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Internal Pricing Mechanism of Virtual Power Plant Considering Uncertainty of Source and Load

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Abstract

To effectively avoid the market risk of double uncertainty of internal renewable energy output and load demand during the operation of virtual power plants, this paper proposes an internal pricing strategy for virtual power plants that considers the double source-load uncertainty and real-time market linkage based on the full consideration of the thermo-electrolytic coupling. The model can not only design a two-tier, two-stage internal pricing model that takes into account the source-load uncertainty based on constructing the revenue functions of producers and consumers, flexible loads, and the virtual plant operator, but also fully identifies and deals with the stochastic nature of the "source-load" side of the system to formulate the economically optimal operation strategy to avoid resource wastage, and effectively characterizes the relationship between system operation cost and default risk. It can also effectively characterize the correlation between system operation cost and counterparty risk, providing a theoretical basis for decision-makers to evaluate the risk of energy supply default and economic benefits.

Keywords: Flexible loads; virtual power plant; prosumer; operation cost; default risk

1. Introduction

The electricity market, as an important regulatory tool for the optimal allocation of power generation plans, is settled in the market mainly based on economic indicators. Each market participant declares its bidding strategy to the Power Trading Center by the rules of the power market, and the Power Trading Center completes the release of the transaction results of the trading varieties by the established clearing rules. Due to the diversity of virtual power plant (VPP) composition and strong functionality, VPP can participate in the bidding and clearing of various trading varieties in the power market. It can participate in the energy market, auxiliary services market, and financial derivatives market. The power market is an important regulatory tool for the optimal allocation of power generation plans. It is mainly based on economic indicators for the settlement basis. Due to the diversity of virtual power plant composition and strong functionality, VPP can participate in the bidding and clearing of various trading varieties in the power market. It also can participate in the energy market, auxiliary services market, and financial derivatives market bidding. A virtual power plant is a system that integrates distributed energy resources and is designed to mimic the operation of a traditional large-scale power plant to provide a reliable supply of electricity. A virtual power plant can integrate distributed energy resources from multiple locations, including solar, wind, and energy storage, to improve energy utilization and economics. It allows real-time scheduling based on market prices, changes in demand, and other factors to ensure the stability and economy of power supply. Through the integrated management of virtual power plants, the predictability and controllability of renewable energy is improved, helping to reduce dependence on traditional fossil energy, promote energy transition and mitigate climate change. The intelligent scheduling capabilities of virtual power plants can improve grid stability and reliability, reduce the impact of energy fluctuations on the grid, and enhance the resilience of the power system. The participation of virtual power plants can also increase the competitiveness and transparency of the electricity market, provide consumers with more choices, and promote the innovation of new technologies and business models. Virtual power plant has an important role in the energy system. It can effectively integrate decentralized resources, improve energy efficiency, enhance grid stability, promote the development of renewable energy and facilitate the development and progress of the energy market. Virtual power plants, as an emerging energy management paradigm, aim to integrate decentralized energy resources to provide reliable power supply. However, virtual power plants face a number of challenges in their operation, the most prominent of which is the uncertainty of power sources and loads. This uncertainty stems from a variety of factors, mainly including but not limited to weather conditions, fluctuations in load demand, and instability in the energy market. As renewable energy sources such as solar and wind continue to make up an increasing portion of the energy mix, weather conditions are having an increasingly significant impact on power production. Changes in light and wind speed lead to volatility in renewable energy sources, which in turn affects the overall power output of the virtual power plant. At the same time, constant changes in power loads are a significant source of load uncertainty for virtual power plants. Changes in peaks and valleys of demand make virtual power plants face load management challenges while meeting user demands. In addition, price fluctuations and changes in supply and demand in the energy market also have a significant impact on the operation of virtual power plants, adding to the power and load uncertainty. Therefore, an in-depth understanding of the root causes of power and load uncertainty in virtual power plants is important for developing effective management strategies and optimization schemes. The aim of this paper is to provide insights and solutions to address the uncertainty in virtual power plant operations through comprehensive analysis and discussion.

