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Energy Pricing and Management for the Integrated Energy Service Provider: A Stochastic Stackelberg Game Approach

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Abstract: As a retailer between the energy suppliers and end users, the integrated energy service provider (IESP) can effectively coordinate the energy supply end and the energy use end by setting energy prices and energy management. Because most of the current research focuses on the pricing of electricity retailers, there are few studies on IESP energy pricing and management, which are still at the initial stage. At the same time, the existing research often does not consider the impact of demand response (DR) and uncertainties, such as natural gas and electricity wholesale prices, on the pricing of IESP. It is necessary to model the DR and uncertainties in the integrated energy system. Aiming at the inadequacy of the existing research and to address the energy pricing and management of IESP, this paper develops a two-stage stochastic hierarchical framework, which comprehensively considers the DR strategy of the user end, characteristics of the electricity/gas/heat storage and the uncertainties of electricity and gas wholesale prices. The proposed hierarchical model for energy pricing and management is a two-layer model: the upper layer is the problem of maximizing the benefits of IESP, and the lower layer is the problem of minimizing the energy cost of user agents. Through the complementary transformation, the linearization method and the strong duality principle in the optimization theory, the model is transformed into a mixed-integer linear programing (MILP) problem, which can be easily solved by the off-shelf commercial solver. Finally, the simulation results are provided to demonstrate the interactive operation between the IESP and user agent through energy prices setting, DR strategy and energy management.

Keywords: integrated energy service provider; stochastic programing; Stackelberg game; demand response; interactive operation

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1. Introduction

With the increasingly tight coupling of electricity–gas–heat and other forms of energy, integrated energy services become more and more urgent. In the traditional energy supply mode, the power supply, gas supply and heat supply belong to different public utility groups, and different energy supply entities are independent of each other. The energy supply mode is single, and the complementary and synergistic effects among different energy sources cannot be exerted. The integrated energy service integrates the power supply, gas supply and heat supply, and it can effectively improve energy utilization efficiency and reduce user energy costs through energy complementarity and synergy [1–3]. As a retailer between energy suppliers and end users, the IESP can effectively coordinate the energy supply end and the energy use end by setting energy prices and energy management.

Retail competition is relatively mature in the electricity market. In this mode, both parties are free to compete, the competition among the sellers is the most intense, and the buyer has the largest choice. Power generation, transmission, distribution enterprises and users are separated into independent economic legal persons. In addition to the power distribution companies (or retailers), the power users can also directly purchase electricity from power generation enterprises within or outside the network [4,5]. Different from electricity, gas does not need to be piped in some areas because of its storability. As an end user, it is impossible to purchase natural gas directly from the manufacturers, transporters and distributors. Consumers need to use natural gas energy retailers as an intermediary to obtain directly usable natural gas [6,7].

At present, the research on energy pricing and management of IESP is still in its infancy, and more researches are focused on electricity retailers. Aiming at the two different objects of the wholesale energy market and end users, Wei et al. [8] adopt the hierarchical pricing structure to deal with the energy pricing and dispatching, which makes the energy management of the smart grid more flexible. A scenario-based model is proposed in Ref [9] to solve the problem of power retailers' bilateral contracting and sales pricing in an uncertain smart grid environment. By comparing the price structure of fixed pricing, time-of-use pricing and real-time pricing, it is found that the sales price based on real-time pricing brings more profits to the retailers. In order to comprehensively sort the latest pricing of power retailers, Yang et al. [10] investigate and discuss the decision-making process of power retailers from many aspects, and the most suitable strategy is formulated for the objective of optimal retail pricing. Sheikhahmadi et al. [11] propose a two-layer optimization approach to address the challenges and risks associated with the variability of renewable energy resources and demand, which can increase the operational flexibility of distribution companies.

The process of a retailer's energy pricing and management often involves a hierarchical game of different stakeholders, such as the Stackelberg game [12–14]. Generally, the Stackelberg game model has the characteristics of a two-layer structure. According to the decision-making order of participants, it includes the leader's decision-making problem and the followers' decision-making problems. Based on the risk of future prices, a Stackelberg game approach is proposed in Ref [15] to analyze the energy transactions between the consumers and the grid, which can maximize profits by setting optimal pricing strategies. In consideration of consumers and from the perspective of a microgrid operator, Liu et al. [16] propose a Stackelberg game approach to manage effective energy sharing. Khazeni et al. [17] establish a two-layer game model between energy retailers and consumers, and a solution method based on discrete technology to approximate the Nash point is proposed to solve the model, so that energy retailers can derive more profits and reduce the production and user cost.

At present, with a large number of wind turbines connected to the grid, their own uncertainty will affect the development of real-time grid scheduling. A large number of scholars have studied wind power output uncertainty. Jiarui et al. [18] propose a two-stage energy management model based on rolling optimization to solve the uncertainty and randomness of renewable energy and loads and minimize the operation cost. Ali M et al. [19] introduce a new demand response strategy (DRS) implemented by a fuzzy logic controller to solve the uncertainty of wind energy, which can minimize the energy cost and load loss rate of the integrated energy system. Mahmoud A et al. [20] adopt a new control scheme to improve the dynamic performance of wind turbines, thus effectively reducing the uncertainty of wind power output.

With the gradual improvement of the market and the continuous development of demand response technology, many scholars have conducted research on DR. Vahedipour et al. [21] discuss the optimal bidding strategy for virtual power plants and consider DR. Tumuluru et al. [22] propose a two-stage method for the day-ahead energy dispatch problem considering demand response, which verifies a series of benefits of incorporating demand response into the unit commitment problem. Guo et al. [23] propose a community energy system configuration framework that considers the impact of DR. Majed A et al. [24] propose a DR management strategy that substantially reduces energy costs and increases the benefits of renewable energy systems.

However, with the continuous coupling of multiple systems and the gradual complexity of the user side, the demand response is also facing uncertainty [25]. User-side uncertainty is mainly affected by user behavior and other incentives. Similar to the uncertainty of new energy generation, such as wind power, the current methods to solve DR uncertainty include stochastic optimization, robust optimization, fuzzy interval optimization, etc. Compared with stochastic optimization and robust optimization, fuzzy optimization can describe uncertainty more accurately in the absence of uncertain variable information or incomplete information [26]. At present, there are many researches on DR in the power system. the uncertainty of DR in integrated energy system needs to be further studied [27].

