,b}$, $p_t^{IES,b}$, $p_t^{IES,s}$ respectively to obtain Formula (32):

Table 1
Comparison of optimization algorithms [31–35].

Algorithm	Principle	Characteristic
Genetic Algorithm	Based on the theory of simulated biological evolution, the variables are directly selected, crossed, mutated, which is not easy to fall into the state of local convergence	The coding requirements are high, and the cross mutation method can also be set manually, which has the problems of long solution time and inaccuracy
Particle Swarm optimization	Based on the random predation behavior of birds, the optimal solution is searched by following the optimal particle memory	The particles do not have diversity, and the calculation is easy to fall into the local optimal solution
ant colony optimization	Based on the foraging behavior of ants, according to the pheromone exchange between individuals, the positive feedback mechanism is used to optimize	The convergence speed of the algorithm is slow, easy to fall into local optimization, and prone to stagnation.
Simulated annealing algorithm	Based on the object annealing principle, the global optimal solution can be quickly obtained in the solution set considering the probability jump property	The demand sample data is large and the calculation time is relatively long
DDE	Relying on the thought of population evolution, the game process of cooperation and competition between individual and group strategy is continuously promoted to the direction of optimal fitness objective function	In the process of optimization, the optimal solution will be recorded continuously, and the means of subject interaction will be adopted to realize the evolution of the population, so as to adjust and balance the contradiction between convergence speed and population diversity

$$\begin{cases} \dfrac{\partial R^{IESO}}{\partial p_t^{IESO,s}} = q_t^{IESO,s} = -q_t^{IESO} \\ \dfrac{\partial R^{IESO}}{\partial p_t^{IES,b}} = \sum_{i\in M} P_{i,t}^{L} + \dfrac{b_n + \varpi_i \tau_i + p_t^{IES,b}}{2a_n} - \dfrac{p_t^{IES,s} - b_m}{2a_m} \\ \dfrac{\partial R^{IESO}}{\partial p_t^{IES,s}} = \dfrac{p_t^{IES,s} - b_m}{2a_m} - \dfrac{b_n + \varpi_i \tau_i + p_t^{IES,b}}{2a_n} - \sum_{i\in M} P_{i,t}^{L} \end{cases} \tag{32}$$

Therefore, the Hessian matrix of the leader utility function is shown in Formula (33)::

$$H = \begin{pmatrix} 0 & 0 & 0 \\ 0 & \dfrac{1}{2a_n} - \dfrac{1}{2a_m} & 0 \\ 0 & 0 & \dfrac{1}{2a_m} - \dfrac{1}{2a_n} \end{pmatrix} < 0 \tag{33}$$

It can be found that Hessian matrix is negative definite, so there is a maximum point. When the follower takes other extreme points, it can also prove that the leader has a unique optimal solution. The proof of other scenarios is similar to the above process, which will not be repeated in this paper.

To sum up, the Stackelberg game model proposed in this paper has a unique Stackelberg Equilibrium.

3.2. Solving algorithm

According to Formula (24), the key essence of the Stackelberg game equilibrium solution is the bilevel programming problem. The upper layer is the solution of the optimal day ahead price strategy $\left\{p_t^{IESO,b^*}, p_t^{IESO,s^*}\right\}$, and the lower layer is the solution of the IESO optimal economic dispatching strategy $\left\{q_{i,t}^{IES,s^*}, q_{i,t}^{IES,b^*}\right\}$ under the optimal price strategy $\left\{p_t^{IESO,b^*}, p_t^{IESO,s^*}\right\}$. Formula (11) shows that the IES operation cost minimization problem is a quadratic programming problem with linear equality constraints and linear inequality constraints, which can be solved by constructing Lagrange function and using optimization tools. Formula (24) shows that the minimization of IES operation cost and environmental cost has a min-min form, and it is difficult to directly obtain the functional relationship between the optimization variable set $\left\{q_{i,t}^{IES,s}, q_{i,t}^{IES,b}\right\}$ and the internal power price set $\left\{p_t^{IESO,b}, p_t^{IESO,s}\right\}$ through the Karush-Kuhn-Tucker (KKT) [18,20]condition.

Therefore, considering the characteristics of various optimization algorithms (see Table 1), this paper improves the differential evolution algorithm (DE) and plans to use the double mutation differential evolution algorithm (DDE) to search the upper optimal price strategy. Taking the individual in the population as a price strategy of IESO, the optimal price strategy is obtained through the variation, crossover and selection of the population.

In 1995, American scientists Store and Price mentioned a heuristic random search method, the standard differential evolution (DE) algorithm [36]. This method has the characteristics of few mathematical parameters and strong adaptability, and is suitable for optimal solution of multiple types problems. However, this algorithm converges quickly and easily falls into local optimum.

In view of the inverse correlation between population diversity and convergence rate, this paper proposes a double mutation strategy to balance population diversity and coordinate the convergence rate [37]. The specific implementation method is that the double mutation strategy introduces the information and conditions of other solutions to the basic strategy, so as to enrich the population diversity. The difference between differential evolution algorithm based on double mutation strategy (DDE) and standard DE algorithm is as follows:

(1) Mutation operation.

Through the mutation strategy, the parent population x_i^G produces the mutation individual v_i^G, which is an important step of the DE.

The core of the DE algorithm is mutation operator, and the problem of operator is adaptability. Mutation operators can be divided into three types, as shown in the following Formulas (34–36):

$$v_i^G = x_{\Gamma 0}^G + F(x_{\Gamma 1}^G - x_{\Gamma 2}^G) \tag{34}$$

$$v_i^G = x_{\text{best}}^G + F(x_{\Gamma 1}^G - x_{\Gamma 2}^G) \tag{35}$$

$$v_i^G = x_{\text{i}}^G + F\left(x_{\text{best}}^G - x_{\Gamma i}^G\right) + F(x_{\Gamma 1}^G - x_{\Gamma 2}^G) \tag{36}$$

where i, $\Gamma 1$ and $\Gamma 2$ are independent and non-conflicting natural numbers; F is the scaling factor, which has the ability to adjust the deviation control vector and can be valued within [0,1].

The mutation operator can be improved to solve the problem of population unity caused by early population maturity. The specific principle is that the individual guidance mechanism of the operator changes, from the optimal guidance to the feasible solution decreasing guidance. The specific expression is shown in Formula (37):

$$v_i^G = x_i^G + F\left(x_{best}^{BFS^G} - x_i^G\right) + F(x_{\Gamma 1}^G - x_{\Gamma 2}^G) \tag{37}$$

where $x_{best}^{BFS^G}$ is a random individual within its range. The specific range can be obtained by calculating rank(G). After calculation, the range becomes [1, rank(G)]. In the calculation, G_M is the maximum number of iterations.

$$rank(G) = NP - (NP - 1)\sqrt{\frac{G}{G_m}} \tag{38}$$

(2) Judge population diversity.