The most extensive participation of VPP is in the day-ahead market. In the day-ahead market, VPPs participate in the market bidding process based on the forecasts of their internal resources, which ultimately determines the capacity value of their participation in the energy market or ancillary services market. To be more realistic in handling uncertainties, Reference [1] developed that Price-Based Unit Commitment (PBUC) uses the probabilistic approach of the Point Estimation Method (PEM) to simulate the uncertainty of market prices and generation sources for optimal bidding of virtual power plants in the day-ahead electricity market. But, it primarily focuses on price uncertainties without a broader range of factors such as different energy sources or emissions considerations, reference [2] developed a VPP day-ahead bidding strategy containing wind turbines and electricity-to-gas plants, analyzing robust bidding strategy and opportunity bidding strategy based on information gap decision theory. In addition, reference [3] analysed the optimal generation scheduling in VPP under the day-ahead market framework using the BAS algorithm under various scenarios. To focus on the market and pricing aspects, reference [4] constructed a multi-objective operation scheduling of distributed energy in the day-ahead model focusing on maximizing the expected day-ahead profit and minimizing the expected day-ahead emissions of the VPP. A coordinated day-ahead bidding strategy handling various uncertainties and market impacts was proposed considering the virtual power plant operators (VPPO) participates in the energy market and peaking market externally, and cooperates with the members internally [5]. The analysis of uncertainties in the VPP in the existing studies is relatively mature, but there are less studies on the impacts of uncertainties on internal pricing in the VPP when it participates in the transactions involving a variety of market prices. To address uncertainties in wind power output and load demand, reference [6] introduces the conditional value-at-risk theory to characterize the uncertainty of wind power output and the uncertainty of load demand. Considering both VPP and distribution grid interests, reference [7] establishes an optimization model based on the maximization of the respective interests of the VPP and the distribution grid according to a typical scenario set, considering the constraints of the distribution grid and the VPP in terms of network structure, tidal current security, and unit output, and proposes a collaborative pricing strategy based on the alternating optimization of the VPP and the distribution grid. However, it does not constructs a comprehensive framework for VPP interactions. Reference [8] constructs a framework for the interaction between virtual power plants and internal resources based on the technical characteristics of VPP and the requirements of the peaking market, analyzes the response compensation mechanism, establishes a resource response behavior prediction model based on recurrent neural network using a large amount of historical electricity consumption information. The model's stochastic nature might not always accurately predict market behavior, reference [9] discusses the pricing decision of VPP by constructing a stochastic two-layer programming model. It verifies that VPP can increase its profit by acting as a price maker in the energy and reserve markets.

The above reference does not take into account the multiple interests at stake, reference [10] systematically studied the market mechanism applicable to the complementary operation of such VPPs and the bidding model based on the mechanism against the background of the existence of different investment subjects within VPPs, based on an in-depth analysis of the intrinsic technical characteristics of VPPs, and focusing on the multiple interests of different participants, but did not consider the uncertainty of supply and demand of VPPs. To formulating optimal pricing strategies, reference [11] used the maximum entropy econometric method to analyze the impact of different distributed generation technology combinations in VPPs on the change of wholesale electricity prices in the EU energy market and formulated price-optimal strategies in different electricity technology combinations. But, it ignores VPP participation in the real-time market, reference [12] establishes a master-slave game model between VPPs and internal producers and consumers, sets the purchase and sale prices of electricity from virtual power plant operators to internal producers and consumers, and guides the producers and consumers to adjust their electricity generation and consumption strategies through the electricity price signals to form the external power of VPPs, but it does not take into account the participation of VPPs in the real-time market. To analyze VPP participation modes and costs, reference [13] analyzes the participation mode and participation cost based on the four types of resources participating in VPP dispatch, namely, customer flexible loads, electric vehicles, energy storage, and distributed power sources, and sets up a cost model according to the differences in resources and discusses the subsidy price policy of VPP by calculating the actual marginal cost of participation of different resources. The model might not be universally applicable due to differing resource types and market conditions. Reference [14] proposes a combination of kinetic evolution and data-driven approach and applies it to the dynamic pricing strategy of power sales companies considering the interaction effect of user-side distributed energy storage. It does not adequately consider changes in market dynamics and the impact of external economic factors. Reference [15] establishes a multi-principal model of the electricity market containing electric vehicles, grid companies, traditional power producers and user groups based on game theory, which effectively increases the total market profit of wind power producers and electric vehicle producers, and the economic behavior of the electric vehicle producers can make the price of electricity of each power supplier less volatile, which serves to smooth out the price of electricity. Reference [16] proposes that VPP, as the power sales operator, formulates reasonable power sales prices to guide EVs to charge in an orderly manner through the master-slave game, and coordinates all kinds of distributed resources to participate in the power market, realizing a win-win situation for both VPPO and EV users. The above reference may face the challenge of coordinating multiple resources and balancing interests in concrete implementation, and reference [17] constructed a dynamic pricing model of master-multiple-slave game optimization between distribution network operators and multiple virtual power plants and proposed an optimization algorithm based on the combination of Kriging meta-model and genetic algorithm. To model the dynamic pricing and energy management between distribution system operators and multiple VPPs, reference [18] builds a one-master-many-slave game model of distribution system operator and multiple VPPs, studies the dynamic pricing behavior of the operator and the energy management model of VPPs, and proposes a master-slave game equilibrium algorithm based on the Kriging meta-model, which combines with the particle swarm optimization algorithm to generate new excellent sampling points, and purposefully corrects the meta-model, to quickly and accurately get the transaction tariffs of VPPs and the output plan. To insight into the electricity market dynamics involving traditional power producers, electricity sellers, and VPPs, enhancing understanding of market competition. However, it lacks a detailed exploration of the specific challenges faced by VPPs compared to traditional power producers. Reference [19] studied the offer model and the optimal clearing model of the electricity market in which traditional power producers, electricity sellers, and VPPs participate in the market competition at the same time. To provide potentially more accurate and adaptive bidding strategies for VPPs, reference [20] used the Q-learning algorithm to find the optimal bidding strategy for VPPs and distributed power sources in a competitive environment. Reference [21] proposes that using RO to determine the worst scenario among all generated scenarios and optimizing the bidding strategy of a virtual power plant based on this scenario can effectively improve the resilience of a virtual power plant against volatility risk.