Regarding the pricing and management of integrated energy services, pioneering work has been carried out in Ref [28]. In order to achieve the level of participation required by multi-energy users in the integrated demand response plan, Gu et al. [28] propose an optimal scheduling model for an industrial park by designing multiple energy price incentives, which enables the agency to determine the optimal integrated energy prices. Because most of the current studies focus on the pricing problem of electricity retailers and do not consider the impact of DR and uncertainties, such as natural gas and electricity wholesale prices, on the pricing of IESP, we develop a two-stage stochastic hierarchical framework to address the energy pricing and management of IESP, which comprehensively considers the DR strategy of the user end, characteristics of the electricity/gas/heat storage and the uncertainties of electricity and gas wholesale prices. The main contributions of this paper can be summarized as follows:

(1) A two-stage stochastic complementarity framework from the perspective of the IESP is developed to study the interactive operation between the IESP and user agent, which comprises energy price setting, DR strategy and energy management.
(2) The proposed hierarchical model for energy pricing and management is transformed into a MILP problem through complementary transformation, the linearization method and strong duality principle in optimization theory.
(3) Through the simulation of the integrated energy system (IES) in an industrial park, the impact of user agent DR and IESP's electricity/gas/heat energy storage on energy pricing and management is analyzed.

The remainder of this paper is organized as follows. Section 2 introduces the physical and market structure for energy pricing and management of IESP. The IESP's upper problem and the user agent's lower problem are formulated in Section 3. Section 4 describes the solving method for the hierarchical model. Section 5 provides the case study to demonstrate the interactive operation between the IESP and user agent. Finally, Section 6 concludes the paper.

2. Problem Description

The physical framework for IESP to interact with energy suppliers and user agents is shown in Figure 1. Energy suppliers include the power distribution system for electricity supply and the natural gas system for gas supply. The IESP owns the assets of renewable energy sources (RES), combined heat and power plants (CHPP) and gas boilers (GB). In addition, electricity storage (ES), heat storage (HS) and gas storage (GS) devices are also included for energy storage. User agents are regarded as aggregators of the electricity load (EL), heat load (HL) and gas load (GL). The IESP acts as a retailer between energy suppliers and user agents. As a price receiver, the IESP purchases electricity and natural gas from the energy suppliers. As a price maker, the IESP sets retail energy prices (including electricity, gas and heat price) to supply the electricity, gas and heat to user agents. Due to the relatively small load capacity of the users, users cannot directly purchase electricity and gas from the energy suppliers, which means that the IESP is the only energy supplier and has strong market power. In order to reduce the market power of the IESP and build a relatively fair market environment, we assume that the IESP and users reach an agreement on the variable range of retail energy prices.

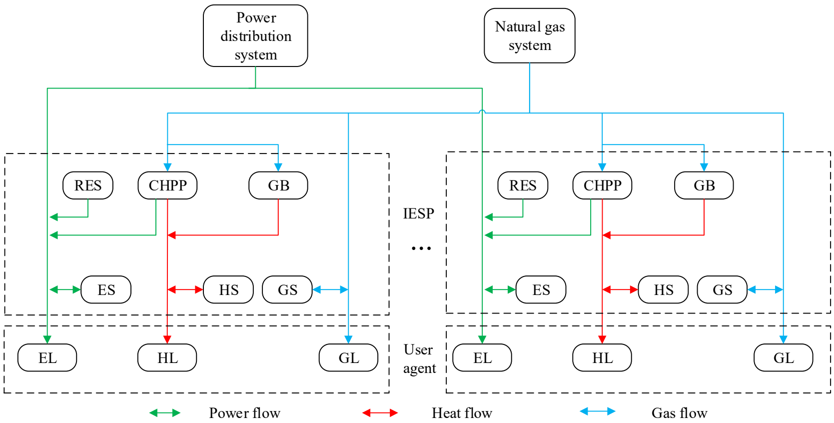

Figure 1. Physical structure for IESP interactive operation.

Figure 2 shows the three-tier market framework for energy pricing and management of the IESP. By purchasing electricity and natural gas in the wholesale energy market, the IESP strategically sets retail energy prices and optimizes the operation of IES to provide users with electricity, gas and heat and pursue the maximization of income. The user agent optimizes the energy consumption pattern through the DR strategy and pursues the minimization of energy cost. The decision-making process of the IESP and the user agent consists of three parts, which can be divided into two stages and two levels:

(1) Set energy prices: In the first stage of the upper-level issue, the IESP determines the retail electricity price, gas price and heat price to be released to the user agent the next day.
(2) DR strategy: In the first stage of the lower-level problem, the user agent determines the DR strategy to optimize energy consumption pattern based on the retail energy prices issued by the IESP.
(3) Energy management: In the second stage, the IESP optimizes IES operation and determines the electricity and gas purchase contracts in the energy wholesale market based on the energy consumption pattern of the user agent.

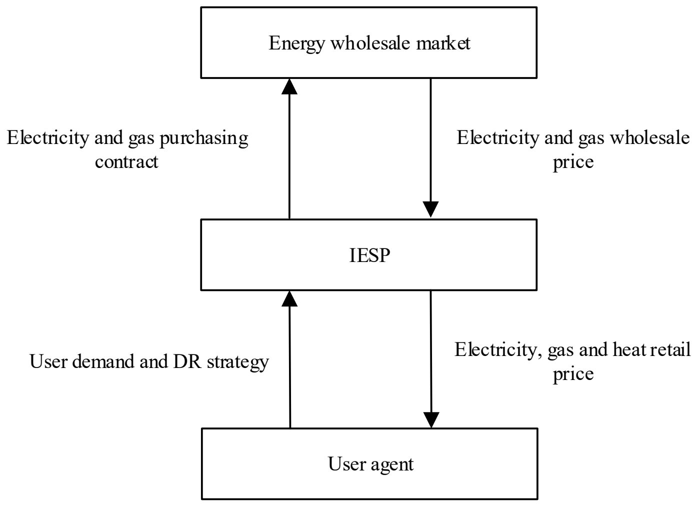

Figure 2. Market structure for energy pricing and management of IESP.