The variance can represent the dispersion of the variable from the

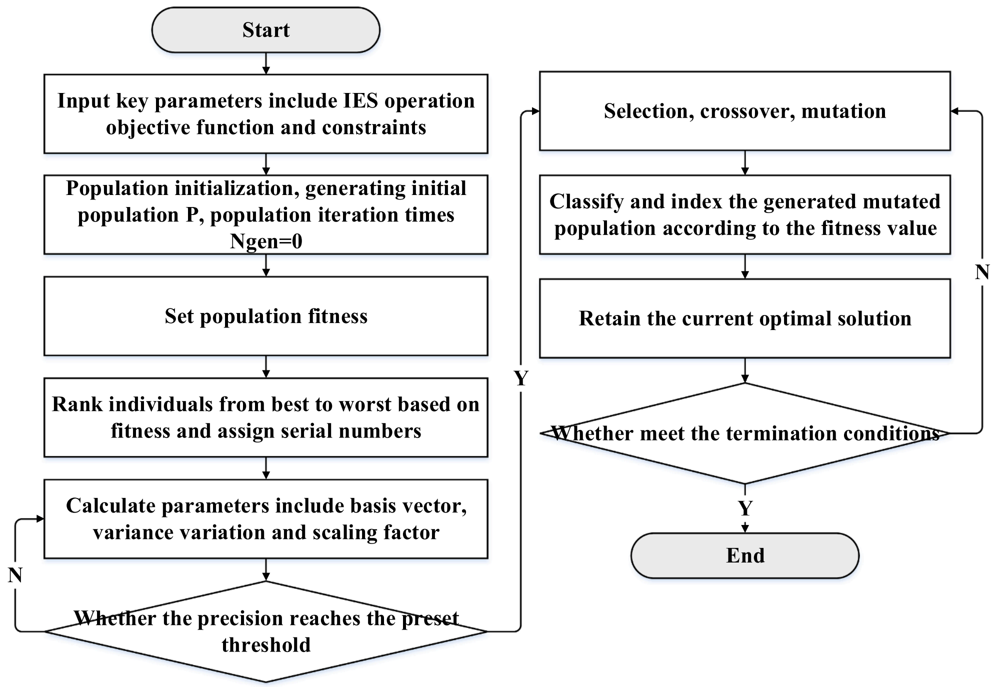


Fig. 4. IES operation optimization flow chart based on DDE algorithm.

expected value. Similarly, in the DDE algorithm, the degree of dispersion can be analyzed by calculating the fitness variance, so as to judge whether the optimal solution is reached.

In a population, assuming that its scale is NP, where f_i is the fitness of i and $\overline{f}$ is the average population fitness, the population variance is:

$$\delta^2 = \frac{1}{N}\sum_{i=1}^{NP}\left|\frac{f_i - \overline{f}}{max|f_i - \overline{f}|}\right| \tag{39}$$

When $\delta^2 = 0$, then $|f_i - \overline{f}| = 0$, that is $f_i = \overline{f}$, which is locally optimal;

When $\delta^2 \neq 0$, then $|f_i - \overline{f}| \neq 0$, if $|f_i - \overline{f}|$ is much greater than 0, it indicates that the individual is far from the average individual and is in the process of solving and searching. If $|f_i - \overline{f}|$ is close to 0, it is in the aggregation state and the optimal solution may appear.

(3) Double mutation strategy.

The mutation operation of DE algorithm is as follows:

$$v_i^G = \begin{cases} x_i^G + F\left(x_{best}^{BFS^G} - x_i^G\right) + F\left(x_{\Gamma1}^G - x_{\Gamma2}^G\right) \text{ (Threshold reached)} \\ x_i^G + F\left(x_{\Gamma1}^G - x_{\Gamma2}^G\right) \text{ (Threshold not reached)} \end{cases} \tag{40}$$

The DDE algorithm judges the population state by calculating the variance [38]. If the variance is close to 0, aggregation occurs. In the improved state, the DDE algorithm makes full use of the mutation operator advantages and solves the mutually exclusive relationship between convergence rate and population size.

According to the above analysis, this paper constructs a DDE algorithm to solve the operation optimization of the follower IES. The specific algorithm flow is shown in Fig. 4:

3.3. Design of IES operation optimization process

The IES operation optimization process based on Stackelberg game model is shown in Fig. 5:

Step 1: Basic data input. The input data includes typical electric, heating and cooling load curve, PV related data, WT related data, equipment pre-output data, energy price, environmental emission coefficient, equipment capacity and operation parameters.

Step 2:IESO price solution and IES operation optimization solution. Input algorithm parameters, according to the input equipment pre-output data and energy demand data, considering power balance constraints, equipment climbing constraints, ES operation constraints and other conditions, according to the non-cooperative Stackelberg game optimization model constructed in section 3.1.3, the system purchase and selling price and equipment output are simulated and calculated by using the double variation differential evolution algorithm.

Step 3: Optimal scheme decision. According to the price strategy and operation optimization scheme obtained in Step 2, judge whether the utility function accuracy of the leader and follower is satisfied. If so, output the optimal scheme; if not, return to Step 2 for iterative calculation.

4. Empirical analysis

4.1. Basic data and model parameters

Take an integrated energy system park in a region of northern China as an example, the IES operation optimization based on non-cooperative Stackelberg game proposed in this paper is simulated and analyzed. The distribution network voltage of the park is 10 kV. There are 3 IESs and 1 IESO in the park, which are named IES1, IES2, IES3.

IES1 basic capacity is 17000 kW, and the equipment including WT, PV, CCHP, HP, ES, EB, and ER. IES2 basic capacity is 12500 kW, including WT, PV, CHP, ES and EB. IES3 basic capacity is 8200 kW, and equipment in IES3 is consistent with IES2. In addition, each IES is carries a proportion of its load. IES gives priority to the load. When the local load cannot be fully absorbed, it can be stored or sold to IESO. IESO basic capacity is 37700 kW.

Table 2 shows the capacity of each IES equipment. Table 3 shows the key parameters of each IES equipment. Fig. 6 shows the typical daily load forecast of each IES.

Both natural gas price and electric price will affect the output of IESs equipment, thus affecting the equipment operation optimization scheme. In this paper, the electric price is divided into the price interacting with the power grid and the price interacting with IESO. The price interacting with the power grid is determined according to the benchmark price, and the price interacting with IESO is formed according to

