

Article

Research on Master–Slave Game Strategy of Integrated Energy System Considering Integrated Demand Response: Improved Snake Optimizer-Quadratic Programming

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Abstract

With the advancement of energy market reform, integrated energy systems (IESs) have achieved rapid development. Considering insufficient research on an electricity–heat coupled master–slave game and the local optimum defect of traditional algorithms, this paper proposes a Stackelberg game optimization strategy for IES considering integrated demand response (IDR), with microgrid operator (MGO) as the leader and load aggregator (LA) as the follower. Firstly, an IDR model containing rigid, shiftable electric loads and reducible thermal loads is established, and a bi-level game model is built: the upper MGO optimizes electricity and heat pricing to maximize profit, while the lower LA adjusts flexible loads for maximum consumer surplus. Secondly, an improved snake optimizer (ISO) is constructed via Hammersley sequence initialization, Lévy flight and random perturbation and combined with quadratic programming (QP) to form the ISO-QP hybrid solving method. Benchmark function and CEC2017 tests verify the superior convergence and stability of ISO against multiple classical intelligent algorithms. Case simulation obtains the Stackelberg equilibrium result, and repeated experiments and parameter sensitivity analysis verify model robustness. Results show that the proposed method smooths load fluctuations via price guidance and synchronously improves MGO revenue and LA consumer surplus on the premise of guaranteed user satisfaction.

Keywords: quadratic programming; master–slave game; distributed collaborative optimization



Academic Editor: Il-Yop Chung

Received: 8 May 2026

Revised: 6 June 2026

Accepted: 15 June 2026

Published: 24 June 2026

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1. Introduction

The rapid development of the world economy, the rising degree of industrialization, and the increasing demand and consumption of energy have gradually triggered a worldwide energy crisis and a series of environmental and ecological problems [1,2]. The construction of a clean, low-carbon, intelligent, and efficient energy system has become the development trend and direction of the world's energy transformation, and promoting human society from an industrial civilization to an ecological civilization has become the consensus of the world's development [3,4].

Through the organic coordination of the whole process of energy production, transmission, conversion, storage, and consumption, an integrated energy system optimizes the

integration of heat, electricity, natural gas, and other forms of energy, realizing the coupling of different types of energy to complement each other and the efficient, gradient use of energy [5–7]. An integrated energy system can meet the diversified energy demand of users and has the characteristics of high efficiency, environmental protection, cost-effectiveness, reliability, and flexibility [8,9]. It is an effective way to realize a clean, low-carbon, safe, and efficient energy supply [10,11].

With the continuous development of integrated energy systems, the system coupling presents the trend of continuous complexity and diversification [12,13]. Optimizing the cooperative operation of IESs involves various types of distributed equipment, thermal and electrical multi-energy systems, other internal system cooperation subjects and users, external energy systems, and other external system cooperation subjects [14]. In increasingly close energy coupling, an IES takes reasonable measures to establish competitive relationships among market players in the source, network, load, storage, and consumption [15]. It uses competition and collaboration among them to maximize each player's interests [16]. Therefore, developing an IES scheduling method suitable for the open energy supply system and integrating each competing subject's interests is especially important [17].

2. Literature Review

With the continuous development and improvement of IESs, many scholars have conducted in-depth research on optimal configuration and economical operation [18,19]. Li et al., 2022 [20] adopted a novel multi-objective arithmetic optimization algorithm to optimize the CCHP system under different operation strategies. Zhao et al., 2022 [21] proposed a hybrid multi-criteria decision-making (MCDM) framework to evaluate the comprehensive performance of the CCHP system. Simulation results show that the proposed MCDM has good applicability and effectiveness. In order to verify the advantages of the proposed system, Wu et al., 2020 [22] conducted economic, energy, and environmental evaluations for five office buildings in different climate zones. The simulation results indicate maximum annual total cost savings, primary energy savings, and CO₂ emission reductions of 49.80%, 69.76%, and 71.55%, respectively. Similarly, Wen et al., 2020 [23] used a genetic algorithm for design optimization and performance analysis of CCHP for some commercial buildings under different operation strategies. Ren et al., 2021 [24] investigated the hybrid CCHP system for three buildings under different operating strategies, which were optimized and compared. The results demonstrate that more benefits are achieved for the three buildings under the following electrical load strategy. However, the above studies only optimize for the source side but ignore the autonomy of the load side.

Several researchers have incorporated demand response mechanisms into optimization models of the IES. Liu et al., 2020 [25] analyzed and discussed the impact of considering energy storage and demand response on the long-term economic planning of the CCHP system. The simulation results demonstrate that introducing energy storage and demand response can reduce the total system cost by 6.45% and 11.73%, respectively. To improve the economics of the CCHP system, Zhao et al., 2022 [26] proposed a two-stage optimal scheduling scheme that considers the demand response. Simulation results show that the proposed method reduces the operating cost by 5.20% and 5.76% on typical days in summer and winter, respectively, compared with no consideration of demand response. Similarly, Gu et al., 2017 [27] proposed a bilateral trading mechanism between a residential CCHP and a load aggregator (LA) that considers the integrated demand response.

Along with reforming the electricity market and developing the IES, the optimal operation of the IES needs to consider the interests of different subjects. However, the traditional centralized optimization method cannot describe the transaction interactions among the subjects. Evolutionary, master-slave, and other game models are

gradually applied to the optimal operation of energy systems and energy management. Wei et al., 2015) [28] considered power sales companies as leaders and customers as followers and analyzed the interaction mechanism between them in the electricity market based on the master–slave game model. Liu et al., 2018 [29] proposed a distributed energy management approach based on master–slave game theory for a CCHP-type community energy internet class, establishing operator pricing strategy and producer–consumer transaction mode selection model. However, the electricity market still dominates the current research in this area, and there needs to be more research on the integrated energy trading of electricity and heat interconnection. Wu et al., 2026 [30] proposed a demand-aware multi-objective pricing optimization framework for EV charging networks based on a Stackelberg game, where charging prices are dynamically adjusted to influence users' spatiotemporal charging behaviors. The proposed strategy improves load balancing, demand distribution stability, and operator revenue, while establishing a pricing foundation for future V2G-enabled bidirectional energy interactions. Li et al., 2026 [31] developed a low-carbon scheduling framework for industrial park integrated energy systems by incorporating carbon emission flow theory, hydrogen blending systems, and carbon capture systems. A Stackelberg game model among the integrated energy system operator, users, and energy suppliers was established to coordinate energy pricing and demand response, achieving significant carbon emission reductions while maintaining system operational performance. Xue et al., 2025 [32] proposed a bi-level optimization and Stackelberg game framework for multi-integrated energy systems based on shared energy storage, where the upper level optimizes economic and environmental objectives and the lower level ensures energy balance. An improved Nash bargaining mechanism was further introduced to achieve fair profit allocation among participating systems, enhancing the effectiveness of demand response coordination and multi-energy collaboration. Existing relevant research mostly focuses on single power-side optimization while neglecting the interactive game between supply and demand sides under coupled electricity-heat conditions; besides, traditional metaheuristic algorithms are prone to local optimum and lack stable solving performance for bi-level game problems, and few studies construct classified regulation functions for rigid, shiftable power loads and curtailable heat loads under integrated demand response. In addition, most existing literature ignores the influences of fluctuating solar irradiance, fuel prices and user loads on the equilibrium benefits of game participants, which motivates the research of this paper.

In summary, with the reform and opening of the energy market and the development of new energy technologies, the relationship between subjects in the integrated energy system is becoming increasingly complex. The cooperation and competition among subjects could be more manageable. Hence, analyzing the game relationship between multiple parties' source, network, load, and storage interests in the game equilibrium has essential research significance. Accordingly, this paper develops an IES operation optimization model based on a master–slave game and integrated demand response for an IES containing a microgrid operator (MGO) and an LA, under the framework of setting the electricity and heating price strategies on the MGO side and considering the demand response. In addition, we introduce the IES energy trading process and mathematical model, then use the proposed ISO algorithm and quadratic programming algorithm to solve the case and analyze and verify the effectiveness of the proposed model. Some of the meaningful contributions of this paper can be summarized as follows.

(1) An integrated demand response (IDR) framework is developed by modeling heterogeneous load types, including rigid, flexible, and curtailable thermal loads, to better capture end-user operational flexibility in realistic energy systems. (2) A bi-level master–slave equilibrium game is formulated to characterize the interaction between the

MGO and LA, where the MGO acts as the leader and the LA responds as the follower under the IDR mechanism. (3) An ISO–quadratic programming (QP) hybrid solution framework is proposed, combining an ISO algorithm with QP to efficiently solve the bilevel optimization problem and ensure convergence to a stable equilibrium. (4) A comprehensive multi-parameter sensitivity analysis is conducted to investigate the influence of key parameters on system performance, and extensive comparative experiments against several state-of-the-art optimization algorithms are performed, demonstrating the effectiveness, robustness, and competitiveness of the proposed approach.

The rest of the paper is organized as follows. The constructed master–slave game model is presented in Section 3. The proposed algorithm for solving the master–slave game model is described in Section 4. The case study is conducted in Section 5. The conclusion of the paper is presented in Section 6.