In the process of energy pricing and management, the IESP needs to predict the energy consumption pattern of the users to formulate retail energy prices, as well as determine the purchase of electricity and gas from energy suppliers. At the same time, due to the stochastic volatility of RES output and the uncertainty of electricity and gas prices in the energy wholesale market, the IESP needs to avoid market risks as much as possible.

Therefore, this paper proposes an IESP energy pricing and management model based on stochastic complementarity modeling to analyze the interactive operation mechanism between the IESP and the user agent.

3. Problem Formulation

3.1. IESP's Problem

The decision-making process of the IESP consists of two stages. In the first stage, the IESP determines the retail energy prices released to the users for every period of the next day. In the second stage, the IESP determines the energy purchasing contract in the wholesale market and optimizes the operation of the IES based on the users' energy consumption. The IES operation includes the scheduling of various units and energy storage devices. The IESP achieves its own profits by purchasing energy in the wholesale market and selling it to the end users. The optimization problem of the IESP can be described as follows:

$$\begin{array}{ll} \max & \sum\limits_{t=1}^{T}\sum\limits_{i=1}^{N_C}\left(\lambda_t^e P_{it}^{e,d} + \lambda_t^g P_{it}^{g,d} + \lambda_t^h P_{it}^{h,d}\right)\Delta t \\ & -\sum\limits_{\omega=1}^{N_\Omega}\pi_\omega \sum\limits_{t=1}^{T}\left(\begin{array}{c} \lambda_{t\omega}^{em} P_{t\omega}^{e} + \lambda_{t\omega}^{gm} P_{t\omega}^{g} + \\ \lambda^{wind}\left(P_{t\omega}^{wind} - P_{t\omega}^{cur}\right) \end{array}\right)\Delta t \end{array} \tag{1}$$

Formula (1) is the objective function of the IESP, which consists of two parts. The first part is the sales revenue of the IESP, in which $\left\{\lambda_t^e, \lambda_t^g, \lambda_t^h\right\}$ is the electricity price, gas price and heat price issued by the IESP to the user agent, respectively; $\left\{P_{it}^{e,d}, P_{it}^{g,d}, P_{it}^{h,d}\right\}$ is the electricity demand, gas demand and heat demand, respectively; N_C indicates the number of user agents. The second part is the sales cost for the IESP expressed as the expected value based on the scenarios of wind power output, electricity price and gas price in the wholesale market. $\left\{\lambda_{t\omega}^{em}, \lambda_{t\omega}^{gm}\right\}$ is the electricity price scenario and gas price scenario in the wholesale market, respectively. $\left\{P_{t\omega}^{e}, P_{t\omega}^{g}\right\}$ is the electricity and natural gas purchased from the wholesale market, respectively. λ^{wind} is the cost of wind energy. $\left\{P_{t\omega}^{wind}, P_{t\omega}^{cur}\right\}$ is the wind power output scenario and the curtailment of wind power, respectively.

The first-stage constraints include the electricity price, gas price and heat price constraints, as shown in Formulas (2)–(8).

$$\lambda_{t,\min}^e \le \lambda_t^e \le \lambda_{t,\max}^e, \forall t \tag{2}$$

$$\sum_{t=1}^{T}\lambda_t^e / T \le \lambda_{av}^e \tag{3}$$

$$\lambda_t^g = \kappa_{1t}\lambda_t^e, \forall t \tag{4}$$

$$\kappa_{1\min} \le \kappa_{1t} \le \kappa_{1\max}, \forall t \tag{5}$$

$$\sum_{t=1}^{T}\lambda_t^g / T \le \lambda_{av}^g \tag{6}$$

$$\lambda_t^h = \kappa_{2t}\lambda_t^e, \forall t \tag{7}$$

$$\kappa_{2\min} \le \kappa_{2t} \le \kappa_{2\max}, \forall t \tag{8}$$

The retail electricity prices issued by the IESP to the user agent shall be within the allowable range, as shown in Formula (2), in which $\left\{\lambda_{t,\min}^e, \lambda_{t,\max}^e\right\}$ is the upper and lower limit of the retail electricity price, respectively. In order to reduce the market power of the IESP, constraint (3) is used to impose an upper limit on the average of the IESP retail price series. Otherwise, $\lambda_t^e = \lambda_{t,\max}^e$ is obviously the best choice for the IESP, but for the user, this is obviously unfair. We assume that the IESP and user agents agree to make the price constraint effective.

For the retail gas price and heat price, they are often associated with the retail electricity price and can be characterized by Formulas (4)–(8), in which $\{\kappa_{1t}, \kappa_{2t}\}$ is the correlation coefficient between the retail gas/heat price and the retail electricity price, respectively; $\{\kappa_{1\min}, \kappa_{1\max}\}$ and $\{\kappa_{2\min}, \kappa_{2\max}\}$ are the upper and lower limits of the correlation coefficient. Similarly, for the retail gas price, the average of the IESP's retail gas price series should not be higher than a certain upper limit.

The IESP needs to determine the energy retail prices released to the user agent in the first stage, and after the user agent determines the energy consumption pattern based on the received energy prices, the IESP then determines the IES operation strategy in the second stage and the electricity and gas purchasing contracts in the wholesale market. Due to the uncertainty of electricity and gas prices in the wholesale market on the second day and the randomness of the output of wind turbines in the IES, the following are f the operating constraints of the second stage of the IESP based on the scenario description:

$$0 \le P^{e}_{t\omega} \le P^{e}_{\max}, \forall t, \omega \tag{9}$$

$$0 \le P^{g}_{t\omega} \le P^{g}_{\max}, \forall t, \omega \tag{10}$$

$$0 \le P^{cur}_{t\omega} \le P^{wind}_{t\omega}, \forall t, \omega \tag{11}$$

$$P^{e}_{t\omega} + P^{wind}_{t\omega} - P^{cur}_{t\omega} + P^{e,chp}_{t\omega} = \sum_{i=1}^{N_C} P^{e,d}_{it} + P^{es,c}_{t\omega} - P^{es,d}_{t\omega}, \forall t, \omega \tag{12}$$

$$P^{g}_{t\omega} - P^{g,chp}_{t\omega} - P^{g,gb}_{t\omega} = \sum_{i=1}^{N_C} P^{g,d}_{it} + P^{gs,c}_{t\omega} - P^{gs,d}_{t\omega}, \forall t, \omega \tag{13}$$