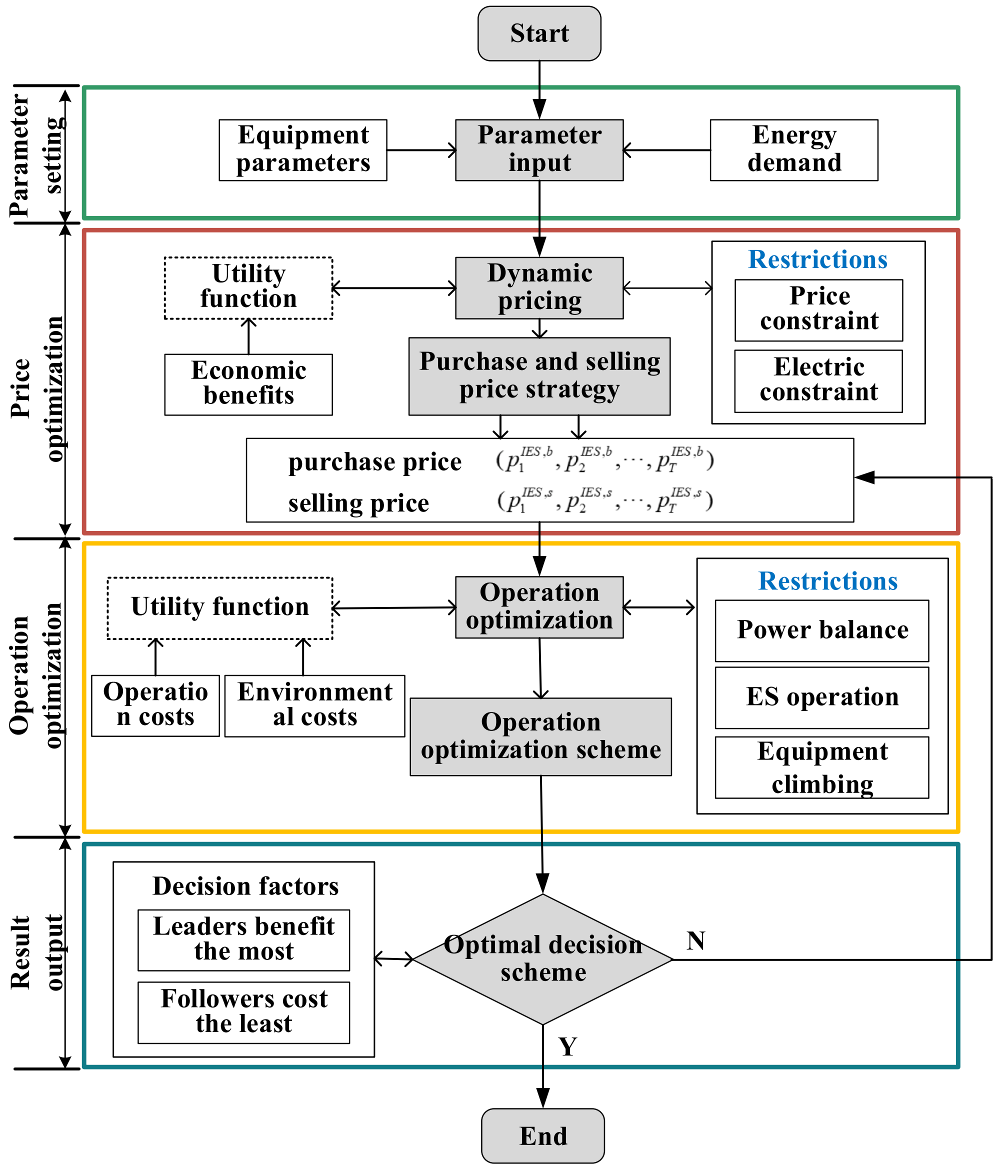


Fig.5. IES operation optimization process.

Table 2
Capacity configuration of energy supply equipment.

Equipment capacity	IES1	IES2	IES3
PV	2000 kW	2000 kW	1000 kW
WT	2500 kW	2000 kW	1200 kW
CCHP	7000 kW	——	——
CHP	——	6000 kW	3000 kW
HP	500 kW	——	——
ES	3000 kW	1000 kW	1000 kW
EB	1000 kW	1500 kW	2000 kW
ER	1000 kW	——	——

Table 3
Key parameters of energy supply equipment.

Parameters	IES1	IES2	IES3
CCHP/CHP electrical efficiency	0.412	0.42	0.38
CCHP/CHP thermal efficiency	0.44	0.43	0.42
ES safety restraint range	[0.1–0.9]	[0.1–0.9]	[0.1–0.9]
ES charge/discharge efficiency	0.96	0.96	0.96
EB operation efficiency	0.96	0.95	0.95
HP efficiency	3.5	——	——
ER system efficiency	3	3	3
CCHP/CHP cost coefficient	0.325	0.33	3
Translatable load range	[0,10%]	[0,15%]	[0,12%]
Compensation price coefficient	0.30	0.28	0.30

the game optimization. The natural gas price is set as a fixed price. As shown in Table 4.

The IES operation must consider the impact on the environment. In the model constructed in this paper, the pollutant emission mainly comes from CCHP unit and CHP unit. Table 5 shows the environmental cost parameters of different pollutants.

In the game model constructed in this paper, the upper leaders take 1 h as the simulation step to calculate the optimal price strategy. The lower followers take the upper price strategy as the basic parameters and the typical daily load as the basic data for simulation analysis to solve the system best operation scheme.

4.2. Algorithm optimization results

In the solution process of this paper, non-cooperative Stackelberg game optimization model using DDE algorithm to solve the optimal

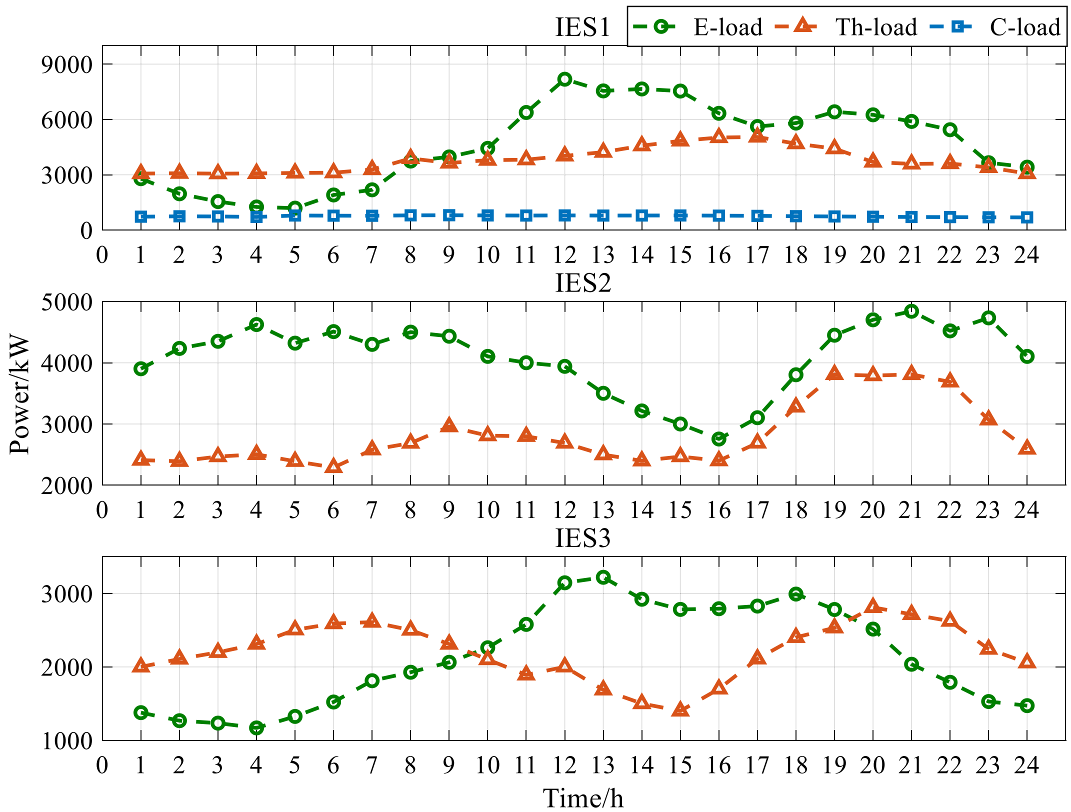


Fig. 6. Typical daily load forecast of each IES.

Table 4
Natural gas price and electric price.