3. Model and Problem

Equating a distributed group of users within a microgrid as an LA. Assume that the integrated energy system consists of two main objects, the MGO and the LA, in the scenario shown in Figure 1.

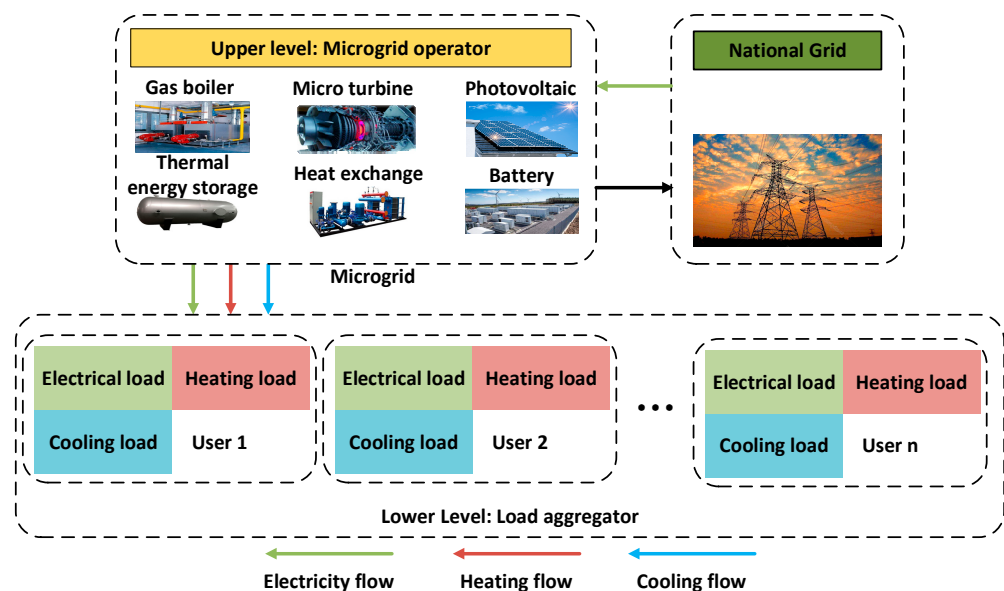


Figure 1. Schematic diagram of the integrated energy system structure.

As seen in Figure 1, the leading equipment within the MGO includes a photovoltaic (PV) system, a microturbine (MT), a gas boiler (GB), a thermal energy storage (TES) system, and a heat exchanger (HE). When the MGO has insufficient power, it needs to purchase some of the power from the grid; when the MGO has excess power, the excess power will be sold to the grid. A more detailed MGO model and LA model will be described in detail below.

3.1. Microgrid Operator

MGO offers a pricing strategy that includes power purchase price, power sale price, and heat sale price. The electricity purchase and sale prices are within the envelope formed by the time-of-use and the feed-in tariff. The price of selling heat is within the envelope of the upper limit of the heat price and the lower limit of the heat price. The corresponding constraint is as follows.

$$\lambda_t^{Grid,b} < \lambda_t^{MGO,s} < \lambda_t^{Grid,s} \quad (1)$$

$$\lambda_t^{Grid,b} < \lambda_t^{MGO,b} < \lambda_t^{Grid,s} \quad (2)$$

$$\gamma_t^{MGO,min} < \gamma_t^{MGO,s} < \gamma_t^{MGO,max} \quad (3)$$

where $\lambda_t^{MGO,s}$ and $\lambda_t^{Grid,b}$ are the electricity purchase and sale prices, respectively. $\lambda_t^{Grid,s}$ and $\lambda_t^{MGO,b}$ are the upper and lower boundaries of the purchase price of electricity, respectively. $\gamma_t^{MGO,s}$ is the MGO selling hot price. $\gamma_t^{MGO,max}$ and $\gamma_t^{MGO,min}$ are the upper and lower boundaries of the purchase price of electricity, respectively.

The relationship between MT fuel cost and unit output power at time period t of the day can be expressed as.

$$C_t^{MT} = \lambda_f F_t^{MT} \quad (4)$$

$$F_t^{MT} = E_t^{MT} / \eta_e^{MT} \quad (5)$$

where C_t^{MT} is the cost of fuel; λ_e^{MT} is the unit price of natural gas; and $E_t^{MT,e}$ is the output power.

The relationship between the MT recovered thermal energy and its output electrical power can be expressed as follows

$$Q_t^{MT,q} = \frac{1 - \eta_e^{MT} - \eta_{loss}^{MT}}{\eta_e^{MT}} \eta_q^{MT} E_t^{MT,e} \quad (6)$$

where $Q_t^{MT,q}$ is the heat output of the MT; η_{loss}^{MT} is the heat loss rate; η_q^{MT} is the heat production coefficient.

The GB uses natural gas as fuel to provide heat energy to the customer side, and the relationship between its fuel cost and the thermal power output of the unit at the t th time period of the day can be expressed as

$$C_t^{GB} = \lambda_f F_t^{GB} \quad (7)$$

$$F_t^{GB} = Q_t^{GB} / \eta_q^{GB} \quad (8)$$

where C_t^{GB} is the fuel cost; Q_t^{GB} is the heat output of GB; λ_f is the unit price of gas; η_q^{GB} is the heat output efficiency of GB.

The output power of the photovoltaic (PV) unit under the grid-forming control strategy is given as follows:

$$E_{pv} = N_{pv} \cdot G \cdot \eta_{pv} / 1000, \quad 0 \leq E_{pv} \leq N_{pv} \quad (9)$$

where E_{pv} denotes the PV output power, N_{pv} represents the installed capacity, G is the solar irradiance, and η_{pv} denotes the conversion efficiency.

The mathematical model of the battery energy storage system under the grid-forming control strategy is given as follows:

$$\begin{cases} E_{BAT}^t = E_{BAT}^{t-1} \cdot (1 - \gamma_{BAT}) + E_{TES,in}^t \cdot \eta_{BAT,in} \\ E_{BAT}^t = E_{BAT}^{t-1} \cdot (1 - \gamma_{BAT}) - E_{TES,out}^t / \eta_{BAT,out} \end{cases} \quad (10)$$

where E_{BAT}^t and E_{BAT}^{t-1} are the stored power energy of BAT at moments t and $t - 1$, respectively; γ_{BAT} , $\eta_{BAT,in}$ and $\eta_{BAT,out}$, and are the power loss rate, power absorption efficiency and power release efficiency of BAT, respectively; $E_{TES,in}^t$ and $E_{TES,out}^t$ are the absorbed and released power energy of BAT at moment t , respectively.

The heat storage and release process of TES is as follows.

$$\begin{cases} Q_{TES}^t = Q_{TES}^{t-1} \cdot (1 - \gamma_{TES}) + Q_{TES,in}^t \cdot \eta_{TES,in} \\ Q_{TES}^t = Q_{TES}^{t-1} \cdot (1 - \gamma_{TES}) - Q_{TES,out}^t / \eta_{TES,out} \end{cases} \quad (11)$$

where Q_{TES}^t and Q_{TES}^{t-1} are the stored thermal energy of TES at moments t and $t - 1$, respectively; γ_{TES} , $\eta_{TST,in}$ and $\eta_{TES,out}$, and are the heat loss rate, heat absorption efficiency and heat release efficiency of TES, respectively; $Q_{TES,in}^t$ and $Q_{TES,out}^t$ are the absorbed and released thermal energy of TES at moment t , respectively, and satisfy $Q_{TES,in}^t \cdot Q_{TES,out}^t = 0$.

The revenue of a microgrid operator in one day can be expressed as.

$$P_{MGO} = P_{MGO}^{Grid,e} + P_{MGO}^{Load,e} + P_{MGO}^{Load,q} - Cost_{MGO} \quad (12)$$

where $P_{MGO}^{Grid,e}$, $P_{MGO}^{Load,e}$, $P_{MGO}^{Load,q}$ and $Cost_{MGO}$ denote the revenue of the microgrid operator from grid power trading, the revenue from supplying electricity to the customer side, the revenue from supplying heat to the customer side and the operating cost of the microgrid operator, respectively. The above items can be further expressed as follows.

$$P_{MGO}^{Grid,e} = \sum_{t=1}^T [\lambda_t^{Grid,b} \cdot E_t^{Grid,b} - \lambda_t^{Grid,s} \cdot E_t^{Grid,s}] \quad (13)$$

$$P_{MGO}^{Load,e} = \sum_{t=1}^T \lambda_t^{MGO,s} (E_t^{Load,f} + \bar{E}_t^{Load,s}) \quad (14)$$

$$P_{MGO}^{Load,q} = \sum_{t=1}^T (\gamma_t^{MGO,s} \cdot Q_t^{Load,n}) \quad (15)$$

$$Cost_{MGO} = \sum_{t=1}^T \lambda_f \cdot (F_t^{MT} + F_t^{GB}) \quad (16)$$

3.2. Load Aggregator

The power load of LA can be divided into rigid and shiftable power load. Therefore, the electric load of LA can be expressed as follows [33].

$$E_t^{Load} = E_t^{Load,r} + E_t^{Load,f} \quad (17)$$

where E_t^{Load} is the total electrical load; $E_t^{Load,r}$ is rigid electrical load; $E_t^{Load,f}$ is the shiftable electrical load.