To be more adaptive to real-world scenarios and uncertainties in load imbalances, reference [22] used matrix information of uncertainty parameters to construct a distributed robust model to evaluate physical characteristics such as VPP maximum capacity and ramping ability. Reference [23] further investigates a data-driven chanceconstrained two-stage stochastic unit combination problem based on the use of historical data information to limit the worst-case scenarios of load imbalance without any specified assumptions on the probability distribution of wind power output. Reference [24] reduces the conservatism of decision-making by constructing a distributed robust optimization model for wind power output power based on historical information of wind power output. Reference [25] adopts conditional value-at-risk to describe the uncertainty of wind power output in a virtual power plant, while reference [26] describes the uncertainty of source load in a virtual power plant based on fuzzy chance constraints. Both focus on describing uncertainties (wind power output and source load, respectively) in innovative ways, enhancing the understanding of risks. These approaches might be too specialized, not addressing other crucial aspects of VPP operation and management. Reference [27] proposed a revenue risk model for virtual power plants based on the consideration of wind-scenery uncertainty.

However, the above literature proposes dynamic pricing strategies that do not adequately consider the impact of changing market dynamics and external economic factors, and do not adequately account for real-time market participation. To this end, this paper proposes a novel internal pricing strategy for virtual power plants to address the challenges posed by dual source load uncertainty and real-time market dynamics. Unlike previous studies that mainly focus on specific uncertainties or market aspects, our model comprehensively considers thermocouple coupling and provides a two-tier internal pricing framework. The framework considers source load uncertainty while constructing revenue functions for producers, consumers, flexible loads, and VPP operators. By identifying and managing the stochastic nature of source load variations, this paper aims to optimize economic operations and minimize resource wastage. In addition, this paper effectively evaluates the correlation between system operating costs and counterparty risk, providing decision makers with a theoretical basis for assessing default risk and economic efficiency. In summary, the research in this paper integrates various aspects of VPP operations and management, providing a comprehensive approach to deal with uncertainty and market complexity, thereby advancing the understanding and optimization of VPP performance.

2. A two-stage pricing model for a virtual power plant considering source-load uncertainty

The virtual power plants (VPP) considered in this paper are mainly composed of four subjects: virtual power plant operator (VPPO), prosumer (pro), energy storage (ES), and flexible load (FL), where n denotes the number of producers and consumers. VPPO is the upper-level manager of the virtual power plant and does not have its generation resources. Consumers and producers have renewable power generation resources such as wind power and solar power, as well as rigid loads, and need to meet certain conditions before they are qualified for power feed-in. Therefore, this paper considers that they trade power in the real-time market through the transaction mode of "self-generation and self-consumption, and sell (buy) the surplus (shortfall)" with the VPPO. In VPP, they are the lower-level follower of the VPPO. The producers and consumers seek the optimal solution of price signal and bidding power through the dynamic game of price and quantity to maximize the benefits for both parties. Flexible loads respond to the demand in the real-time market according to the compensation price set by the VPPO, realizing "load suppression" within the VPP. As an important support of the modern energy system, energy storage is an important flexibility resource, charging during low electricity price hours and discharging during high electricity price hours, externally helping the VPPO to earn income from the electricity market, and internally realizing "load shifting". The VPPO controls the charging and discharging amount of the energy storage system, to have the ability to sell electricity to the real-time electricity market. The VPPO can sell electricity to the real-time electricity market by controlling the charge and discharge of the storage system. The Distribution System Operator (DSO) is the parent grid operator of the VPPO.

Two-stage decision model for a two-tier virtual power plant

1) Decision Modeling for Lower Tier Consumers and Flexible Loads

a) Decision-making model for lower-tier producers and consumers

Each producer and consumer pursues self-sufficiency, based on the internal purchase and sale price of electricity issued by the VPPO, with the decision-making objective of minimizing the amount of electricity purchased. The objective function is shown in the following equation. λ_t^{in} is the values of the internal retail price of electricity. $P_t^{i,b}$ is the amount of electricity generated by each type of micropower source

$$\min\sum_{t\in S_T} \lambda_t^{in} P_t^{i,b} \tag{1}$$

The above optimization objective needs to satisfy the constraints Eq. (2) to Eq. (5). Eq. (2) is the energy balance constraint of producer and consumer, $E_t^{i,b}$ is the energy purchased by producer and consumer i in period t, respectively: Eq. (3) is the constraint of electricity traded in the internal market, $E_{t,max}^{i,b}$ and $E_{t,min}^{i,b}$ are the upper limit and lower limit of electricity traded in the internal market, respectively: Eq. (4) and Eq. (5) are the limitations of the market regulator on the internal retail price of electricity, in which $\lambda_{t,min}^{in}$ and $\lambda_{t,max}^{in}$ are the minimum and maximum values of the internal retail price of electricity.

$$(d_t^i\text{-}P_t^{i,pv}\text{-}P_t^{i,wt})\Delta t=E_t^{i,b} \tag{2}$$

$$E_{t,min}^{i,b} \le E_t^{i,b} \le E_{t,max}^{i,b} \tag{3}$$

$$\lambda_{t,min}^{in} \le \lambda_t^{in} \le \lambda_{t,max}^{in} \tag{4}$$

b) Lower Flexible Load Decision Modeling

The flexible load optimizes its real-time power purchases reported to the VPPO after the VPPO releases its internal purchased (sold) power price peaking (peak shaving and valley filling) compensation price and positive and negative standby demand.