Type	Price (yuan/kWh, yuan/m^3)		
	Valley period 0:00–6:00 23:00–24:00	Flat period 7:00–8:00 13:00–14:00 21:00–22:00	Peak period 9:00–12:00 17:00–20:00
Purchase price	0.5522	0.8185	1.2035
Selling price	0.3644	0.3644	0.3644
Natural gas price	3.24		

Table 5
Environmental cost parameters[39].

Pollutants		SO_2	NO_x	CO_2	CO
Emissions	Coal(kg/t)	18	8	1731	0.26
	NG(kg/10^6m^3)	11.6	0.006	2.01	0
Environmental value (yuan/kg)		6.13	26.00	0.09	1.00
Penalty cost (yuan /kg)		1.00	2.00	0.01	0.16

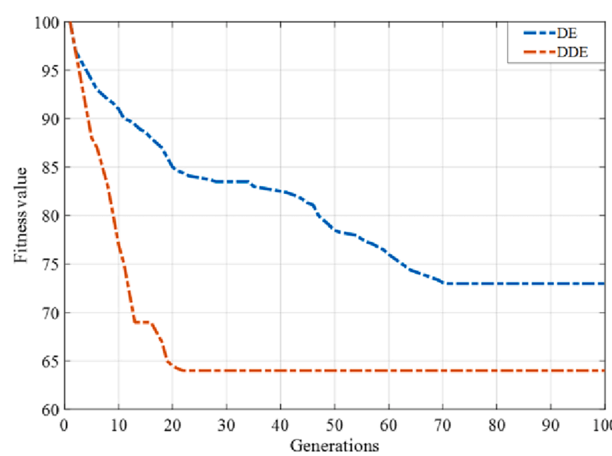


Fig.7. Fitness curve based on DE and DDE algorithm.

operation scheme. In order to judge the effectiveness of the algorithm, the DE algorithm and the DDE algorithm are used respectively. Set the number of iterations to 100, record the minimum value of each generation, and generate the fitness curve as shown in Fig. 7.

As shown in Fig. 7, compared with the DE algorithm, the DDE algorithm can find the optimal solution faster, and the 21st generation converges to find the optimal solution. The DE algorithm has poor convergence, insufficient accuracy and falls into local optimization.

As shown in Fig. 8, as the number of iterations increases, the IES operation cost gradually decreases until convergence. Due to the need to interact with upper IESO, convergence is slow. However, due to the existence of Game mechanism, each IES operation cost is low.

4.3. Multi-IESs operation optimization results

4.3.1. Internal purchase and selling price strategy

The purchase and selling price strategy formulated by the IESO is shown in Fig. 9.

Generally speaking, during 0:00–8:00 and 18:00–23:00, the internal power purchase price is greater than the feed-in tariff, and the internal power selling price is consistent with the TOU tariff. Mainly because in the two periods, the PV output in each IES is small, or even 0. At this time, the power demand is high and the system is generally in a purchasing state, so the internal selling price is consistent with the TOU tariff in order to ensure IESO benefits. In addition, in order to encourage IES to increase power output in these two periods, the internal power purchase price is higher than the feed-in tariff. Especially during 18:00–23:00, IESs can maximize operation benefits by increasing

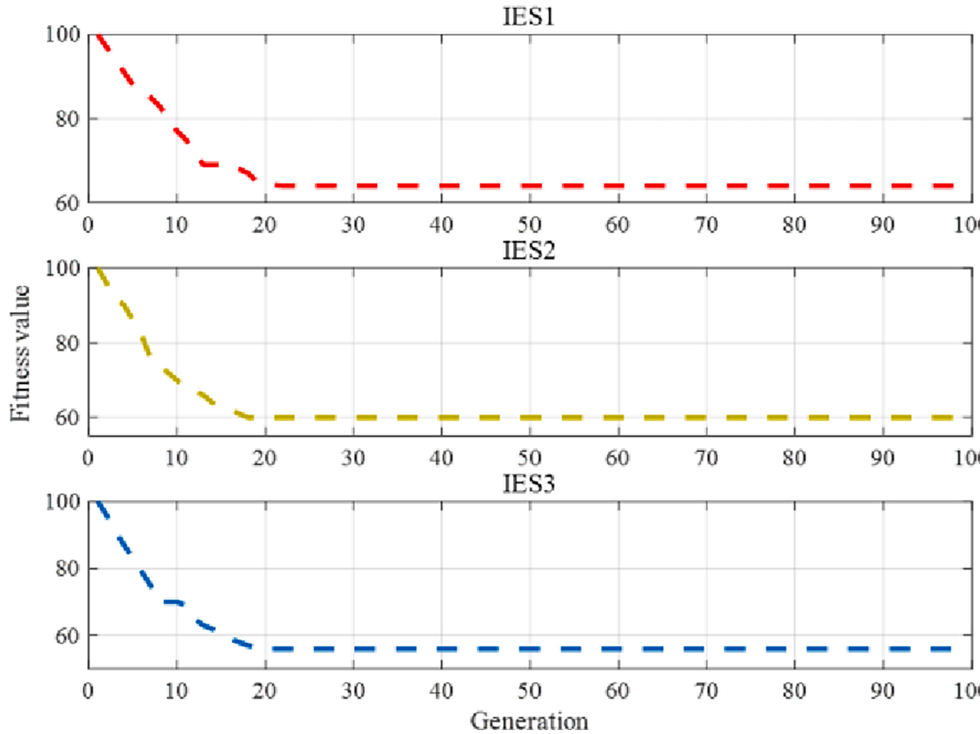


Fig. 8. IES operation optimization fitness curve.

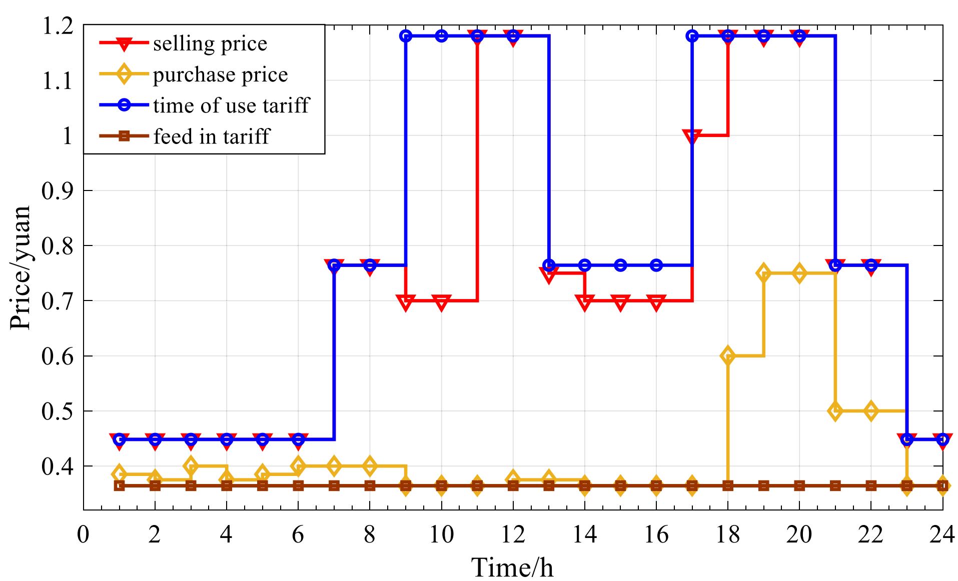


Fig.9. Transaction price curve.

equipment output or adjusting power load.