To avoid the customer satisfaction being affected by a high flexible electric load at a certain time period, we constrain the size of the flexible load for each time period. The relevant constraints are shown below [33].

$$\frac{\bar{E}_t^{Load,f} - E_t^{Load,f}}{E_t^{Load,r} + E_t^{Load,f}} \leq \sigma \quad (18)$$

In addition, the flexible electrical load can only be shifted and not curtailed, with the following constraints [33].

$$\sum_{t=1}^T \bar{E}_t^{Load,f} = \sum_{t=1}^T E_t^{Load,f} \quad (19)$$

$$\sum_{t=1}^T |\bar{E}_t^{Load,f} - E_t^{Load,f}| = k \cdot \sum_{t=1}^T (E_t^{Load,r} + E_t^{Load,f}) \quad (20)$$

where $|\bar{E}_t^{Load,f} - E_t^{Load,f}|$ represents the change in electrical load at time t ; $\bar{E}_t^{Load,f}$ indicates the electrical load after demand response; σ denotes the maximum proportion of flexible load in time period t ; k indicates the proportion of flexible load.

The heat load in this study also contains two components, and the relevant equations are shown below.

$$Q_t^{Load,n} = Q_t^{Load} - Q_t^{Load,a} \quad (21)$$

$$0 \leq Q_t^{Load,a} \leq \delta Q_t^{Load} \quad (22)$$

where $Q_t^{Load,n}$ represents the thermal load after demand response; $Q_t^{Load,a}$ indicates that the heat load can be reduced. δ indicates the proportion of heat load that can be reduced.

LA optimizes its own flexible electric load distribution and the size of the heat load that can be cut for a given energy sales price. Its objective function is the maximum consumer surplus, which can be expressed as follows [33].

$$F_{LA} = \sum_{t=1}^T [f_t^u - (E_t^{Load,n} + Q_t^{Load,n})\Delta t] \quad (23)$$

$$f_t^u = a_e E_t^{Load,n} + b_e E_t^{Load,n} + c \quad (24)$$

where F_{LA} is the consumer surplus, and f_t^u is the utility function. In addition, in this study, a_e is -0.05 , b_e is 4 , and c is 0 .

3.3. Analysis of the Master–Slave Stackelberg Game

The MGO first provides a price strategy, and then the LA adjusts the electric and thermal loads for each period in real-time according to the MGO's pricing scheme. The interaction variables between the MGO and the LA are the price strategy and the load information. When the price strategy of MGO is too high or too low, LA will dynamically adjust the load information. Conversely, the MGO will update its strategy based on the load information of the LA until the best pricing strategy is found. MGO and LA have conflicts in revenue, and their decisions are sequential, so MGO and LA can be regarded as a master–slave game model. The game G is as follows.

$$G = \left\{ N; \left\{ \lambda^{MGO,b}, \lambda^{MGO,s}, \gamma^{MGO,s} \right\}; \left\{ \bar{E}_t^{Load,s}, Q_t^{Load,a} \right\}; F_{MGO}; F_{LA} \right\} \quad (25)$$

where $\bar{E}_t^{Load,f}$ denotes the set of flexible load strategies; $\Delta Q_t^{Load,q}$ denotes the set of strategies for thermal energy reduction; F_{MGO} denotes the revenue of the MGO; F_{LA} denotes the revenue of the LA; $\lambda^{MGO,b}$ and $\lambda^{MGO,s}$ are the purchase and sale price of electricity, respectively. $\gamma^{MGO,s}$ denotes heating price.

For master–slave game, when the follower responds optimally according to the leader's strategy and the leader gets the optimal strategy, it means that the game reaches the Stackelberg equilibrium, and after reaching the equilibrium of the game, all the participants cannot unilaterally change their own strategies to get higher returns.

4. Improved Snake Optimizer

We propose an improved snake optimizer by introducing the Hammersley low-difference sequence, Lévy flight, and random variation strategies in the snake optimizer. The main idea of ISO is to improve the initial convergence of the algorithm by using the randomness and traversal of the Hammersley low-difference sequence strategy to obtain a better population distribution. In addition, to prevent the algorithm from falling into the local optimum and to better regulate the global search ability and local search ability of the algorithm, the Lévy flight and random variation strategies are introduced into the algorithm's position update formula. A more detailed description is as follows.

4.1. Algorithm Description

SO is a new metaheuristic optimization algorithm that simulates different behavior patterns of snakes under different temperatures and food conditions for optimal value search [34]. Like most metaheuristic optimization algorithms, the search process of SO can also be divided into two phases, i.e., exploration and exploitation. However, SO's convergence ability and stability in the later optimization stage need to be further improved. Based on the above description, the SO is improved in this study, and the specific improvement measures are as follows.

4.1.1. Initialization

In this study, we use Hammersley's low-difference sequence-based initialization of the population, which produces a more uniform initial population than that produced by conventional initialization, which helps the algorithm to perform a global search at the early stage and improves the ability of the algorithm to evade local optima.

Figure 2 depicts the distribution of random sampling and Hammersley's low-difference sequence-based sampling. It can be observed that the random sampling is disordered, cluttered and unevenly distributed. On the contrary, the Hammersley low-difference sequence-based sampling points are uniformly distributed, which effectively avoids the algorithm from falling into a local optimum by having too many sampling points distributed together.

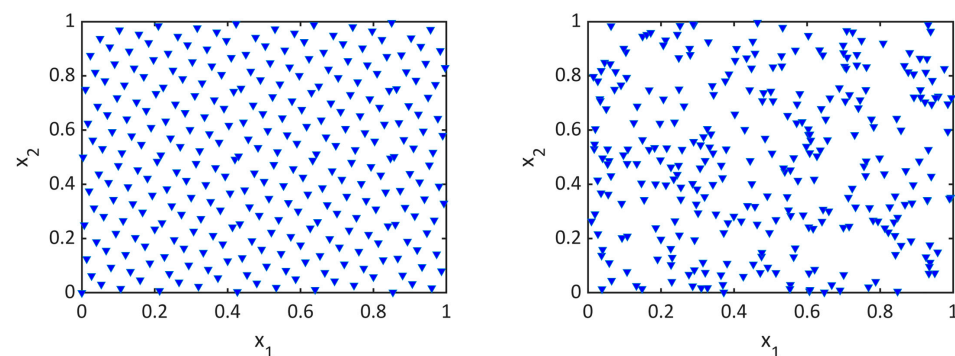


Figure 2. Comparison of random sampling and Hammersley sampling.

4.1.2. Population Division

In this study, the population was divided into two groups: the female group and the male group. The specific division formula is as follows.

$$\begin{aligned} Nm &\approx N/2 \\ Nf &= N - nm \end{aligned} \quad (26)$$

where N is the population size; Nf denotes the number of female individuals; Nm denotes the number of male individuals.

4.1.3. Evaluating Each Group and Defining Temperature and Food Quantity

The *Temp* can be defined as follows.

$$Temp = \exp(-t/T) \quad (27)$$

where t is the current iteration; T is the maximum number of iterations.

The food quantity (Q) can be defined as follows.

$$Q = c_1 \times \exp\left(\frac{t-T}{T}\right) \quad (28)$$

where c_1 is constant.

4.1.4. Exploration Phase (No Food)

The exploration phase can be defined as follows.

$$X_{i,m}(t+1) = X_{rand,m}(t) \pm c_2 \times (X_{min} + rand \times (X_{max} - X_{min})) \times A_m \quad (29)$$

where *rand* is a random number; $X_{rand,m}$ is the position of a random male; $X_{i,m}$ is the i th male position. A_m can be calculated as follows.

$$A_m = \exp(-f_{rand,m}/f_{i,m}) \quad (30)$$

where $f_{i,m}$ is the fitness of the i th individual in the male group; $f_{rand,m}$ is the fitness of $X_{rand,m}$. C_2 is a constant.

$$X_{i,m}(t+1) = X_{rand,m}(t) \pm c_2 \times A_f \times ((X_{max} - X_{min}) \times rand + X_{min}) \quad (31)$$

where $rand$ is a random number between 0 and 1; $X_{rand,f}$ is the position of a random female; $X_{i,f}$ is the i th female position. A_f can be calculated as follows.

$$A_f = \exp(-f_{rand,f} / f_{i,f}) \quad (32)$$

where $f_{i,f}$ is the fitness of i th individual in the female group; $f_{rand,f}$ is the fitness of $X_{rand,f}$.

4.1.5. Exploitation Phase (Food Exists)

The exploitation phase is defined as follows.

$$X_{i,j}(t+1) = (X_{food} - X_{i,j}(t)) \times Temp \times X_{food} \pm c_3 \times rand \quad (33)$$

where c_3 is a constant; X_{food} is the position of the best individuals; $X_{i,j}$ is the position of an individual.

Fight Mode:

$$X_{i,m}(t+1) = X_{i,m} \pm c_3 \times (X_{best,f} \times Q - X_{i,m}(t)) \times rand \times FM \quad (34)$$

where $X_{i,m}$ is the i th male position, FM is the fighting ability of the male agent, and $X_{best,f}$ is the position of the best individual in the female group.

$$X_{i,f}(t+1) = X_{i,f} \pm c_3 \times rand \times FF \times (X_{best,m} \times Q - X_{i,f}(t)) \quad (35)$$

where $X_{i,f}$ is the i th female position, $X_{best,m}$ is the position of the best individual in the male group, and FF is the fighting ability of the female agent.