Two-stage decision model for upper-tier virtual power plant operators

1) Virtual Power Plant Operator Day-ahead Stage Decision Modeling

The most widespread participation of VPPs is in the day-ahead market (DAM). In the DAM, since the producers and consumers are self-sufficient, they will only approach VPPO to sell (buy) electricity when there is a surplus (shortage).

In the DAM, the producers and consumers do not pre-purchase (or pre-sell) electricity with the VPPOs because they are self-sufficient and will only approach the VPPOs to sell (buy) electricity when there is a surplus (shortage), and the VPPOs will make decisions on the value of the capacity to be purchased and sold in the DAM based on the forecasts of wind power and load demand reported by the producers and consumers, the forecasts of the load demand of the flexible loads, and the energy status of the storage system, and the benefits of the DAM are shown in Eq.5. The day-ahead revenue is shown in Eq. 5. The revenue of the day-ahead energy market is shown in Eq. 7. It mainly consists of the cost of power purchase and revenue of power sale in the day-ahead VPPO and DSO transactions and the revenue of the day-ahead power purchase of the flexible loads.

$$\Pi_{VPPO}^{DA} = \sum_{t\grave{o}S_T}\left(\lambda_{t,s}^{DA} P_{t,s}^{DA} - \lambda_{t,b}^{DA} P_{t,b}^{DA}\right) + \sum_{t\in S_T} \lambda_t^{in} d_{t,e}^{FL} \tag{5}$$

where Π_{VPPO}^{DA} denotes the revenue of the VPPO in the day-ahead period, and $P_{t,b}^{DA}$ denotes the electricity purchased and sold by the VPPO to the DSO in the day-ahead market in time t. The day-ahead node price is the feed-in price of the VPPO. s_1 denotes the set of all producers and consumers, $\lambda_{t,b}^{DA}$ denotes the day-ahead nodal tariff in time t, and $\lambda_{t,s}^{DA}$ is the day-ahead feed-in tariff of the VPPO.

The VPPO's day-ahead decision needs to satisfy the constraints in Eqs. (6) through (9), Eqs. (6) and (7) restrict the VPPO from purchasing or selling electricity in the day-ahead market at different times, and restrict the amount of electricity traded in the day-ahead of the VPPO, where μ_t^{DA} is a Boolean variable denoting the power purchased or sold by the VPPO in the day-ahead market in period t. When $\mu_t^{DA}=1$, the VPPO purchases electricity in the day-ahead market, and when $\mu_t^{DA}=0$, VPPO sells electricity in the day-ahead market. Equations (8) and (9) represent the restrictions imposed by the market regulator on the day-ahead retail price. where P_{max}^{DSO} is the maximum value of the power exchanged between the virtual power plant and the distribution grid, the value of which needs to be considered the capacity of the transformer at the node connecting the virtual power plant and the distribution grid as well as specific policy factors. The minimum and maximum values of $\lambda_{\mathrm{t,b}}^{\mathrm{DA,min}}$ and $\lambda_{\mathrm{t,b}}^{\mathrm{DA,max}}$ day-ahead retail prices indicate the average value of day-ahead retail electricity prices allowed by the market regulator.

$$0 \le \mu_t^{DA} P_{t,b}^{DA} \le P_{max}^{DSO}, \forall t \in S_T \tag{6}$$

$$0 \le (1-\mu_t^{DA}) P_{t,s}^{DA} \le P_{max}^{DSO}, \forall t \in S_T \tag{7}$$

$$0 \le (1-\mu_t^{DA}) P_{t,s}^{DA} \le P_{max}^{DSO}, \forall t \in S_T \tag{8}$$

$$\sum_{t \in S_T} \lambda_{\mathrm{t,b}}^{\mathrm{DA}} / T_N \le \lambda_{\mathrm{t,b}}^{\mathrm{DA,av}}, \quad \forall t \in S_T \tag{9}$$

2) Real-Time Stage Decision Modeling for Virtual Power Plant Operators

Renewable energy from virtual power plants is volatile and often requires participation in the real-time power balancing market (RBM) to minimize its impact on the safe operation of the grid. Unlike the day-ahead market, the real-time market is opened on a time-period basis, segment by segment. The overall economy and risk resistance of VPPs can be effectively improved by formulating a reasonable strategy for purchasing and selling power in the real-time market. In this study, the VPP is traded in the real-time phase with h as the unit period, and the energy management system of the VPPO will determine the amount of energy of the energy storage system to be called up and the amount of flexible load transfer or interruption to be dispatched to determine the amount of electricity to be purchased and sold in the real-time electricity market through the consumption and output of the actual consumers and producers. At the same time, it is necessary to set the compensation price for the energy storage discharge and the compensation price for the interruption or transfer of controllable loads for each period in the process. The revenue of the real-time operation phase of the VPPO is shown in Equation (10), which includes the revenue (or cost) of the VPPO for the sale of electricity to each producer and consumer, the real-time cost of the purchase of electricity and the revenue from the sale of electricity, the cost of compensating the storage discharge, the cost of compensating the participation of flexible loads in demand response, and the cost of compensating the flexible loads in demand response. load participation in demand response.