$$P^{h,chp}_{t\omega} + P^{h,gb}_{t\omega} = \sum_{i=1}^{N_C} P^{h,d}_{it} + P^{hs,c}_{t\omega} - P^{hs,d}_{t\omega}, \forall t, \omega \tag{14}$$

$$P^{e,chp}_{t\omega} = \eta_{e,chp} P^{g,chp}_{t\omega}, \forall t, \omega \tag{15}$$

$$P^{h,chp}_{t\omega} = \eta_{h,chp} P^{g,chp}_{t\omega}, \forall t, \omega \tag{16}$$

$$P^{h,gb}_{t\omega} = \eta_{gb} P^{g,gb}_{t\omega}, \forall t, \omega \tag{17}$$

$$0 \le P^{in}_{t\omega} \le P^{in}_{\max}, \forall t, \omega \tag{18}$$

$$-P^{d} \le P^{in}_{t\omega} - P^{in}_{(t-1)\omega} \le P^{u}, \forall t, \omega \tag{19}$$

$$W^{s}_{t\omega} = W^{s}_{(t-1)\omega} + \eta_{s,c} P^{s,c}_{t\omega} \Delta t - \frac{1}{\eta_{s,d}} P^{s,d}_{t\omega} \Delta t \tag{20}$$

$$W^{s}_{\min} \le W^{s}_{t\omega} \le W^{s}_{\max}, \forall t, \omega \tag{21}$$

$$0 \le P^{s,c}_{t\omega} \le P^{s,c}_{\max}, \forall t, \omega \tag{22}$$

$$0 \le P^{s,d}_{t\omega} \le P^{s,d}_{\max}, \forall t, \omega \tag{23}$$

Formulas (9) and (10) indicate that the IESP purchases electricity and natural gas in the wholesale market subject to the cap of the contract, in which $\left\{P^{e}_{\max}, P^{g}_{\max}\right\}$ is the maximum amount of electricity and natural gas that the IESP can purchase in the wholesale market, respectively. Formula (11) restricts that the curtailed wind power generation in the wind power generation reduction strategy should not be greater than the output power of the wind turbine in a certain scenario. Formulas (12)–(14) are the power balance equations for electricity, gas and heat in the IES, respectively. $\left\{P^{e,chp}_{t\omega}, P^{h,chp}_{t\omega}\right\}$ is the electric power and heat power output of the CHPP, respectively; $\left\{P^{g,chp}_{t\omega}, P^{g,gb}_{t\omega}\right\}$ is the natural gas power input of the CHPP and GB, respectively; $P_{t\omega}^{h,gb}$ is the heat power output of the GB. $\left\{P_{t\omega}^{es,c}, P_{t\omega}^{es,d}\right\}$ is the charge and discharge power of the ES device, respectively; $\left\{P_{t\omega}^{gs,c}, P_{t\omega}^{gs,d}\right\}$ is the charge and discharge power of the GS device, respectively; $\left\{P_{t\omega}^{hs,c}, P_{t\omega}^{hs,d}\right\}$ is the charge and discharge power of the HS device, respectively. Formulas (15) and (16) are the electric power and heat power conversion equations of the CHPP, respectively. $\left\{\eta_{e,chp}, \eta_{h,chp}\right\}$ is the electric conversion coefficient and heat conversion coefficient of the CHPP. Formula (17) is the heat power conversion equation of the GB, in which η_{gb} is the heat conversion coefficient of the GB. Formula (18) indicates that the CHPP and the GB are limited by the maximum input gas power. $P_{t\omega}^{in}$ represents the set $\left\{P_{t\omega}^{g,chp}, P_{t\omega}^{g,gb}\right\}$; $P_{\max}^{in}$ represents the set $\left\{P_{\max}^{g,chp}, P_{\max}^{g,gb}\right\}$, which is the maximum natural gas power input of the CHPP and the GB. Formula (19) is the ramp constraint of the CHPP and the GB, in which $\left\{P^{d}, P^{u}\right\}$ is, respectively, the set of down ramp power and up ramp power of the CHPP and the GB. Formulas (20)–(23) represent the energy storage constraints for the ES, GS and HS devices. Formulas (20) and (21) are the energy conversion equations and capacity constraints of the energy storage devices, respectively. $W_{t\omega}^{s}$ is the capacity of the energy storage devices, which represents the set $\left\{W_{t\omega}^{es}, W_{t\omega}^{gs}, W_{t\omega}^{hs}\right\}$.$\left\{W_{\max}^{s}, W_{\min}^{s}\right\}$ is the upper and lower capacity limits set of energy storage devices, respectively. Formulas (22) and (23) are the charging and discharging constraints of energy storage devices, respectively. $\left\{P_{\max}^{s,c}, P_{\max}^{s,d}\right\}$ is the set of maximum charging and discharging power of the energy storage devices, respectively. $\left\{\eta_{s,c}, \eta_{s,d}\right\}$ is the set of charging efficiency and discharging efficiency of the energy storage devices, respectively.

3.2. User Agent's Problem

In the first stage of the lower model, the user agent optimizes theenergy consumption pattern according to the retail prices released by the IESP. The user agent aims to maximize the energy efficiency. The optimization decision of the i'th user agent can be described as follows:

$$\max \quad \sum_{t=1}^{T}\left[U_{it}^{e,d}+U_{it}^{g,d}+U_{it}^{h,d}-\left(\lambda_t^e P_{it}^{e,d}+\lambda_t^g P_{it}^{g,d}+\lambda_t^h P_{it}^{h,d}\right)\Delta t\right] \tag{24}$$

$$U_{it}^{e,d} \leq a_{it}^{k} P_{it}^{e,d}\Delta t + b_{it}^{k}, \forall i,t,k : o_{it}^{k} \tag{25}$$

$$P_{it}^{e,d} = P_{it}^{e,d,f} + P_{it}^{e,d,if}, \forall i,t \tag{26}$$

$$\sum_{t=1}^{T} P_{it}^{e,d,f}\Delta t = 0, \forall i : \mu_i \tag{27}$$

$$P_{it,\min}^{e,d,f} \leq P_{it}^{e,d,f} \leq P_{it,\max}^{e,d,f}, \forall i,t : \nu_{it}^{\min}, \nu_{it}^{\max} \tag{28}$$