FM and FF are defined as follows.

$$FM = \exp(-f_{best,f} / f_i) \quad (36)$$

$$FF = \exp(-f_{best,m} / f_i) \quad (37)$$

where $f_{best,m}$ is the fitness of the male group, $f_{best,f}$ is the fitness of female group, and f_i is the agent fitness.

Mating Mode:

$$X_{i,m}(t+1) = X_{i,m} \pm c_3 \times (X_{i,f} \times Q - X_{i,f}(t)) \times rand \times M_m \quad (38)$$

$$X_{i,f}(t+1) = X_{i,f} \pm c_3 \times (X_{i,m} \times Q - X_{i,m}(t)) \times rand \times M_f \quad (39)$$

where $X_{i,m}$ is the i th individual of the male group; $X_{i,f}$ is the i th individual of female group; M_m and M_f are the mating ability of the male and female, respectively. They are defined as follows.

$$M_m = \exp\left(\frac{-f_{i,f}}{f_{i,m}}\right) \quad (40)$$

$$M_f = \exp\left(\frac{-f_{i,m}}{f_{i,f}}\right) \quad (41)$$

The formula for updating the current worst female and male individuals is as follows.

$$X_{worst,m} = (-X_{min} + X_{max}) \times rand + X_{min} \quad (42)$$

$$X_{worst,f} = (-X_{min} + X_{max}) \times rand + X_{min} \quad (43)$$

where $X_{worst,f}$ is the worst position in the group of female snakes; $X_{worst,m}$ is the worst position in the group of male snakes.

4.1.6. Levy Flight Strategy

In order to improve the algorithm's search capability, we introduce the Lévy flight strategy, which is described in detail as follows.

$$x'_i(t) = x_i(t) + l \oplus Levy(\lambda) \quad (44)$$

where $Levy$ denotes the path that obeys the Lévy distribution and satisfies: $Levy \sim u = t^{-\lambda}$, $1 < \lambda \leq 3$; x_b is the current optimal solution; $x_i(t)$ denotes the i th solution in the t th generation; l denotes the weight of the control step; $l = 0.01(x_i(t) - x_b)$.

4.1.7. Stochastic Perturbation Strategy

To improve the algorithm's optimization ability, we introduce a random perturbation strategy, which is described in detail as follows.

$$x'_i(t) = x_i(t) + \varepsilon(x_j(t) - x_k(t)) \quad (45)$$

where $x_j(t)$ and $x_k(t)$ are two random solutions in the t th generation; ε is a scaling factor satisfying: $\varepsilon \sim U(0, 1)$.

The optimization process of ISO is shown in Figure 3.

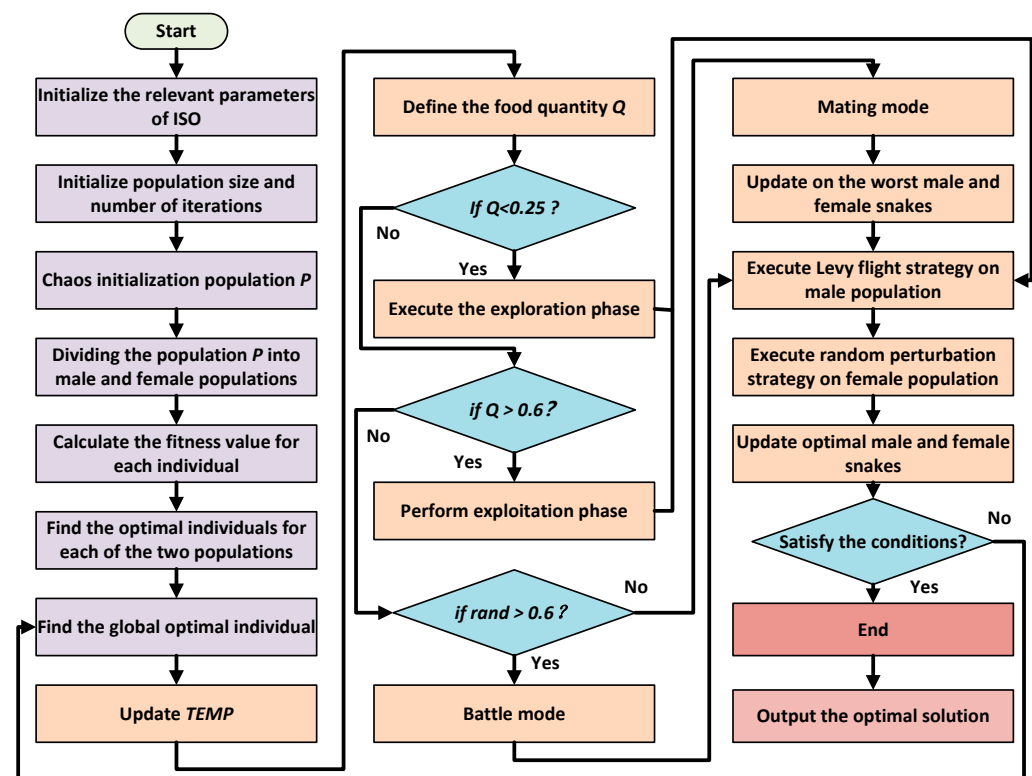


Figure 3. Optimization flow chart of ISO.

4.2. Performance Testing

Thirteen different test functions are for testing. The selected test functions have unimodal, multimodal, and nonlinear characteristics and are, therefore, widely used in testing the performance of intelligent algorithm searches. The unimodal test function has only one maximum value point, so it evaluates the algorithm's development capability. The multimodal test function has multiple extreme value points, so they can be used to evaluate

the exploration capability of the algorithm. In addition, several comparison algorithms are used to demonstrate the effectiveness of the algorithm improvement measures in this study. The selected comparison algorithms include the snake optimizer (SO), the seagull optimization algorithm (SOA) [35], and the sine cosine optimization algorithm (SCA) [36]. Table 1 shows the relevant parameter settings of all algorithms. To ensure the fairness of the experiments, the population size of each algorithm is 50, and the maximum number of iterations is 500. Thirty independent simulation experiments were conducted for each algorithm. The mean and standard deviation of each test function in 30 sets of simulation tests were calculated and recorded. The mean value is used to evaluate the algorithm's convergence, and the standard deviation is to evaluate the algorithm's stability.

Table 1. Control parameters of the algorithms.

Algorithms	Parameters
ISO	$C_1 = 0.5, C_2 = 0.5, C_3 = 2$
SO	$C_1 = 0.5, C_2 = 0.5, C_3 = 2$
SOA	$fc = 2$
SCA	$p = 0.5$

4.2.1. Comparison of Performance

The optimization results of the test functions in Table 2 show that the optimal values and mean values found by the four algorithms are different for both unimodal and multimodal test functions. Among them, the proposed ISO can provide the optimal mean and standard deviation, which proves that ISO has good convergence and stability.

Table 2. Optimization results of test functions.

Problem		ISO	SO	SOA	SCA
F1	<i>std</i>	1.53×10^{-94}	2.80×10^0	1.89×10^1	2.95×10^{-11}
	<i>ave</i>	4.33×10^{-95}	2.11×10^1	1.16×10^1	1.55×10^{-11}
F2	<i>std</i>	2.22×10^{-45}	1.95×10^{-1}	7.65×10^{-2}	1.73×10^{-8}
	<i>ave</i>	1.18×10^{-45}	2.19×10^0	2.92×10^{-2}	2.04×10^{-8}
F3	<i>std</i>	7.58×10^{-55}	1.23×10^3	4.65×10^3	1.63×10^{-4}
	<i>ave</i>	1.39×10^{-55}	4.48×10^3	8.04×10^3	7.24×10^{-5}
F4	<i>std</i>	5.23×10^{-40}	5.67×10^0	1.31×10^1	7.77×10^{-3}
	<i>ave</i>	3.44×10^{-40}	2.07×10^1	3.86×10^1	4.49×10^{-3}
F5	<i>std</i>	1.28×10^1	3.72×10^2	3.51×10^5	4.37×10^{-1}
	<i>ave</i>	2.05×10^1	5.23×10^2	8.53×10^4	2.83×10^1
F6	<i>std</i>	1.30×10^{-1}	3.13×10^0	3.79×10^1	4.45×10^{-1}
	<i>ave</i>	1.45×10^{-1}	2.13×10^1	2.93×10^1	3.27×10^0
F7	<i>std</i>	1.21×10^{-4}	2.50×10^{-2}	1.18×10^{-1}	2.61×10^{-3}
	<i>ave</i>	1.61×10^{-4}	9.98×10^{-2}	1.13×10^{-1}	2.99×10^{-3}
F8	<i>std</i>	1.81×10^2	5.99×10^2	2.16×10^2	4.28×10^2
	<i>ave</i>	-1.25×10^4	-9.69×10^3	-3.64×10^3	-5.10×10^3
F9	<i>std</i>	5.17×10^0	1.44×10^1	3.85×10^1	5.95×10^0
	<i>std</i>	2.66×10^0	8.14×10^1	3.85×10^1	3.08×10^0
F10	<i>ave</i>	0.00×10^0	1.33×10^{-1}	9.01×10^0	1.70×10^{-3}
	<i>std</i>	4.44×10^{-15}	2.59×10^0	1.19×10^1	2.00×10^1
F11	<i>std</i>	1.26×10^{-2}	1.74×10^{-2}	4.22×10^{-1}	2.04×10^{-2}
	<i>ave</i>	4.02×10^{-3}	1.21×10^0	8.86×10^{-1}	1.20×10^{-2}
F12	<i>std</i>	4.01×10^{-2}	2.59×10^0	4.00×10^5	1.85×10^{-1}
	<i>ave</i>	1.67×10^{-2}	7.36×10^0	1.40×10^5	3.52×10^{-1}
F13	<i>std</i>	2.05×10^{-1}	1.33×10^{-1}	3.54×10^5	1.78×10^{-1}
	<i>ave</i>	1.22×10^{-1}	9.36×10^{-1}	1.32×10^5	2.04×10^0

The comprehensive simulation results above show that ISO can jump out more easily in dealing with the local optimal solution problem and has a strong search capability and exploitation capability to a certain extent. Compared with the other three algorithms in the paper, ISO has obvious advantages and the best comprehensive stability.