$$\begin{aligned}\Pi_{VPPO}^{RT} = &\sum_{t \in S_T}\sum_{i \in S_i} \lambda_t^{in} (\mathrm{d}_\mathrm{t}^\mathrm{i} \text{-} \mathrm{P}_\mathrm{t}^\mathrm{i,pV} \text{-} \mathrm{P}_\mathrm{t}^\mathrm{i,wt}) + \\ &\left(\lambda_{t,s}^{RT} P_{t,s}^{RT} - \lambda_{t,b}^{RT} P_{t,b}^{RT}\right) - \lambda_{\mathrm{dis,t}}^{\mathrm{ES}} \mathrm{P}_{\mathrm{et}}^{\mathrm{ES,dis}} - \lambda_t^{\mathrm{FL}} (\mathrm{d}_t^{\mathrm{FL,pf}} + \mathrm{d}_t^{\mathrm{FL,vf}})\end{aligned} \tag{10}$$

where, $P_{t,b}^{RT}$, $P_{t,s}^{RT}$ denotes the power purchased and sold by the VPPO from the DSO in the real-time market at period t, the latter being the actual surplus of power produced and consumed by the producer and the external discharges of the storage device, $\lambda_{t,b}^{RT}$ denotes the real-time node price at period t, and $\lambda_{t,s}^{RT}$ is the real-time feed-in tariff of the VPPO.

3. Internal Pricing Model for Virtual Power Plants Considering Source Load Uncertainty

In this paper, we consider the source-load dual uncertainty of the renewable power output ($\mathrm{P}_\mathrm{t}^\mathrm{i,pV}$, $\mathrm{P}_\mathrm{t}^\mathrm{i,wt}$), which robustly portrays the source-load uncertainty using the boxed uncertainty set and the budgeted uncertainty set.

Eqs. (11) to (13) construct the uncertainty sets U_{PV}, U_{WT} and U_{FL} for the generator-consumer i PV output, wind power output, and flexible load power, respectively. where $P_t^{i,wt}$, $P_t^{i,pv}$ and $\mathrm{d}_\mathrm{t}^\mathrm{FL}$ are the uncertain variables of wind power output, PV power, and a flexible load of consumer i after considering the introduction of uncertainty, $P_{t,max}^{i,wt}$, $P_{t,\min}^{i,wt}$, and $P_{t,e}^{i,\mathrm{wt}}$ are the upper and lower bounds of wind power output and the predicted value of wind power output of consumer i at period t, $P_{t,max}^{i,PV}$ $P_{t,max}^{i,PV}$ and $P_{t,e}^{i,PV}$ are the upper and lower bounds of PV power output of consumer i and the predicted value of PV power output of consumer i at period t, and $\mathrm{d}_{\mathrm{t}}^{\mathrm{FL,max}}$, $\mathrm{d}_{\mathrm{t}}^{\mathrm{FL,min}}$ and $\mathrm{d}_{t,e}^{\mathrm{FL}}$ are the upper, lower limits and predicted values of the actual load demand of flexible load at time t. $\Gamma_T^{i,PV}$,$\Gamma_T^{i,wt}$ and Γ_T^{FL} are the uncertainty adjustment parameters introduced in the paper, which can be used to adjust the conservatism of the optimal solution, the larger the value is, the more conservative the solution is, and vice versa, the more risky the solution is, and the range of their values is [0, N_T], and N_T is an integer. In this paper, we consider a virtual power plant in real-time operation, i.e., $N_T = 24$ in a scheduling cycle. If $\Gamma_T^{FL} = 0$, the "worst case scenario" is not considered in all periods, and the strategy is full of risks. If $\Gamma_T^{FL} = 24$, the worst-case scenario is considered in all periods and the corresponding strategy is the most conservative. In the virtual power plant studied in this paper, photovoltaic, wind power output to the minimum value of the interval, flexible load power to the maximum value of the interval, the virtual power plant operating costs will be more expensive, more load "worst-case scenario" definition, so the formula (11) to formula (12) can be rewritten as follows (13) to (16) form. where, $\mu_{\mathrm{t}}^{\mathrm{pV}}$ μ_{t}^{WT} μ_{t}^{FL} for the uncertainty variable to the worst scenario Boolean variables, take 1 when the corresponding period of the uncertainty variable to the worst interval boundary. z, A, products for the production and consumption of photovoltaic power, wind power output, and the actual power of flexible loads allow the maximum fluctuation of deviation, both are positive.