The user agent's objective function (24) consists of two parts: the energy utility and the energy cost, in which U_{it}^{d} represents the set of the utility function of electricity, gas and heat usage. The utility function is usually a non-decreasing and concave function, which can usually be characterized by a piecewise linear function or a quadratic function. Generally, a piecewise linear function can approximate a quadratic function. We choose to use a piecewise linear function to characterize the utility function, as shown in Formula (25). a_{it}^{k} and b_{it}^{k} represent the primary coefficient and constant, respectively. o_{it}^{k} is the associated dual variable. The user agent's EL can participate in the DR, and formula (26) indicates that the user agent's EL consists of two parts: the flexible load $P_{it}^{e,d,f}$, which participates in the DR, and the inflexible load $P_{it}^{e,d,if}$, which does not participate in the DR. Formula (27) indicates that the flexible load participating in the DR keeps the total load constant during the load transfer process. When the value of $P_{it}^{e,d,f}$ is positive, it indicates that the flexible load is transferred in during the period. Additionally, the negative value indicates that the flexible load is transferred out during the period. μ_i is the dual variable associated with this constraint. At the same time, the flexible load participating in the DR satisfies the upper and lower limit constraint (28) in each period. $P_{it,\min}^{e,d,f}$ and $P_{it,\max}^{e,d,f}$ are the minimum and maximum flexible loads participating in the DR, respectively. $\nu_{it}^{\min}$ and $\nu_{it}^{\max}$ represent the dual variables associated with the corresponding constraints.

4. Solving Method

The above stochastic complementarity model is a two-level model. The retail energy prices released by the IESP are the decision variables in the upper-level model, which can be regarded as constant values after being passed to the lower-level model. Since the objective function and constraints of the lower-level model can be expressed linearly, the user agent's model is a convex optimization problem [29,30]. For convex problems, the optimal solution can be solved by converting the lower-level model to its Karush–Kuhn–Tucker (KKT) conditions. The KKT conditions of the lower user agent's model are as shown in Formulas (29)–(34):

$$\sum_{t=1}^{T}\left(P_{it}^{e,d}-P_{it}^{e,d,if}\right)\Delta t=0,\forall i \tag{29}$$

$$\lambda_t^e-\mu_i-\nu_{it}^{\min}+\nu_{it}^{\max}-\sum_{k=1}^{N_K}a_{it}^k o_{it}^k=0,\forall i,t \tag{30}$$

$$\sum_{k=1}^{N_K}o_{it}^k=1,\forall i,t \tag{31}$$

$$0\le a_{it}^k P_{it}^{e,d}\Delta t+b_{it}^k-U_{it}^{e,d}\perp o_{it}^k\ge 0,\forall i,t,k \tag{32}$$

$$0\le P_{it,\max}^{e,d,f}-P_{it}^{e,d,f}\perp \nu_{it}^{\max}\ge 0,\forall i,t \tag{33}$$

$$0\le P_{it}^{e,d,f}-P_{it,\min}^{e,d,f}\perp \nu_{it}^{\min}\ge 0,\forall i,t \tag{34}$$

4.1. Linearization of Complementary Constraints

Among them, formulas (32)–(34) are complementary relaxation conditions, which can be linearized by the big M method [31]. The core idea of the big M method is to linearize the nonlinear constraint by introducing a 0–1 variable, where the value of M is a large number. The above complementary conditions can be converted to formulas (35)–(43). Take the complementary relaxation condition (32) as an example. When $z_{it}^k=0$, the constraint (36) is relaxed, and the constraint (35) is converted into $a_{it}^k P_{it}^{e,d}\Delta t+b_{it}^k-U_{it}^{e,d}=0$; when $z_{it}^k=1$, the constraint (35) is relaxed, and the constraint (36) is converted into $o_{it}^k=0$. Therefore, the conversion result is equivalent to the complementary relaxation conditions.

$$0\le a_{it}^k P_{it}^{e,d}\Delta t+b_{it}^k-U_{it}^{e,d}\le z_{it}^k M,\forall i,t,k \tag{35}$$

$$0\le o_{it}^k\le\left(1-z_{it}^k\right)M,\forall i,t,k \tag{36}$$

$$z_{it}^k\in\{0,1\},\forall i,t,k \tag{37}$$

$$0\le P_{it,\max}^{e,d,f}-P_{it}^{e,d,f}\le z_{it}^{\max}M,\forall i,t \tag{38}$$

$$0\le \nu_{it}^{\max}\le(1-z_{it}^{\max})M,\forall i,t \tag{39}$$

$$z_{it}^{\max}\in\{0,1\},\forall i,t \tag{40}$$

$$0\le P_{it}^{e,d,f}-P_{it,\min}^{e,d,f}\le z_{it}^{\min}M,\forall i,t \tag{41}$$

$$0 \le \nu_{it}^{\min} \le \left(1 - z_{it}^{\min}\right) M, \forall i, t \tag{42}$$

$$z_{it}^{\min} \in \{0, 1\}, \forall i, t \tag{43}$$

4.2. Linearization of Bilinear Terms

So far, the lower-level user agent's model has been transformed into linear constraints and can be included in the upper-level energy service provider's model. Through observation, it can be found that the constraints in the upper problem are all linear, and there are three bilinear terms in the objective function, that is, the multiplication of the two variables $\lambda_t^e P_{it}^{e,d}$, $\lambda_t^g P_{it}^{g,d}$ and $\lambda_t^h P_{it}^{h,d}$. The bilinear term of the upper problem also appears in the lower problem, and the strong duality principle [32] in the original dual problem is used for conversion. The principle of strong duality means that for the original problem with a deterministic solution, the dual problem also has a deterministic solution, and the objective functions of the original problem and the dual problem are equal. Therefore, the objective function in the lower-level problem can be equivalent to the objective function of its dual problem, as shown in Formula (44).

$$\begin{aligned}
&\sum_{t=1}^{T}\left[\left(\lambda_t^e P_{it}^{e,d} + \lambda_t^g P_{it}^{g,d} + \lambda_t^h P_{it}^{h,d}\right)\Delta t\right.\\
&\left.-\left(U_{it}^{e,d} + U_{it}^{g,d} + U_{it}^{h,d}\right)\right]\\
&= \mu_i \sum_{t=1}^{T} P_{it}^{e,d,if} - \sum_{t=1}^{T}\sum_{k=1}^{N_K} o_{it}^k b_{it}^k\\
&+ \sum_{t=1}^{T} \nu_{it}^{\min}\left(P_{it,\min}^{e,d,f} + P_{it}^{e,d,if}\right)\\
&- \sum_{t=1}^{T} \nu_{it}^{\max}\left(P_{it}^{e,d,if} + P_{it,\max}^{e,d,f}\right), \forall i
\end{aligned} \tag{44}$$