4.2.2. Convergence Behavior Analysis

To study the convergence speed of ISO, we obtained the convergence curves of all optimizers on benchmark functions. From Figure 4, it can be seen that ISO achieves a faster convergence speed to the exact solution than the three advanced optimizers. This can prove the effectiveness and feasibility of the improvement of ISO in this study.

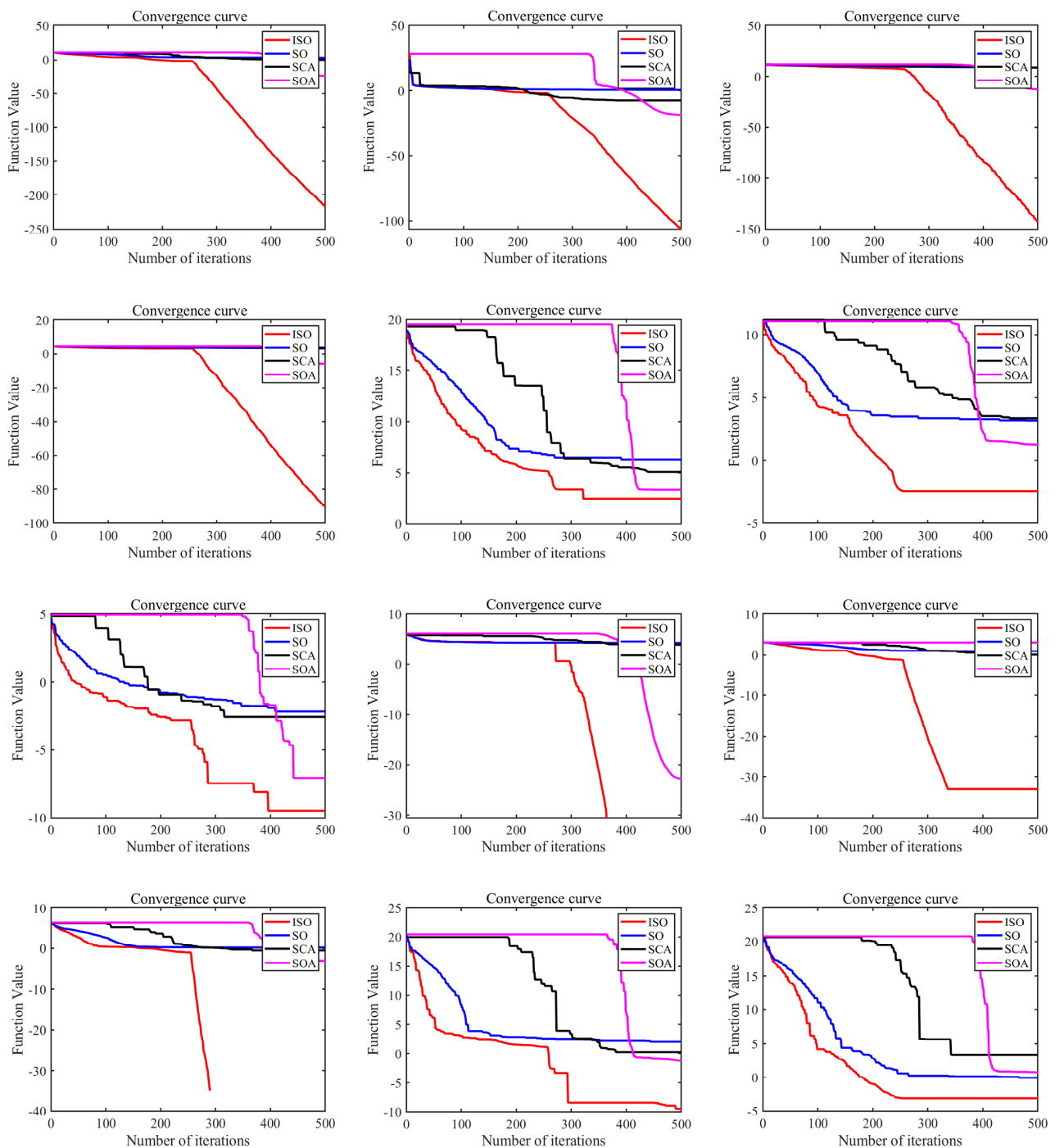


Figure 4. Convergence graphs of ISO and three other algorithms for benchmark functions.

4.2.3. Comparison with Other Advanced Algorithms

To further validate the effectiveness and novelty of the proposed ISO algorithm, additional experiments were conducted on the IEEE CEC 2017 benchmark suite, which provides a more comprehensive and challenging evaluation environment than conventional benchmark functions. Moreover, several state-of-the-art metaheuristic algorithms widely adopted in integrated energy system optimization, including the Marine Predators Algorithm (MPA), the Harris Hawks Optimization (HHO), Adaptive Differential Evolution with Optional External Archive (JADE), and the Grey Wolf Optimizer (GWO), were incorporated as comparison baselines to assess the competitiveness and robustness of the proposed method. For each benchmark function, all algorithms were independently executed 30 times under the same experimental conditions, and the mean and standard deviation of the obtained results were recorded for statistical comparison.

Table 3 presents the comparative results of ISO and four state-of-the-art metaheuristic algorithms, namely JADE, HHO, GWO, and MPA, on the IEEE CEC 2017 benchmark suite. Each algorithm was independently executed 30 times on every test function, and the mean and standard deviation of the obtained objective values were recorded. As observed, the proposed ISO algorithm achieved the best performance on the majority of benchmark functions, particularly on F1, F3–F13, F16, F20, F22, and F26, demonstrating superior optimization accuracy and convergence capability. Although JADE and HHO outperformed ISO on a few functions, such as F14, F15, F18, F19, F23–F25, and F28–F30, the overall performance advantage of ISO remained evident. Furthermore, ISO generally exhibited smaller standard deviations than the competing algorithms, indicating enhanced robustness and solution stability across independent runs. These results confirm that the proposed hybrid improvement strategies effectively enhance the global search ability and exploitation performance of the original algorithm, enabling ISO to maintain competitive performance on complex multimodal, hybrid, and composition optimization problems.

Table 3. Statistical results of the proposed ISO and competing algorithms on the IEEE CEC 2017 benchmark suite.