$$U_{PV}\begin{cases} P_{t,min}^{i,pv} \le P_t^{i,pv} \le P_{t,max}^{i,pv}, t = S_T^{pv,i}, \forall i \\ \sum_{t\in S_T} \left| \dfrac{P_t^{i,pv} - P_{t,e}^{i,pv}}{P_{t,max}^{i,pv} - P_{t,pv}^{i,pv}} \right| \le \Gamma_T^{i,pv}, \forall i \end{cases} \tag{11}$$

$$U_{WT}\begin{cases} P_{t,min}^{i,wt} \le P_t^{i,wt} \le P_{t,max}^{i,wt}, t = S_T^{wt,i}, \forall i \\ \sum_{t\in S_T} \left| \dfrac{P_t^{i,wt} - P_{t,e}^{i,wt}}{P_{t,max}^{i,wt} - P_{t,\min}^{i,wt}} \right| \le \Gamma_T^{i,pv}, \forall i \end{cases} \tag{12}$$

$$U_{FL}\begin{cases} \mathrm{d}_{\mathrm{t,min}}^{\mathrm{FL}} \le \mathrm{d}_{\mathrm{t}}^{\mathrm{FL}} \le \mathrm{d}_{\mathrm{t,max}}^{\mathrm{FL}} \\ \sum_{t\in S_T} \left| \dfrac{\mathrm{d}_{\mathrm{t}}^{\mathrm{FL,max}} - \mathrm{d}_{\mathrm{t,e}}^{\mathrm{FL}}}{\mathrm{d}_{\mathrm{t}}^{\mathrm{FL,max}} - \mathrm{d}_{\mathrm{t}}^{\mathrm{FL,min}}} \right| \le \Gamma_T^{FL} \end{cases} \tag{13}$$

$$U_{PV}\begin{cases} P_t^{i,pv} = P_{t,e}^{i,pv} - \mu_t^{\mathrm{pV}} \Delta P_{t,h}^{i,pv} \\ \Delta P_{t,h}^{i,pv} = \dfrac{P_{t,max}^{i,pv} - P_{t,min}}{2} \\ \sum_{t\in S_T} \mu_{\mathrm{t}}^{\mathrm{pV}} \le \Gamma_T^{i,pv}, \forall i \end{cases} \tag{14}$$

$$U_{WT}\begin{cases} P_t^{i,wt} = P_{t,e}^{i,wt} - \mu_t^{WT} \Delta P_{t,h}^{i,wt} \\ \Delta P_{t,h}^{i,wt} = \dfrac{P_{t,max}^{i,wt} - P_{t,min}^{i,wt}}{2} \\ \sum_{t\in S_T} \mu_{\mathrm{t}}^{wT} \le \Gamma_T^{i,wt}, \forall i \end{cases} \tag{15}$$

$$\mathrm{d}_{\mathrm{t}}^{\mathrm{FL}} = \mathrm{d}_{\mathrm{t,e}}^{\mathrm{FL}} + \mu_{\mathrm{t}}^{\mathrm{FL}} \Delta \mathrm{P}_{\mathrm{t,h}}^{\mathrm{FL}} U_{FL}\begin{cases} \Delta P_{t,h}^{FL} = \dfrac{\mathrm{d}_{\mathrm{t}}^{\mathrm{FL,max}} - \mathrm{d}_{\mathrm{t}}^{\mathrm{FL,min}}}{2} \\ \sum_{t\in S_T} \mu_t^{\mathrm{FL}} \le \Gamma_T^{\mathrm{FL}} \end{cases} \tag{16}$$

In the actual operation of the virtual power plant, there is a merging relationship between the day-ahead and real-time markets, and the decision of the VPP in the real-time phase may affect its pricing strategy in the day-ahead market, therefore, the total revenue of the VPPO after considering the hybrid time scale bidding is the sum of the revenue of the day-ahead phase and the real-time phase, and the maximization of its revenue is used as the operation objective, as shown in Equation (17). This objective function considers the effect of uncertainty rather than relying solely on forecast accuracy for pricing, and the resulting pricing scheme will be more robust. The model is a two-tier two-stage uncertain pricing model whose objective is to jointly optimize the two-stage decision-making while taking into account the uncertainty in the second-stage parameter ($\mathrm{d}_\mathrm{t}^\mathrm{FL}$, $\mathrm{P}_\mathrm{t}^{i,b}$), and to optimize the internal pricing parameter [$\lambda_\mathrm{t}^\mathrm{in}$, $\lambda_\mathrm{dis,t}^\mathrm{ES}$, $\lambda_\mathrm{t}^\mathrm{FL}$] when the second-stage parameter is taken to the worst-case two-stage decision corresponding to the total objective value (maximizing the revenue of VPPO). This pricing scheme will result in a more stable operation of the VPP and a more efficient market operation.