During 9:00–11:00 and 13:00–18:00, IES1 is in power purchase state, while IES 2 and IES3 are in power selling state. In order to encourage power trading between systems, the internal power selling price is set to be lower than the TOU tariff. The power purchase cost in IES is reduced, IES can reduce the operation cost by increasing load demand or charging for ES. In other periods, the system is basically in equilibrium, and the internal power purchase and selling price is not much different from that of the power grid.

4.3.2. Power transaction results

Price strategy is formulated through game optimization, the power trading results are shown in Fig. 10.

According to Fig. 10.

In general, IES1 power selling time is concentrated in the period of 0:00–10:00, and the power purchase time is concentrated in 12:00–22:00. During the period from 0:00 to 10:00, IES1 is in a state of sufficient power due to the low load demand, which can increase the electric trading quantity, thereby maximizing the electric selling benefits. Since the power purchase price is low from 13:00 to 16:00, IES 1 purchases more power from IESO by adjusting the load and energy storage strategy. In view of the high purchase and selling price during 17:00–20:00, IES 1 can reduce power purchases while increasing electric selling quantity by optimizing equipment output, so as to increase benefits.

In general, IES2 power selling time is concentrated in the period of

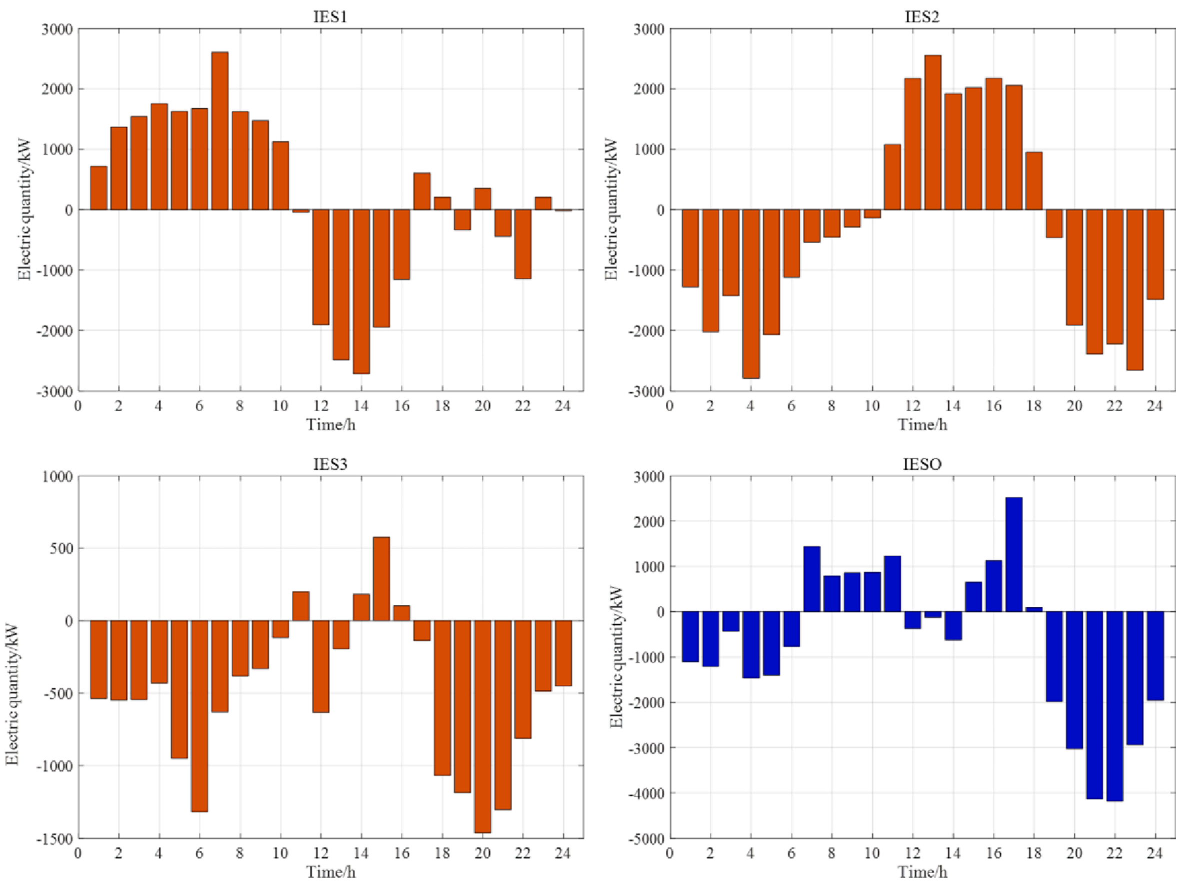


Fig.10. Power trading results.

11:00–18:00, and the power purchase time is concentrated in 0:00–10:00 and 19:00–24:00. From 0:00 to 6:00, IES2 increases the power purchase quantity due to the low power purchase price, and reduces the subsequent power consumption by adjusting the load or charging the Energy Storage. Due to the high purchase price during 19:00–22:00, IES 2 reduces the power purchase of quantity by discharging energy storage and reducing load demand, so as to reduce the power purchase cost. IES2 chooses to sell power during the 11:00–13:00 and 17:00–18:00 periods to increase benefits.

IES3 is generally in the state of power purchase due to the small installed capacity. From 0:00 to 5:00, due to the low power purchase price, IES3 reduces the power purchase cost by increasing the transaction power quantity. From 17:00 to 20:00, due to the high power purchase price, IES3 chooses energy storage discharge and load reduction to reduce power purchase quantity. In addition, due to the low purchase and selling price during 9:00–10:00, IES3 chooses to purchase additional power to charge the Energy Storage, thus increasing the power selling quantity in subsequent periods.

According to the above analysis, the IES power supply will affect the establishment of IESO internal purchase and selling price. Through the above analysis, it can be seen that the power supply of IES will affect the price strategy of IESO. Similarly, IESO guides IES to optimize the power purchase and selling behavior by setting prices, thereby increasing the power sharing in the system and reducing transactions with the power grid, which can become an auxiliary means of regional autonomy.

4.3.3. IES operation optimization results

(1) Analysis of electrical system.

The power supply equipment of IES1 includes WT, PV, CCHP and ES. IES2 power supply equipment includes WT, PV, CHP and ES. IES3 power supply equipment includes WT, PV, CHP and ES.

As shown in Fig. 11, when the power supply–demand in IES is unbalanced, IES1 will trade with IESO to ensure the balance through power purchase and selling measures. Similar to IES1, IES2 increases the power purchase during periods of low purchase price, and increases output during periods of power selling, so as to increase benefits. In response to the purchase and selling price, IES3 applies ES and translation load to meet the power load demand and reduce the system operation cost.

(2) Analysis of heating system and cooling system.

The heating equipment in IES1 includes CCHP, HP and EB, and the heating equipment in IES2 and IES3 is CHP and EB. The cooling equipment in IES1 includes CCHP and ER. CCHP is preferred for cooling when the system is supplied, and ER is selected for energy supply when the supply of CCHP is insufficient.

As shown in Fig. 12.

Analysis of heating system: Due to the application of ES and translation load, IES1 has abundant power supply. In order to reduce the environmental problems caused by the CCHP operation, IES1 increases the EB output. The heating strategy of IES 2 and IES3 is to increase the EB output when the purchase price is low and reduce the EB output when the selling price is high, so as to reduce heating costs and increase power selling benefits.