Function	ISO Mean	ISO Std	JADE Mean	JADE Std	HHO Mean	HHO Std	GWO Mean	GWO Std	MPA Mean	MPA Std
F1	1.01×10^2	3.10×10^{-11}	1.03×10^2	4.52×10^{-11}	1.03×10^2	3.87×10^{-11}	1.03×10^2	3.12×10^{-11}	1.04×10^2	3.41×10^{-11}
F3	2.98×10^2	1.38×10^1	3.00×10^2	1.34×10^3	3.00×10^2	1.54×10^3	3.00×10^2	2.52×10^4	3.00×10^2	2.94×10^4
F4	4.45×10^2	2.87×10^1	4.53×10^2	3.46×10^1	4.61×10^2	3.14×10^1	4.56×10^2	3.32×10^1	4.71×10^2	3.83×10^1
F5	5.41×10^2	1.12×10^1	5.67×10^2	1.39×10^1	5.74×10^2	1.27×10^1	5.59×10^2	1.18×10^1	5.82×10^2	1.45×10^1
F6	6.02×10^2	1.00×10^{-2}	6.19×10^2	2.00×10^{-2}	6.25×10^2	3.00×10^{-2}	6.21×10^2	2.00×10^{-2}	6.30×10^2	3.00×10^{-2}
F7	7.85×10^2	1.14×10^1	8.12×10^2	1.46×10^1	7.98×10^2	1.03×10^1	8.27×10^2	1.28×10^1	8.46×10^2	1.69×10^1
F8	8.56×10^2	1.32×10^1	8.75×10^2	1.75×10^1	8.91×10^2	1.54×10^1	8.74×10^2	1.45×10^1	8.97×10^2	1.87×10^1
F9	9.79×10^2	9.84×10^1	1.04×10^3	1.26×10^2	1.01×10^3	1.14×10^2	1.05×10^3	1.19×10^2	1.10×10^3	1.38×10^2
F10	3.30×10^3	3.82×10^2	3.59×10^3	4.59×10^2	3.57×10^3	4.21×10^2	3.48×10^3	4.16×10^2	3.76×10^3	5.04×10^2
F11	1.13×10^3	1.35×10^1	1.17×10^3	1.83×10^1	1.16×10^3	1.18×10^1	1.18×10^3	1.48×10^1	1.17×10^3	1.29×10^1
F12	5.48×10^3	3.16×10^3	6.02×10^3	3.53×10^3	5.81×10^3	2.95×10^3	5.89×10^3	3.05×10^3	6.14×10^3	3.68×10^3
F13	1.38×10^3	2.69×10^1	1.40×10^3	3.36×10^1	1.41×10^3	2.97×10^1	1.42×10^3	3.19×10^1	1.46×10^3	3.54×10^1
F14	1.42×10^3	5.12×10^0	1.41×10^3	4.28×10^0	1.42×10^3	4.84×10^0	1.44×10^3	5.46×10^0	1.45×10^3	6.13×10^0
F15	1.54×10^3	8.84×10^0	1.52×10^3	7.64×10^0	1.53×10^3	8.15×10^0	1.55×10^3	8.74×10^0	1.57×10^3	1.03×10^1
F16	1.89×10^3	1.69×10^2	1.99×10^3	2.15×10^2	1.95×10^3	1.97×10^2	1.97×10^3	1.88×10^2	2.03×10^3	2.26×10^2
F17	1.79×10^3	3.57×10^1	1.82×10^3	4.78×10^1	1.78×10^3	2.96×10^1	1.83×10^3	3.95×10^1	1.85×10^3	4.28×10^1
F18	1.83×10^3	1.06×10^1	1.82×10^3	8.72×10^0	1.85×10^3	1.22×10^1	1.86×10^3	1.32×10^1	1.87×10^3	1.45×10^1
F19	1.94×10^3	6.13×10^0	1.92×10^3	4.82×10^0	1.92×10^3	5.16×10^0	1.96×10^3	6.78×10^0	1.98×10^3	7.45×10^0
F20	2.12×10^3	5.84×10^1	2.15×10^3	7.93×10^1	2.17×10^3	6.84×10^1	2.14×10^3	6.48×10^1	2.22×10^3	7.89×10^1
F21	2.33×10^3	1.02×10^1	2.36×10^3	1.36×10^1	2.32×10^3	8.41×10^0	2.36×10^3	9.16×10^0	2.39×10^3	1.29×10^1
F22	2.30×10^3	0.00×10^0	2.30×10^3	1.50×10^{-1}	2.30×10^3	1.80×10^{-1}	2.30×10^3	2.20×10^{-1}	2.30×10^3	3.10×10^{-1}
F23	2.72×10^3	1.13×10^1	2.69×10^3	8.64×10^0	2.71×10^3	7.95×10^0	2.77×10^3	9.56×10^0	2.80×10^3	1.18×10^1
F24	2.86×10^3	1.27×10^1	2.85×10^3	1.08×10^1	2.87×10^3	1.13×10^1	2.89×10^3	1.18×10^1	2.90×10^3	1.25×10^1
F25	2.90×10^3	1.63×10^0	2.91×10^3	1.84×10^0	2.89×10^3	1.38×10^0	2.92×10^3	1.95×10^0	2.94×10^3	2.12×10^0
F26	3.60×10^3	6.48×10^2	3.90×10^3	8.52×10^2	3.84×10^3	7.12×10^2	3.78×10^3	7.25×10^2	4.02×10^3	8.96×10^2
F27	3.22×10^3	8.74×10^0	3.25×10^3	9.65×10^0	3.20×10^3	7.52×10^0	3.27×10^3	1.02×10^1	3.29×10^3	1.13×10^1
F28	3.11×10^3	6.21×10^1	3.08×10^3	4.28×10^1	3.13×10^3	5.52×10^1	3.16×10^3	5.38×10^1	3.17×10^3	4.87×10^1
F29	3.47×10^3	7.84×10^1	3.43×10^3	5.64×10^1	3.49×10^3	6.93×10^1	3.52×10^3	6.85×10^1	3.57×10^3	8.42×10^1
F30	5.09×10^3	1.95×10^2	5.02×10^3	1.44×10^2	5.14×10^3	1.68×10^2	5.28×10^3	2.08×10^2	5.36×10^3	2.36×10^2

5. Case Study

5.1. Results and Discussion

A microgrid is used as the research object, and the relevant load and environmental data are obtained from the U.S. Department of Energy. The price strategy of the upper MGO is updated using ISO, and the load information of the lower LA is solved using CPLEX. The optimization results are shown below. All numerical experiments were carried out on a personal computer running Windows 10, featuring an Intel Core i5-10210U processor (1.60 GHz, 4 cores, 8 threads) and 16 GB of memory. The developed optimization framework was implemented in MATLAB R2021a with the assistance of the YALMIP modeling environment and solved using the Gurobi 10.0.3 solver. To ensure computational efficiency and solution quality, the relative optimality gap for mixed-integer programming was specified as 0.1, the NonConvex option was configured to 2 for handling non-convex quadratic formulations, and the maximum computation time was limited to 100 s.

The energy balance of the microgrid is shown in Figure 5. The operation strategy used in this study for the microgrid is to follow the electrical load. When the microgrid generates too much electricity, it will sell some of it to the grid. When the microgrid has an electricity shortage, it will seek to purchase electricity from the grid. The thermal balance analysis is similar to that of the electrical balance, and the TES can improve the efficiency of energy use during the microgrid operation.

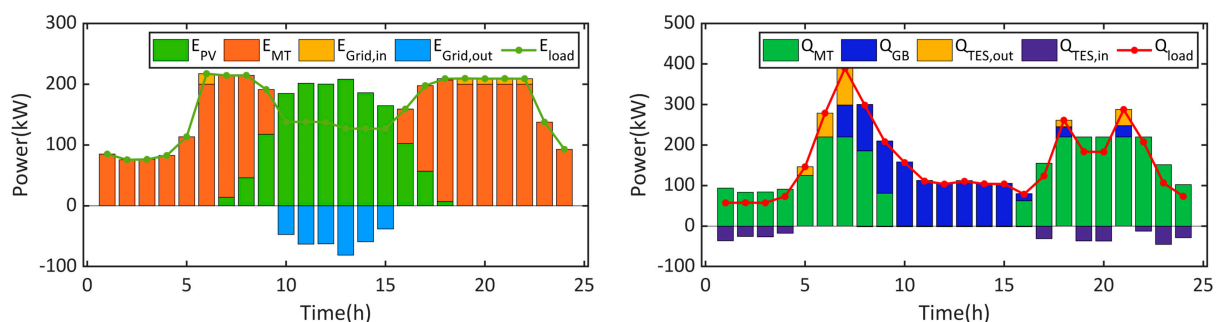


Figure 5. Energy balance diagram.

The information on the electrical and thermal loads of LA before and after the demand response is shown in Figure 6. The demand response model constructed in this paper effectively achieves the transfer of electrical load and reduction in thermal load while ensuring the customer's satisfaction with energy use.

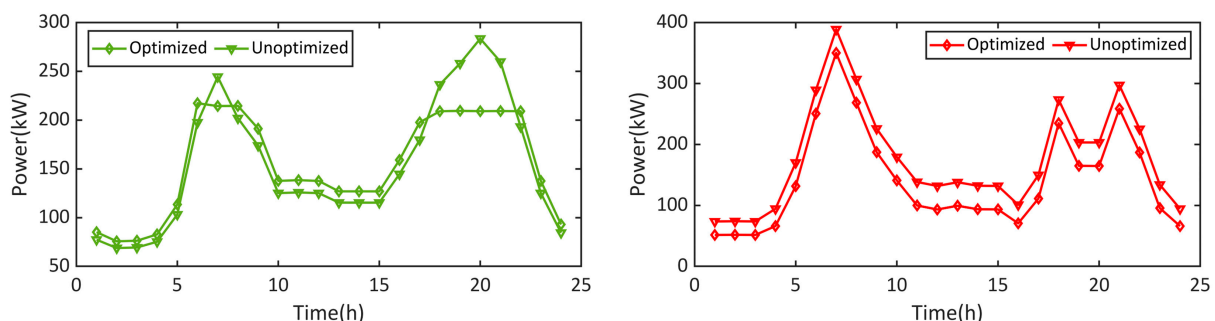


Figure 6. Load diagram of LA before and after demand response.

The pricing strategy for the upper-level MGO is shown in Figure 7. The price of selling electricity is slightly higher than the purchase price of the store because the MGO wants to ensure its revenue. The price of selling heat is close to the price ceiling, again because the MGO is pursuing its interest.