$$\begin{aligned}\max_{x\in X} \Bigg\{ &\sum_{t\in S_T}\left(\lambda_{t,s}^{DA}P_{t,s}^{DA}-\lambda_{t,b}^{DA}P_{t,b}^{DA}\right)+\overset{min}{\mathbf{u}\in U}\quad \overset{\max}{\mathbf{y}\in \mathbf{Y}}\sum_{t\in S_T}\sum_{t\in S_i}\lambda_t^{in}(\mathrm{d}_\mathrm{t}^\mathrm{i}\text{-}\mathrm{P}_\mathrm{t}^\mathrm{i,pv}\text{-}\mathrm{P}_\mathrm{t}^\mathrm{i,wt}) \\ &+\sum_{t\in S_T}\left[\lambda_\mathrm{t}^\mathrm{in}\mathrm{d}_\mathrm{t,e}^\mathrm{FL}+\lambda_{t,s}^{RT}P_{t,s}^{RT}-\lambda_{t,b}^{RT}P_{t,b}^{RT}-\lambda_\mathrm{dis,t}^\mathrm{ES}\mathrm{P}_\mathrm{t}^\mathrm{ES,dis}-\lambda_\mathrm{t}^\mathrm{FL}(\mathrm{d}_\mathrm{t}^\mathrm{FL,pf}+\mathrm{d}_\mathrm{t}^\mathrm{FL,vf})\right] \Bigg\}\end{aligned} \tag{17}$$

where x, u, and y are the decision variables, u is the uncertainty variable, and U is its variable space, defined by Eqs. (18) to (20)y is the second-stage decision variable, which is a function of x and u, i.e., $\mathbf{y}\in\mathbf{Y}=F(x,u)$, which denotes the feasible domain of decision variable y, given a set of (x,u). the feasible domain of the decision variable y.

$$x=[\lambda_t^{in},\lambda_{\mathrm{dis},t}^\mathrm{ES},\lambda_t^\mathrm{FL},P_{t,s}^{DA},P_{t,b}^{DA},\mu_t^{DA}]^T \tag{18}$$

$$u=[\mathrm{d}_t^\mathrm{FL},P_t^{i,pv},P_t^{i,wt}]^T \tag{19}$$

$$\mathbf{y}=[P_{t,s}^{RT},P_{t,b}^{RT},P_t^\mathrm{ES,ch},P_t^\mathrm{ES,dis},\mathrm{d}_t^\mathrm{FL,vf},\mathrm{d}_t^\mathrm{FL,pf},\mu_t^{RT},\mu_t^\mathrm{ES}]^T \tag{20}$$

4. Results

A *Basic Parameter Setting*

If a virtual power plant contains three consumers, one flexible load and one energy storage device, the network topology of the virtual power plant test system is shown in Fig 1. The network topology of the virtual power plant test system is shown in Fig. 1: Consumer 1 is a residential type, consumer 2 is a commercial type, and the power generation resources owned by both residential and commercial type consumers are distributed photovoltaic units (power of 4.2 MW and 3.1 MW, respectively.). Consumer 3 is an industrial type, which owns power generation resources of distributed wind turbines (5 MW). In the actual operation of the virtual power plant, due to the production and consumer loads being rigid loads, the volatility of the prediction deviation is small. The predicted value of the loads is directly used as the real-time market load. The load prediction of each producer and consumer is shown in Fig 2. The maximum fluctuation deviation allowed for flexible load power and wind power output and PV output can be set according to the previous historical forecast deviation. In this paper, we consider that the fluctuation deviation of the flexible load power, wind power, and PV output is 10%, 10%, and 15%, respectively. The forecasted value of each consumer-produced wind and PV output is as shown in Fig. 1 .

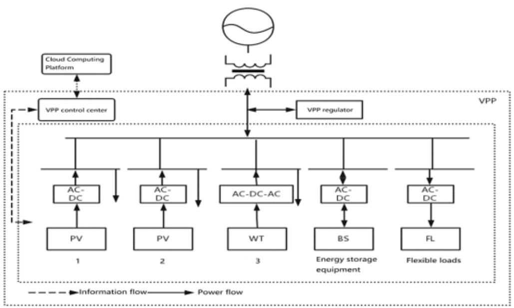

Fig.1 The topology of the VPP test system

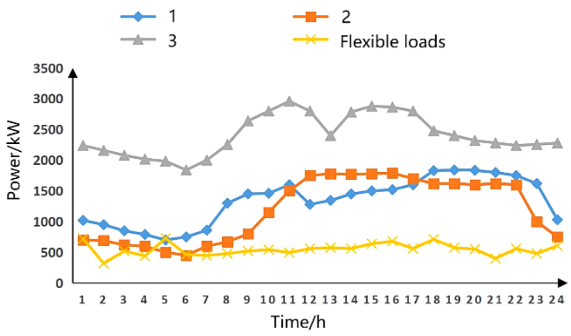

Fig.2 Load of Prosumers and Flexible

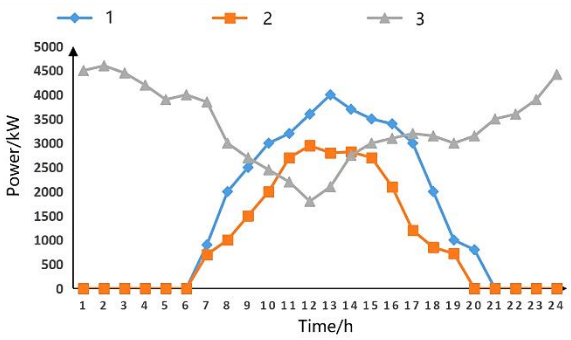

Fig.3 Renewable energy generation of each prosumer

According to the two-tier two-stage robust pricing model established in this paper, the internal pricing of VPP under different scenarios is simulated and analyzed to maximize the revenue of VPPO and minimize the amount of power purchased by producers and consumer.