Analysis of cooling system: In response to the internal purchase-selling price, IES1 reduces the CCHP output power, resulting in lower power consumption cost. Considering the environmental cost of CCHP operations, IES 1 increases the ER output, reducing CCHP operation costs while mitigating environmental impacts.

5. Discussion

In order to verify the effectiveness of the model proposed in this paper, two operation scenarios are developed in this section:

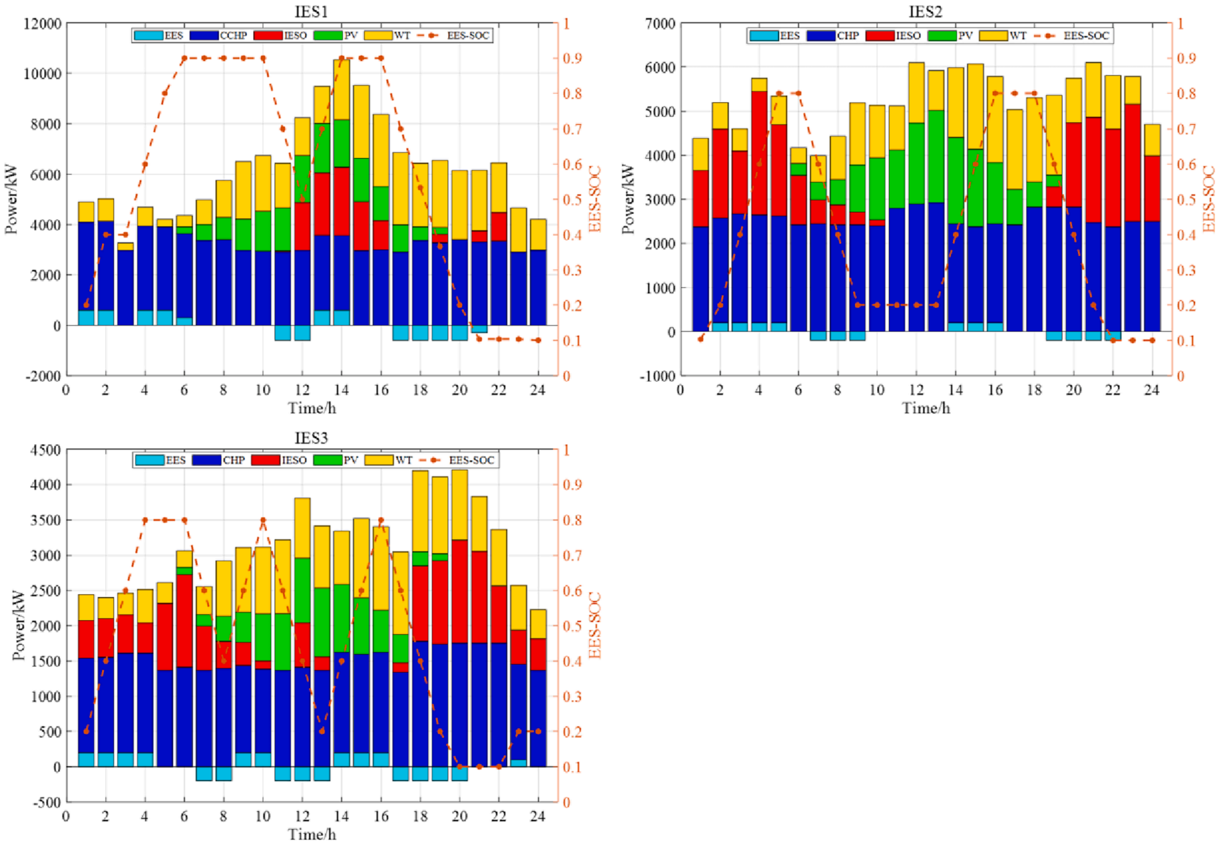


Fig.11. Output curve of power supply equipment.

Scenario 1–Independent operation mode

There is no game between IESO and IESs. IESO takes feed-in tariff and TOU tariff as price strategy.

(2) Scenario 2–Joint operation mode

IESO and IESs conduct game optimization, and obtain the transaction price and transaction electric quantity through the solution algorithm.

5.1. Economic benefit analysis

(1) IES economic cost.

Table 6 and Table 7 show the results of IESs operation optimization in different scenarios.

As can be seen from Table 6 and Table 7, the economic cost of IES varies significantly in different scenarios. Among them, the reduction of power purchase cost and the increase of power selling benefits are the main factors to reduce the total operation cost. Scenario 2 is optimized by game. IESs trades with IESO through the internal power purchase and selling price. Due to the low purchase and high selling, power selling benefits of each IES is increased and the power purchase cost is reduced.

The economic cost of each time in a typical day is shown in Fig. 13.

In conclusion, through Game optimization, the internal purchase and selling price in scenario 2 is lower than the feed in tariff in scenario 1. Each IES can reduce the power purchase cost and increase the power selling benefits by applying ES and load translation, so as to improve the total operation cost.

(2) IESO benefits.

There is price optimization in scenario 2, where the more electric quantity traded, the more benefit IESO is able to obtain. In other words, IESO benefits are closely related to power purchase. Fig. 14 shows the relationship between IESO benefits and power purchase cost.

As shown in Fig. 14, IESO in scenario 2 has higher benefits in the periods of 12:00 and 18:00–20:00 compared with scenario 1. This is mainly because this period is at the peak demand of power, and the purchase price is the same as the TOU tariff. However, the selling price is high, so each IES has a strong intention to sell power.

Table 7 shows the benefits of IESO in different scenarios. In scenario 1, there is less power interaction between IESs and IESO due to the lack of price optimization, and the IESO needs to purchase power from the power grid. Although the IESO receives higher benefits from power selling based on TOU tariff, the power purchase cost is high, resulting in lower profit. In scenario 2, the enthusiasm of IES to sell power is increased by optimizing the price, and IESO reduces the purchase cost from the power grid. Although the power selling benefits is lower than that in scenario 1, the profit is higher.

5.2. Environmental cost analysis

The pollutants in IESs constructed in this paper mainly come from CHP or CCHP. Fig. 15 shows the environmental cost $C_{E,t}$ of IESs in different scenarios.

It can be seen from Fig. 15 that in each IES, the environment cost in scenario 2 is lower than that in scenario 1 at most times. This is mainly because the power interaction between IESs and IESO in Scenario 2 increases, and the ES charging-discharging strategy and load shift are changed, which reduces the output power of the CCHP and CHP in Scenario 2, resulting in lower environmental costs.