4.3. Equivalent MILP

By incorporating the above-mentioned shift term into the objective function of the upper-level problem, the aforementioned stochastic complementarity model can be transformed into a MILP problem as follows. The objective function is (45), and the constraints are (2)–(23), (29)–(31), (35)–(43).

$$\begin{aligned}
\max \quad &\sum_{t=1}^{T}\sum_{i=1}^{N_C}\left[\mu_i P_{it}^{e,d,if} - \sum_{k=1}^{N_K} o_{it}^k b_{it}^k\right.\\
&+\nu_{it}^{\min}\left(P_{it,\min}^{e,d,f} + P_{it}^{e,d,if}\right)\\
&-\nu_{it}^{\max}\left(P_{it}^{e,d,if} + P_{it,\max}^{e,d,f}\right)\\
&\left.+\left(U_{it}^{e,d} + U_{it}^{g,d} + U_{it}^{h,d}\right)\right]\\
&-\sum_{\omega=1}^{N_\Omega}\pi_\omega\sum_{t=1}^{T}\left(\begin{array}{c}\lambda_{t\omega}^{em} P_{t\omega}^{e} + \lambda_{t\omega}^{gm} P_{t\omega}^{g} + \\ \lambda^{wind}\left(P_{t\omega}^{wind} - P_{t\omega}^{cur}\right)\end{array}\right)\Delta t
\end{aligned} \tag{45}$$

subject to: (2)–(23), (29)–(31) and (35)–(43).

5. Case Study

5.1. System Description

This section takes an IES in an industrial park as an example to verify the effectiveness of the above-mentioned hierarchical energy pricing and management model. We study the interactive operation strategy between the IESP and user agents. Further, we analyze the impact of the user agent's DR strategy and the IESP's electricity/gas/heat storage on energy pricing and management.

Taking twenty-four hours a day as the research period, the time precision is set to an hour, that is, the various parameters are assumed to remain unchanged within every hour.

The electricity/gas/heat consumption in an industrial park during the day is shown in Figure 3, and the consumption is all converted into power units of MW. The wind power capacity is 8 MW, and 20 wind power scenarios of equal probability are generated based on historical wind data of a wind farm, which is as shown in Figure 4a. Five scenarios of equal probability are generated for electricity and gas prices in the wholesale market, as shown in Figure 4b and 4c. The IESP's minimum and maximum retail electricity prices are, respectively, 0.9 times and 1.1 times the average of the electricity price scenarios in the wholesale market. The minimum and maximum retail gas prices are also 0.9 times and 1.1 times the average of the gas price scenarios in the wholesale market. The minimum and maximum retail heat prices are 1 and 1.5 times the average gas price in the wholesale market, respectively. The IESP's largest purchases of electricity and gas from the wholesale market are 10 MW and 20 MW, respectively.

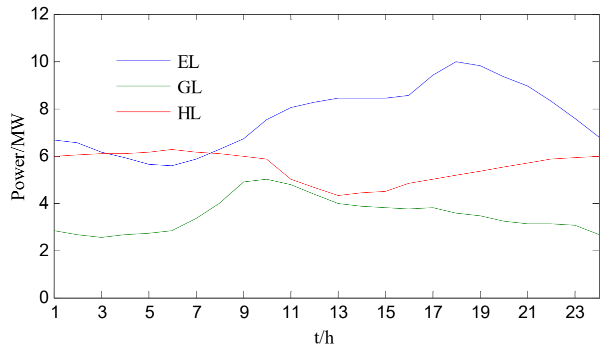

Figure 3. The electricity/gas/heat consumption in industrial park during the day.

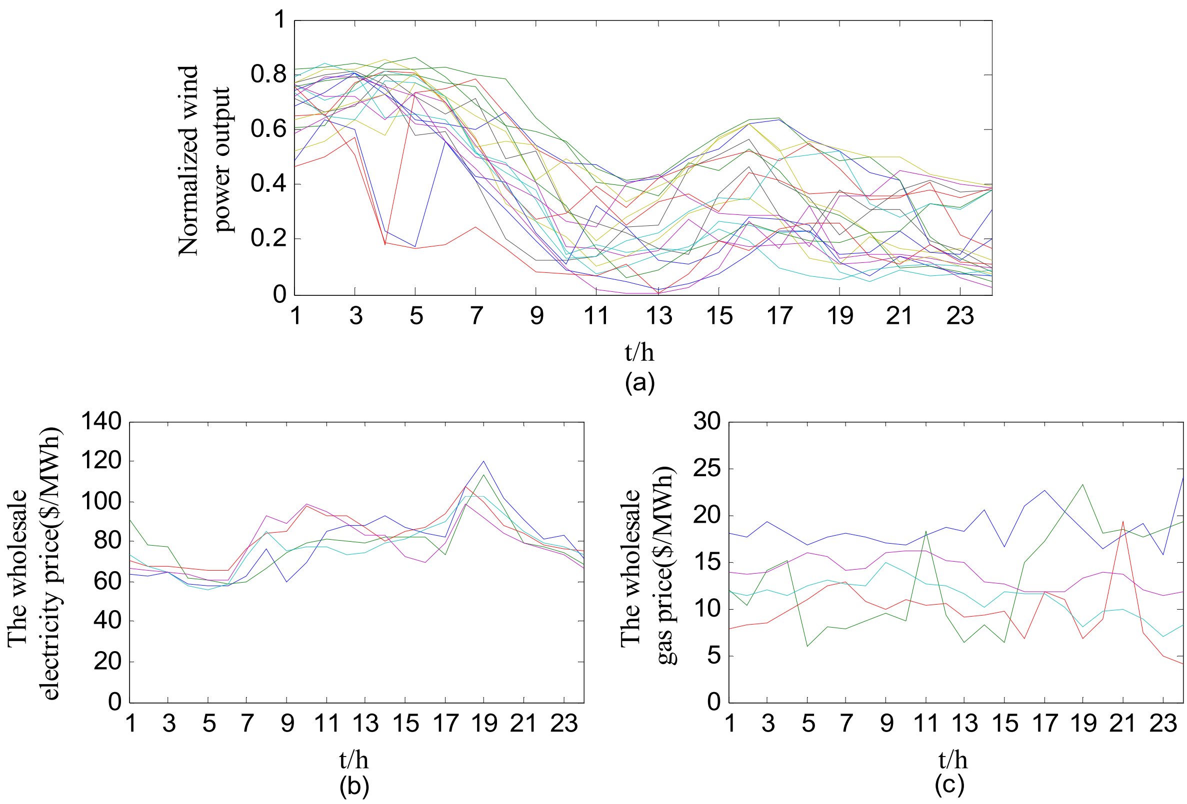

Figure 4. (**a**) Normalized wind power scenarios, (**b**) electricity price scenarios, (**c**) gas price scenarios.