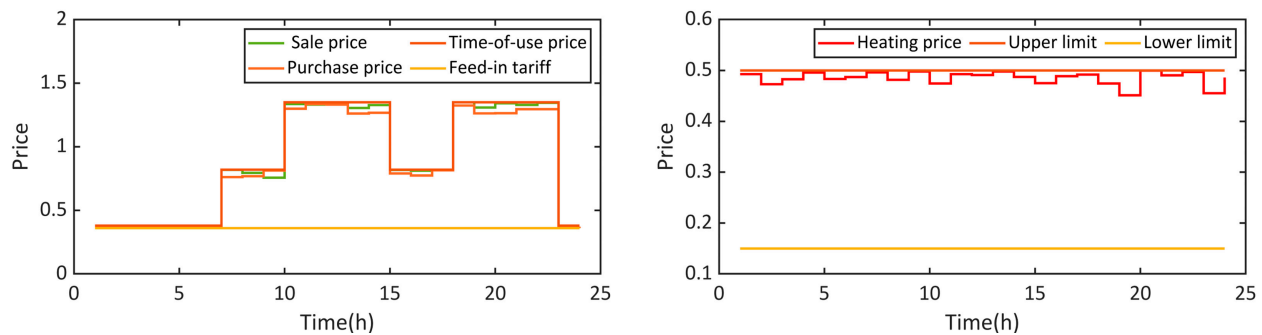


Figure 7. Optimized pricing strategy for MGO.

The optimization trajectories of the MGO profit and the LA consumer surplus are illustrated in Figure 8. It can be observed that the proposed algorithm converges within 200 iterations, demonstrating good convergence performance and computational stability. Moreover, the leader–follower interaction exhibits distinct and opposite convergence trends. As the iteration proceeds, the profit of the MGO gradually increases, while the consumer surplus of the LA correspondingly decreases, reflecting the inherent competitive–cooperative game relationship between the two parties. At convergence, the final optimized results show that the MGO achieves a profit of 21,747.4 CNY, whereas the LA obtains a consumer surplus of 3743.8 CNY.

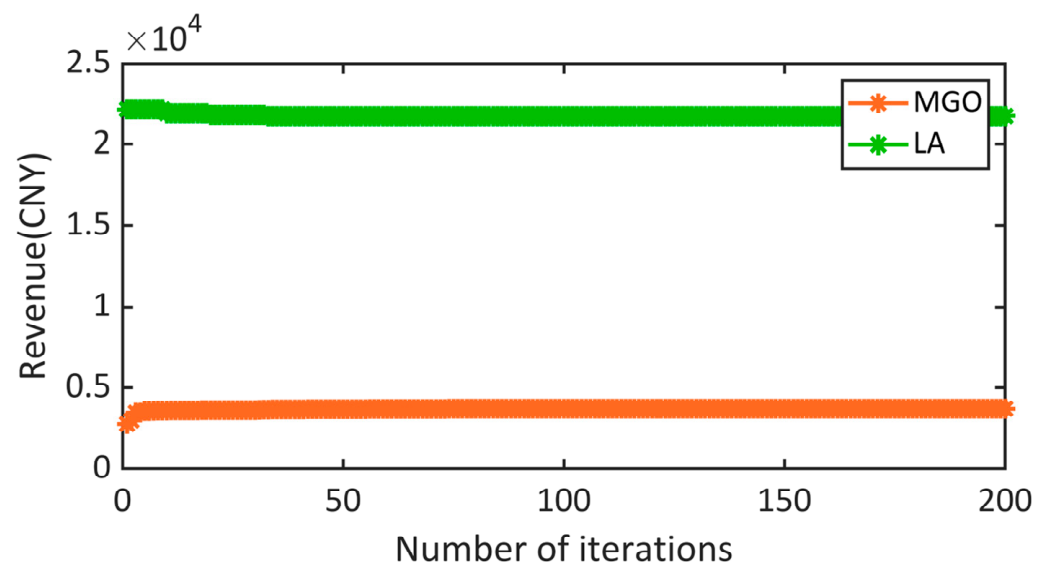


Figure 8. Stackelberg equilibrium convergence results.

To evaluate the robustness and stability of the proposed optimization framework, each case study was independently executed 20 times. The mean and standard deviation of the MGO profit and LA consumer surplus were calculated and reported to assess the consistency of the obtained solutions and the algorithm's reliability under repeated runs.

Figure 9 presents the mean values and standard deviations of the MGO profit and LA consumer surplus obtained from 20 independent runs. The average MGO profit reaches 21,748.46 CNY with a standard deviation of 20.78 CNY, while the average LA consumer surplus is 3744.15 CNY with a standard deviation of 5.53 CNY. The relatively small error bars indicate that the proposed optimization framework exhibits excellent convergence stability and robustness. Furthermore, the low variability across repeated runs demonstrates the reliability of the algorithm in consistently obtaining high-quality solutions.

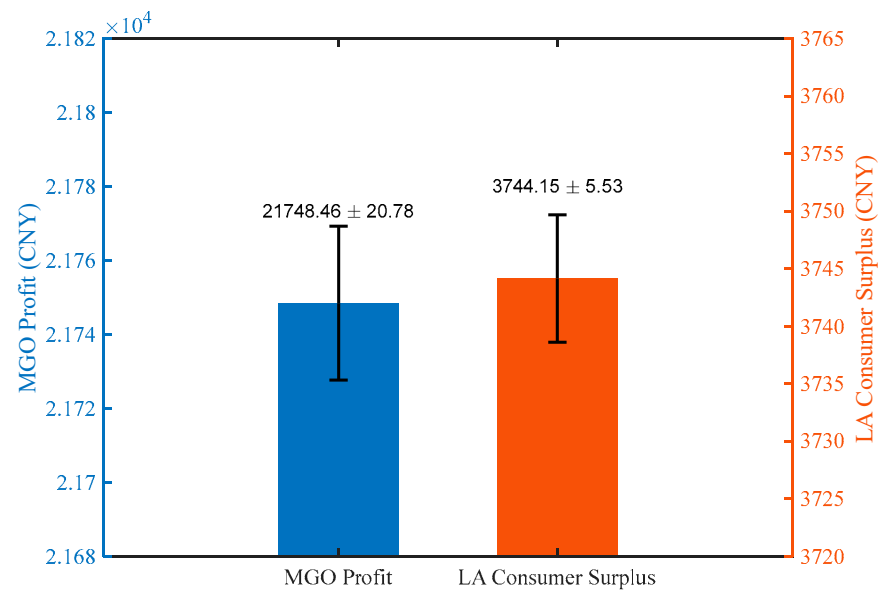


Figure 9. Statistical results over 20 independent runs.

5.2. Sensitivity Analysis of Parameters

To evaluate the robustness of the proposed Stackelberg game-based integrated energy system under external uncertainties, a sensitivity analysis was conducted on several key parameters, including solar irradiance, load demand, time-of-use (TOU) electricity price, and natural gas price. The impacts of these parameters on MGO profit and LA consumer surplus were investigated to reveal the economic characteristics and adaptability of the proposed framework.

Figure 10 illustrates the effects of solar irradiance variations on MGO profit and LA consumer surplus. As the solar irradiance coefficient increases, both indicators exhibit a noticeable upward trend. Enhanced photovoltaic generation reduces the dependence on external energy procurement and lowers operating costs, thereby improving the economic performance of the MGO and increasing consumer welfare. Furthermore, the gradually diminishing growth rates indicate the presence of marginal benefit reduction under high solar irradiance conditions.

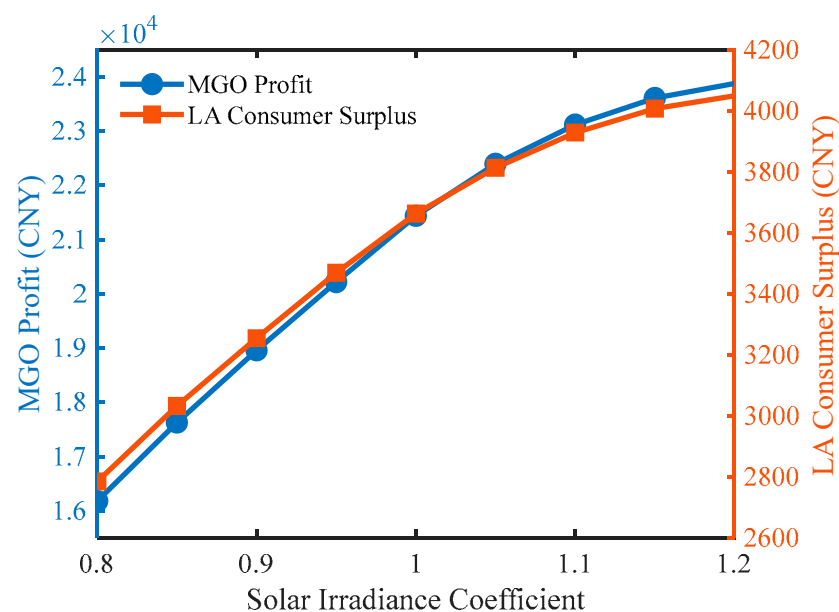


Figure 10. Sensitivity of MGO profit and LA consumer surplus to solar irradiance variations.

Figure 11 illustrates the effects of load demand variations on MGO profit and LA consumer surplus. As the load coefficient increases, the MGO profit continuously rises due to increased energy sales and improved utilization of system resources. Meanwhile, the LA consumer surplus initially increases and then gradually stabilizes, suggesting that the marginal utility of additional energy consumption decreases under high-load conditions.