The environment cost is closely related to the operation of CCHP and

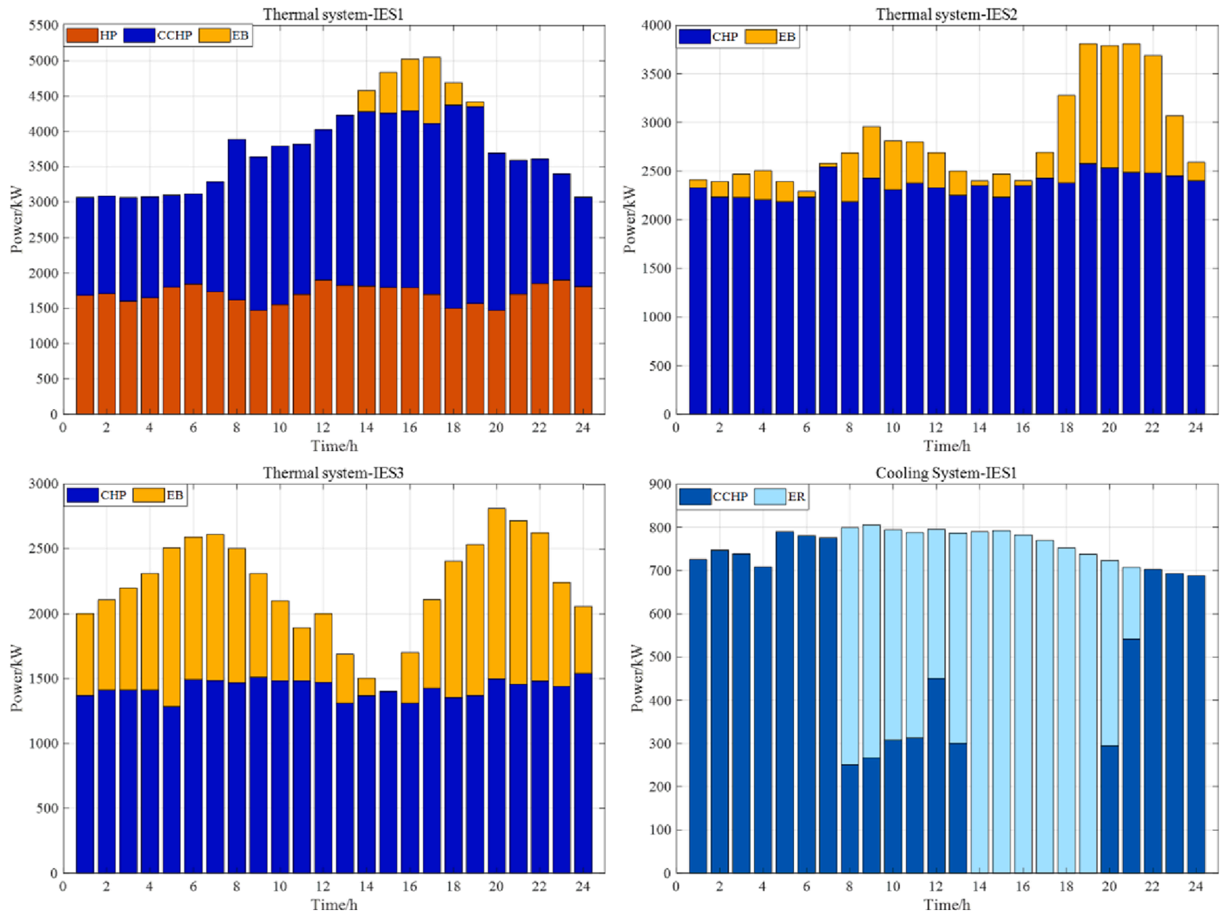


Fig.12. Output curve of heating and cooling equipment.

Table 6
IESs operation optimization results in Scenario 1.

Operation optimization result/yuan	IES1	IES2	IES3
C^{IES}	64212.13	57953.68	41877.81
Power purchase cost	9980.56	16716.69	13064.91
$C_{DG,t}$	46898.91	35776.49	22934.13
$C_{AL,t}$	1354	750	424.
Power selling benefits	5431.02	4205.31	111.01
$C_{OM,t}$	11409.68	8915.81	5565.73

Table 7
IESs operation optimization results in Scenario 2.

Operation optimization result/yuan	IES1	IES2	IES3
C^{IES}	60487.1	55542.9	38838.84
Power purchase cost	9379.79	15551.63	10472.08
$C_{DG,t}$	45558.94	35385.6	22310.13
$C_{AL,t}$	1833	1443.8	888
Power selling benefits	7638.32	5710.13	386.15
$C_{OM,t}$	11353.69	8872.01	5279.64

CHP system, and the higher the output power, the higher the environment cost. The output power determines the energy cost. Table 8 shows the environment cost and energy cost of each IES under the two scenariosTable 9..

Compared with Scenario 1, the environmental cost of each IES in Scenario 2 is reduced by 2.47%, 3.95% and 6.88% respectively. Meanwhile, the energy cost of Scenario 2 is also reduced.

6. Conclusion

Driven by the energy revolution and power system reform, IES has ushered in an opportunity for development. IES with power generation resources can participate in power transactions through the mode of "spontaneous generation and self-use, surplus power on the grid", and increase economic benefits while meeting their own load demands. In this context. In this context, this paper proposes an operation optimization strategy of integrated energy system based on Stackelberg game, which takes IESO as the leader and IES as the follower, solves its equilibrium interaction strategy, and realizes multi-agent distributed collaborative optimization operation, in order to provide reference for the development of integrated energy system.

Firstly, this paper takes the IESO as the leader and each IES as the follower, constructs the Stackelberg game operation framework, and puts forward the transaction mode of IES, IESO and regional power grid. Secondly, a Stackelberg game model between IESO and IESs is constructed, in which IESO takes the purchase and selling price as the game strategy and IES takes the multi-objective operation optimization scheme as the game strategy; According to the characteristics of the research problem and the specificity of the bilevel game model, the double mutation differential evolution algorithm is used to solve the problem. Thirdly, an integrated energy system park is selected as an example to verify the effectiveness and scientificity of the model established in this paper. Finally, two scenarios are set to demonstrate the advantages of game optimization from two aspects of economic benefits and environmental costs. The results show that:

1) IES aims to minimize the operation cost and environmental cost, the optimized trading power will affect the formulation of price by IESO, while IESO can guide IESs to purchase and sell electricity reasonably

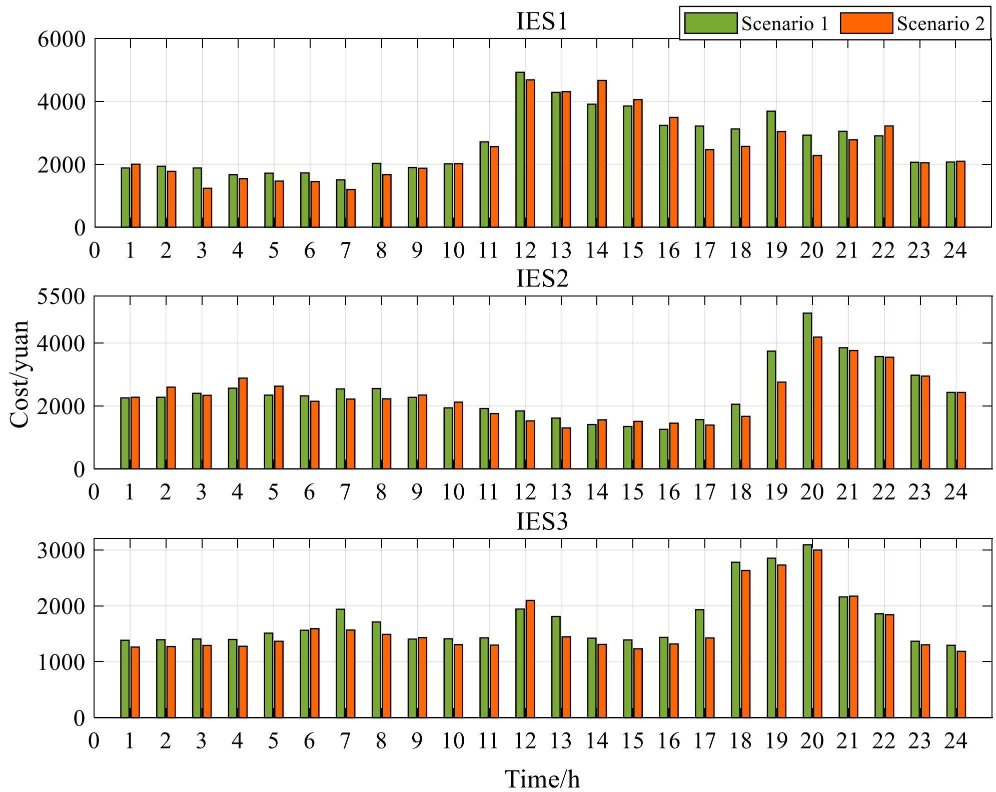


Fig.13. IES operation optimization cost.