The parameters of the CHPP and GB in the IES are shown in Table 1, and the parameters of the ES, GS and HS devices in the IES are shown in Table 2. In the process of solving the model, the value of the large M parameter is set to 10,000.

Table 1. Parameters of combined heat and power plant and gas boiler.

	$P^{in}_{\max}$ (MW)	P^{in}_{0} (MW)	P^{u} (MW/h)	P^{d} (MW/h)	η_e	η_h
CHPP	12	6	1.2	0.6	0.35	0.35
GB	16	8	2.4	1.2	-	0.75

Table 2. Parameters of electricity/gas/heat storage devices.

	$W^{s}_{\max}$ (MWh)	$W^{s}_{\min}$ (MWh)	W^{s}_{0} (MWh)	$P^{s,c}_{\max}$ (MW)	$P^{s,d}_{\max}$ (MW)	$\eta_{s,c}$	$\eta_{s,d}$
ES	1.8	0.4	0.6	0.8	1	0.9	0.9
GS	2.7	0.6	0.9	1.5	2.1	0.95	0.95
HS	2.25	0.5	0.75	1.25	1.5	0.85	0.85

5.2. Impact of DR on Energy Pricing and Management

Select different DR strategies, that is, the different proportions of the flexible load to the total EL, and analyze the impact of DR strategies on the energy management of the IESP and user agent. The results are shown in Table 3. It can be found that as the proportion of the flexible load increases, the expected profit of the IESP gradually increases. Comparing the non-flexible load with 40% of the flexible load that participates in DR, the expected profits for the IESP increase by 6.68%. On the contrary, the cost for the user agent gradually decreases with the increase of the proportion of flexible load. Comparing the non-flexible load with 40% of the flexible load that participates in DR, the cost for the user agent is reduced by 3.62%. By comparison, it can be found that the increase in DR's benefits for the IESP is obviously better than the reduction in the user agent's cost. At the same time, the daily reduction in wind power is also reduced from 10.41 MWh with no flexible load participating in DR to 1.69 MWh with 40% flexible load participating in DR, which is a drop of 83.77%. The participation of flexible load in DR has a significant effect on improving wind power consumption.

Table 3. Impact of demand response on IESP's expected profits, user agent's cost and daily wind power curtailment.

DR	No DR	10% DR	20% DR	30% DR	40% DR
IESP's expected profits (USD)	6634.43	6806.78	6930.53	7039.01	7077.55
User agent' cost (USD)	17,616.5	17,365.9	17,163.4	17,051.2	16,979.6
Daily wind power curtailment (MWh)	10.41	6.76	3.92	2.25	1.69

Figure 5a shows the retail electricity price of the IESP under different DR strategies. The participation of flexible load in the DR strategy makes retail electricity prices rise gradually during the low period and gradually fall during peak hours. Generally, the retail electricity price during the study period tends to be flat. Since the gas load and heat load are both supplied by the gas system, the DR strategy has no effect on the retail gas price and heat price of the IESP.

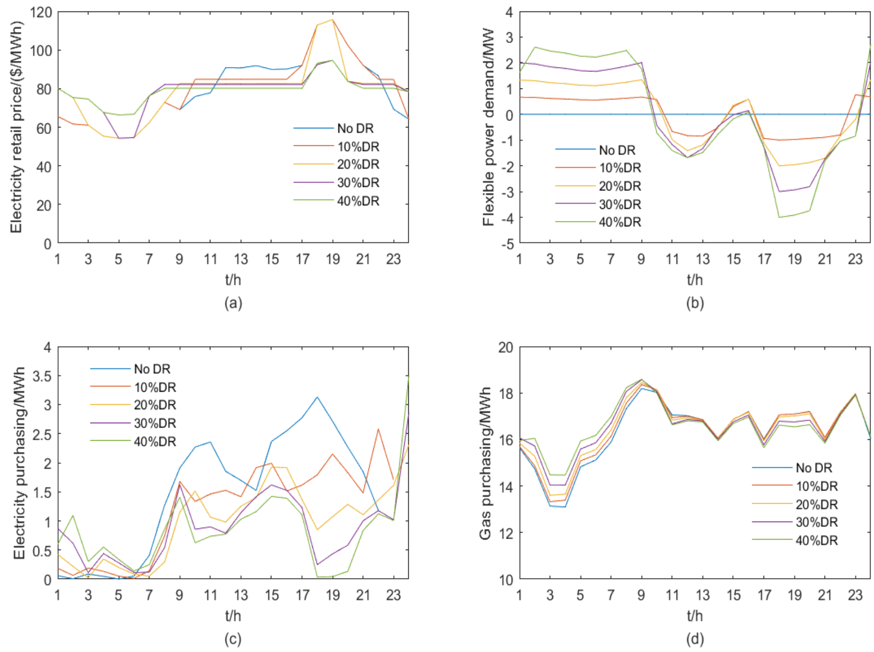

Figure 5. (**a**) Electricity retail price, (**b**) flexible power demand, (**c**) electricity bought from the wholesale market and (**d**) gas bought from the wholesale market with different DR.

Figure 5b shows the flexible load of each period under different DR strategies. A positive value of the flexible load indicates that there are flexible loads transferred in during this period, and a negative value indicates that there are flexible loads transferred out during this period. The flexible load is transferred in during the valley load period and is transferred out during the peak load period, and as the proportion of users participating in the DR strategies increases, the flexible load gradually increases.