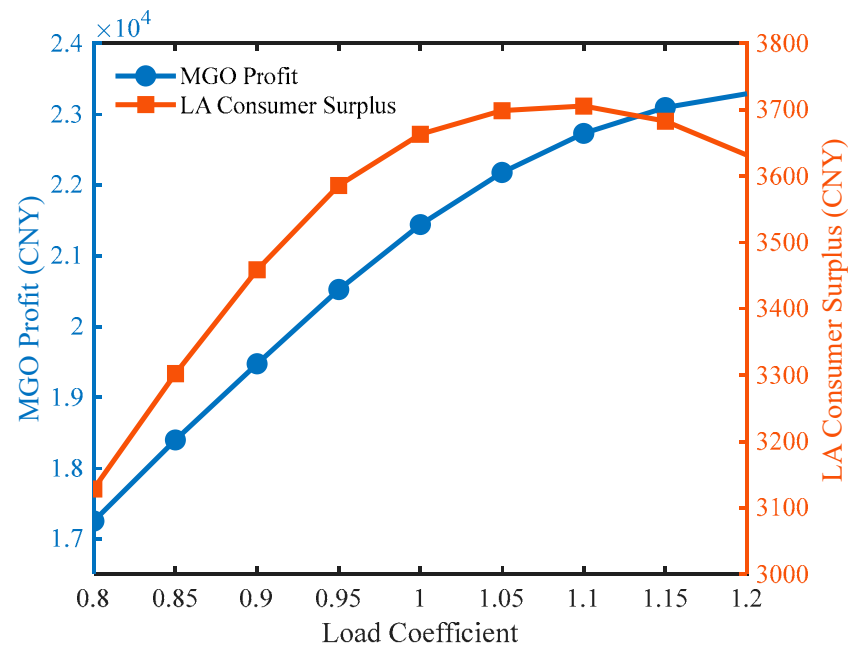


Figure 11. Sensitivity of MGO profit and LA consumer surplus to load demand variations.

Figure 12 illustrates the effects of TOU electricity price variations on MGO profit and LA consumer surplus. As the electricity price coefficient increases, the MGO profit decreases significantly because of the rising electricity procurement cost from the utility grid. In contrast, the LA consumer surplus exhibits only a slight decline, indicating that the proposed framework can effectively mitigate the impact of electricity price fluctuations on end users.

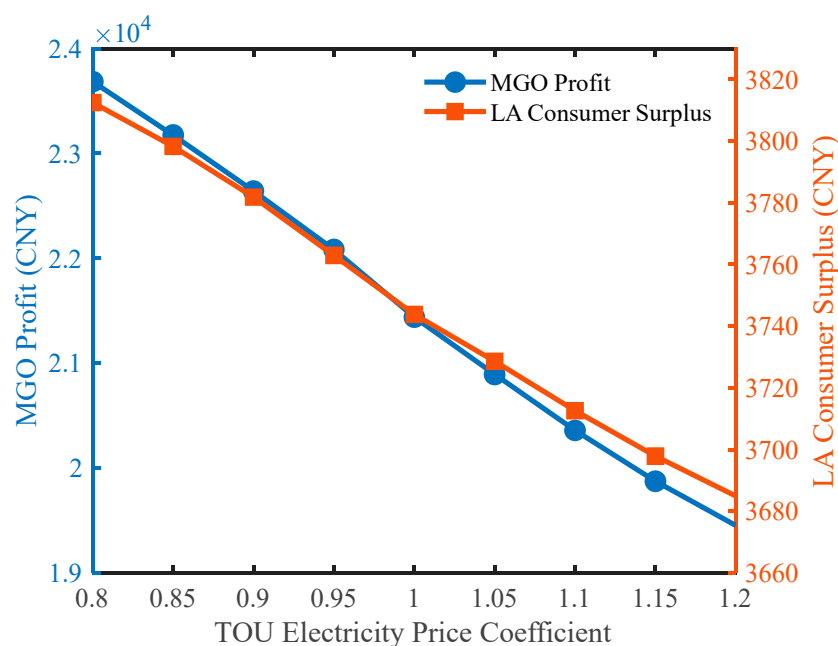


Figure 12. Sensitivity of MGO profit and LA consumer surplus to TOU price variations.

Figure 13 illustrates the effects of natural gas price variations on MGO profit and LA consumer surplus. As the natural gas price coefficient increases, the MGO profit gradually decreases due to the higher operating costs of the gas turbine and gas boiler. However, only a marginal reduction in LA consumer surplus is observed, demonstrating that fluctuations in upstream fuel prices have a limited influence on consumer welfare under the proposed Stackelberg game framework.

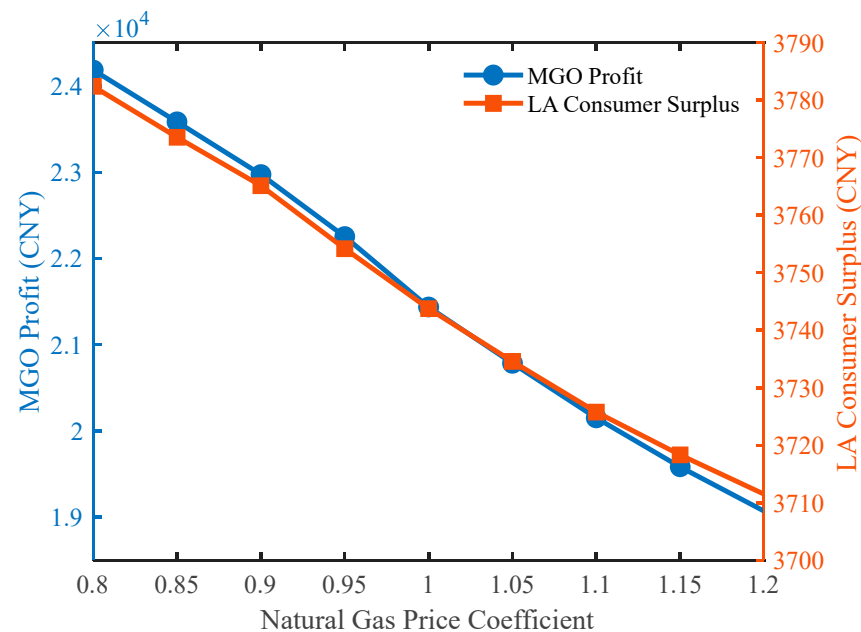


Figure 13. Sensitivity of MGO profit and LA consumer surplus to natural gas price variations.

6. Conclusions

This paper constructs a Stackelberg game optimization model for integrated energy systems with integrated demand response, where MGO acts as the leader and LA as the follower. Corresponding regulation strategies and utility functions are established for rigid/shiftable electric loads and curtailable thermal loads. The upper-layer MGO maximizes profit by setting electricity and heat prices, while the lower-layer LA optimizes flexible loads to maximize consumer surplus. An ISO is proposed and combined with quadratic programming to form the ISO-QP hybrid solver. Benchmark and CEC2017 tests verify that ISO surpasses SO, SCA, SOA, HHO and GWO in optimization performance. In the case study, the equilibrium profit of MGO is 21,747.4 CNY, and LA's consumer surplus reaches 3743.8 CNY. Over 20 repeated simulations, the average MGO profit is 21,748.46 CNY with a standard deviation of 20.78, and the average consumer surplus of LA is 3744.15 CNY with a standard deviation of 5.53, which confirms high model stability. Guided by price signals, flexible load scheduling reduces load fluctuation and improves the economic benefits of both sides without deteriorating user satisfaction. Sensitivity analysis quantifies the separate impacts of solar irradiance, base load, TOU price and natural gas price on economic returns. The distributed ISO-QP algorithm obtains a Stackelberg equilibrium and protects participants' data privacy. Only electricity and heat transactions are considered in this paper.

Although the proposed framework effectively captures the economic interaction between the MGO and LA under integrated demand response, several limitations remain. First, user comfort is not explicitly modeled through discomfort cost functions or multi-period comfort constraints, such as indoor temperature deviation limits. Second, the demand response parameters adopted in this study are selected based on commonly used

assumptions and may not fully reflect the characteristics of different customer groups or practical demand response standards. Future research will incorporate detailed comfort-aware demand response models, behavioral factors, and standards-based parameter calibration to further enhance the realism and applicability of the proposed framework in practical energy management scenarios.

Author Contributions: Conceptualization, D.Y. and C.P.; Methodology, D.Y., C.P. and H.W.; Software, D.Y. and C.P.; Validation, D.Y. and C.P.; Formal analysis, P.D.; Investigation, Z.Y.; Resources, Z.Y., M.Z. and H.W.; Data curation, Z.Y., M.Z., H.W. and Z.W.; Writing—original draft, H.W., P.D. and Z.W.; Writing—review & editing, P.D. and Z.W.; Visualization, Z.W.; Project administration, M.Z. All authors have read and agreed to the published version of the manuscript.

Funding: This paper was supported by the Ministry of Education’s “Chunhui Plan” Collaborative Research Project (HZKY20220242) and the Tianjin Municipal Science and Technology Plan Project (24ZXTKSN00030).

Data Availability Statement: No new data were created or analyzed in this study.

Conflicts of Interest: Authors Dequan Yang, Chang Peng, Zeming Yang, Miao Zhang, Haotian Wang and Pengchong Dou were employed by the POWERCHINA Hebei Electric Power Survey and Design Research Institute. 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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