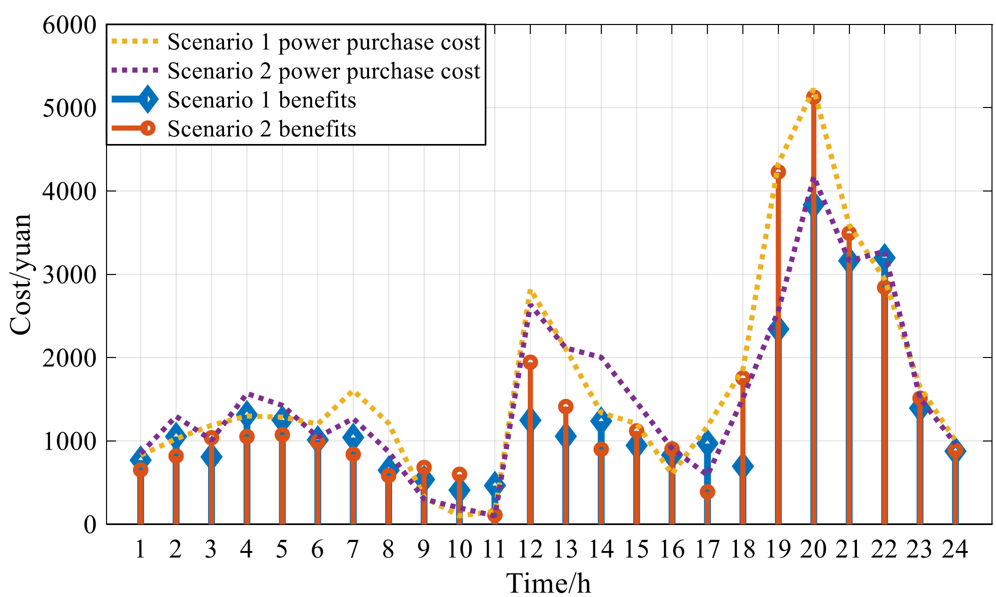


Fig.14. IESO benefits.

through dynamic pricing. There is an interest game relationship between IESO and IESs. 2) In the established Stackelberg game model, IESO promotes the power sharing between IESs through the price optimization, which can not only improve its own benefits, but also reduce the IES operation cost. 3) The double mutation differential evolution algorithm is used to search the optimal price strategy of IESO. Taking the individual in the population as a price strategy of IESO, the optimal price strategy is obtained through the variation, crossover and selection of the population.

This paper still has some deficiencies, and the following aspects need further analysis: In the transaction process between the IESO and the regional power grid constructed in this paper, the feed in tariff and the time-of-use tariff of the power grid are selected as the constraint boundary of the operator's power price strategy. With the development of the power spot market, the operators constructed in this paper need further research on how to consider the node energy price and formulate the price strategy under the constraints of the complex power grid structure.

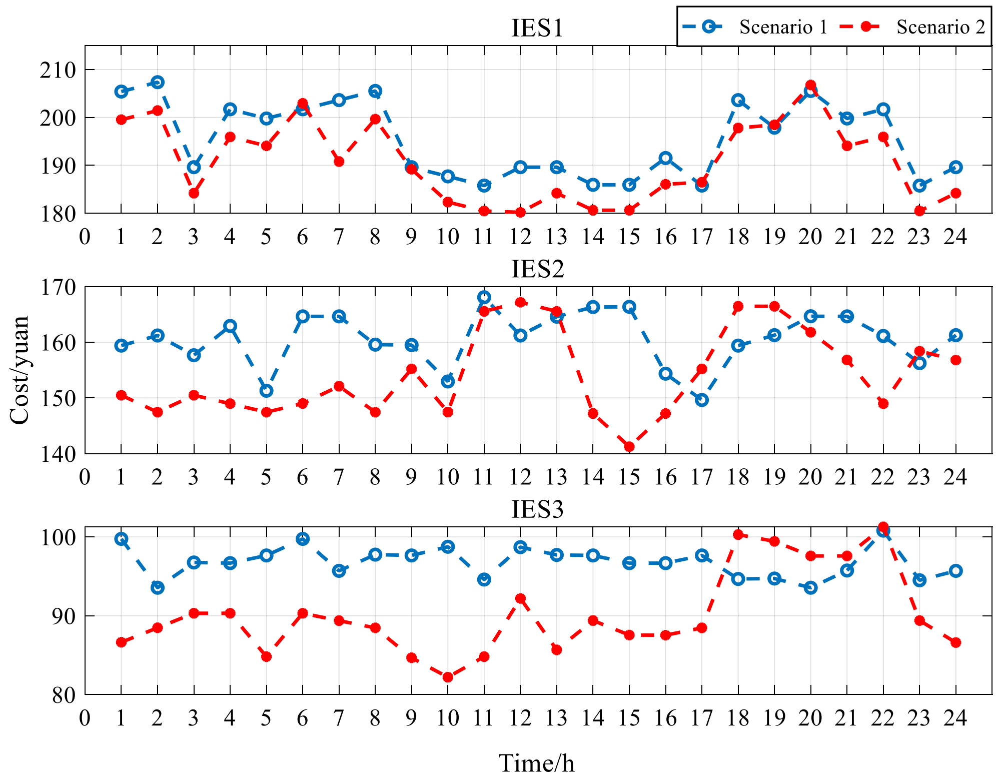


Fig.15. IES operation environment cost.

Table 8
IESO benefits results.

Transaction result/yuan	Scenario 1	Scenario 2
R^{IESO}	5765.29	6755.10
Power purchase cost	34944.94	30944.15
Power selling benefit	40710.23	37699.27

Table 9
Environmental costs.

Cost/yuan	IES1	IES2	IES3
$C_{E,t}$ in Scenario1	4689.89	3852.85	2323.32
$C_{E,t}$ in Scenario 2	4573.89	3700.74	2163.41
Energy cost in Scenario1	46898.91	35776.49	22918.13
Energy cost in Scenario 2	45558.94	35585.61	22310.13

CRediT authorship contribution statement

Yuanyuan Zhang: Conceptualization, Writing – original draft. **Huiru Zhao:** Conceptualization, Writing – review & editing. **Bingkang Li:** Data curation. **Xuejie Wang:** Data curation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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