Figures 5c and 5d, respectively, depict the electricity and gas purchases of the IESP in the wholesale market under different DR strategies. On the whole, the impact of the DR strategy on the electricity purchased by the IESP is greater than that of the gas purchased. With the increase in the proportion of flexible load, the electricity purchased by the IESP in the wholesale market generally decreases, especially to alleviate the electricity purchase of the IESP during the peak electricity consumption period. User agents participate in DR through flexible loads, so that the electricity and gas purchases in the wholesale market will increase during the valley period of electricity and gas consumption and decrease during the peak period of electricity and gas consumption. As a whole, the electricity and gas purchases in the wholesale market by the IESP tend to steady in various periods.

5.3. Sensitivity Analysis of Energy Storage Capacity

Compared with user agents adopting different DR strategies to interact with the IESP, this section analyzes the impact of electricity/gas/heat energy storage devices on the energy management of the IESP. Select different energy storage capacities—that is, the capacity of one type of energy storage device changes, and the capacity of the other two types of energy storage devices remains unchanged—to study the impact of electricity/gas/heat energy storage devices on the profit of the IESP and the daily curtailment of wind power. The results are as shown in Table 4. When the ES capacity changes from −50% of the base capacity to +50% of the base capacity, the profits of the IESP increase by 9.49%, and the daily curtailment of wind power decreases by 24.29%. When the GS capacity changes from −50% of the base capacity to +50% of the base capacity, the profits of the IESP increase by 0.34%, and the daily curtailment of wind power remains unchanged. When the HS capacity changes from −25% of the base capacity to +50% of the base capacity, the profits of the IESP increase by 0.35%, and the daily curtailment of wind power increases by 3.48%. It can be found that the change in the capacity of the ES device has a more obvious effect on the profits of the IESP, and at the same time, it is more conducive to the utilization of wind power. The GS device and the HS device have little effect on the profits of the IESP, and the effect can be ignored. It should be noted that the increase in the capacity of the HS device exacerbates the problem of wind power utilization. This is because as the capacity of the HS device increases, the CHPP can output more heat power to meet the heat load, but at the same time, output more electrical power, which squeezes out the output power of wind turbines.

Table 4. Sensitivity analysis of energy storage capacity.

Energy Storage Capacity Variation	IESP's Expected Profits (USD)			Wind Power Curtailment (MW)		
	ES	GS	HS	ES	GS	HS
−50%	6279.05	6790.09	-	7.74	6.76	-
−25%	6770.34	6799.62	6789.86	7.18	6.76	6.6
0	6806.79	6806.78	6806.78	6.76	6.76	6.76
+25%	6841.27	6810.35	6812.23	6.31	6.76	6.83
+50%	6874.73	6812.99	6813.41	5.86	6.76	6.83

Figure 6 depicts the operation strategy of the ES, GS and HS devices under different energy storage capacities. It can be found that the stored energy of the ES, GS and HS devices increases significantly in different periods with the increase in energy storage capacity. The ES device adopts a charging strategy during the 1–8 h period and adopts a discharge strategy during the 17–19 h period. The GS device and the HS device adopt gas storage and heat storage strategies during the 11–16 h period, which is closely related to the significant decrease in gas load and heat load during this period. The operating strategy curves of the GS and HS devices are roughly the same. This is because the gas load and heat load are both supplied by the gas system, and the energy change of the GS and HS is affected by gas supply.

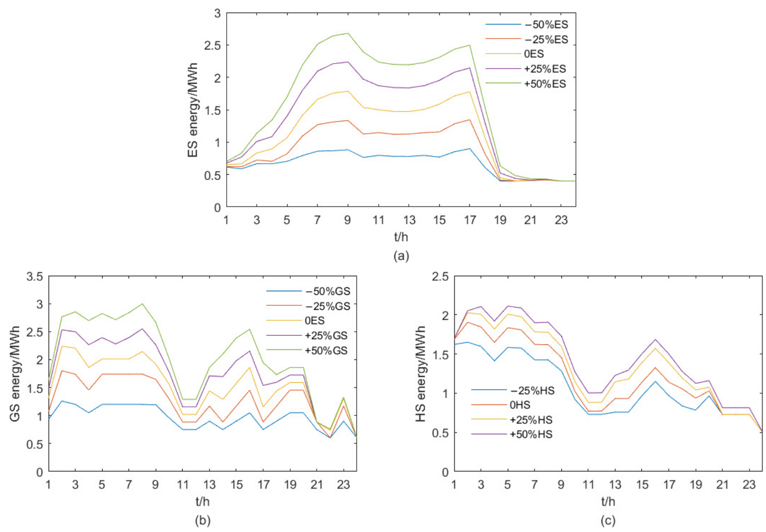

Figure 6. (**a**) ES, (**b**) GS and (**c**) HS operation strategy.

The model in this section is solved entirely using the solver CPLEX [33] on GAMS (The version: 23.8.2) [34,35], and the solution time of the model largely depends on the linearization constant M. The appropriate choice of the M value is very important and usually requires a simple process of repeated experiments. In order to avoid the use of constants, the alternative branch and bound method can be used.

6. Conclusions

This paper proposes an energy pricing and management model for the IESP based on stochastic complementary modeling and studies the interactive operation mechanism between the IESP and user agents. The IESP sets energy prices at the day-ahead stage, including electricity prices, gas prices and heat prices. The user agents optimize energy consumption patterns based on the energy prices issued by the IESP. Then, the IESP optimizes the operation of the IES and determines the energy contracts in the energy wholesale markets based on the energy consumption patterns of user agents. The model is transformed into a MILP problem for solution by using the linearization method and the strong duality principle in the optimization theory. The main conclusions are as follows:

(1) The participation of user agents in DR through flexible loads can effectively increase the profits of the IESP, reduce the energy cost of user agents and significantly promote the wind power utilization.
(2) The IESP's formulation of retail electricity prices is significantly affected by the DR strategy. The participation of flexible load in the DR can reduce retail electricity price fluctuations without affecting retail gas prices and heat prices.
(3) The change in the ES capacity of the IESP has a significant impact on the profits of the IESP, and at the same time, it is more conducive to wind power utilization. GS and HS devices have little effect on the profits of the IESP, and the effect can be ignored.

In future work, in addition to the interactive operation between the IESP and the user agent in this paper, we can continue to study the interactive operation mechanism between different IESPs.

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