(1) Analysis of VPP internal pricing for various scenarios

Fig 4 shows the three pricing scenarios within the virtual power plant under deterministic scenario 1. It can be seen that 1) the trend of the internal purchasing (selling) tariff under scenario 1 is the same as that of the real-time market tariff; 2) Since there is no uncertainty in the wind power and the demand of the flexible loads, the pre-purchased power at the day-ahead stage can satisfy the real-time demand. The demand of flexible loads is not required in scenario 1; 3) the VPP internal purchasing (selling) tariff is the same as the real-time market tariff; 4) the VPP internal purchasing (selling) tariff is the same as the real-time market tariff. response in Scenario 1; 3) The VPPO schedules energy storage to charge during the low tariff (~\$0.38/kWh) hours of 1:00-4:00 a.m. in the day-ahead phase and discharge during the high tariff (~\$0.52/kWh) hours of 8:00-10:00 a.m. in the real-time phase to earn energy revenue. It compensates the energy storage with a compensation price for the corresponding time.

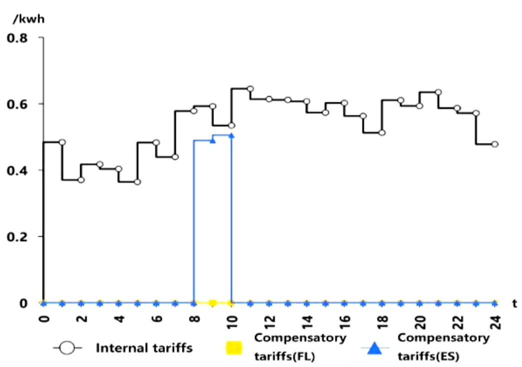

Fig.4 Internal pricing of VPP under Scenario

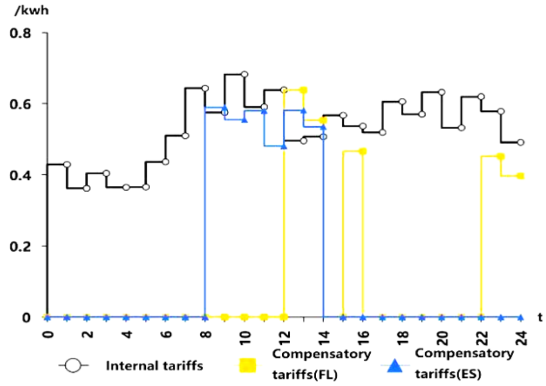

Fig.5 Internal pricing of VPP under Scenario 2

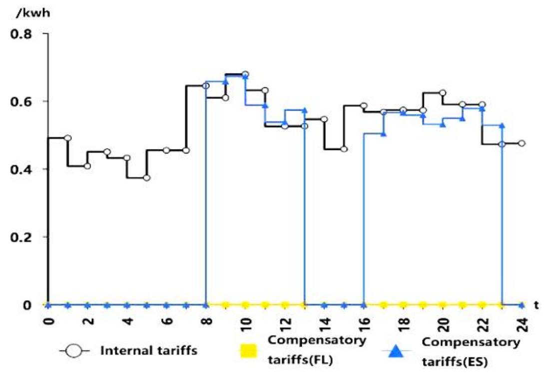

Fig.6 Internal pricing of VPP under Scenario 3

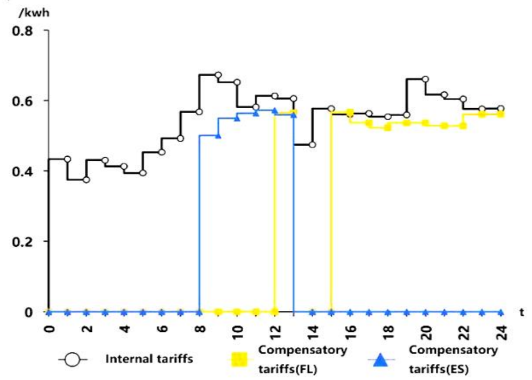

Fig.7 Internal pricing of VPP under Scenario 4

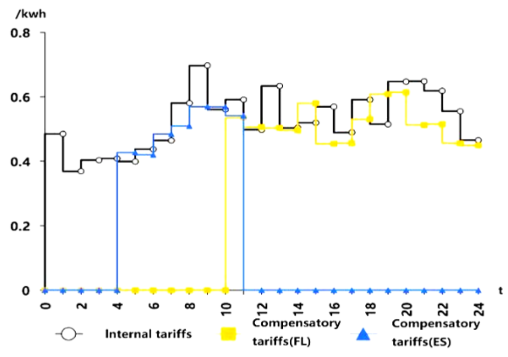

Fig.8 Internal pricing of VPP under Scenario 5

Figs 5-8 show the internal pricing under source uncertainty, load uncertainty, natural source , load uncertainty, and extreme source. It can be seen that 1) when the source is certain and the load is uncertain, the virtual plant does not price the flexible loads, and it only dispatches the storage to balance the internal energy supply: 2) the pricing in Scenarios 2, 3, 4 and 5 shows that the virtual plant strictly adheres to the principle of self-balancing between generators and consumers first, then calling the storage to replenish the energy during the insufficient period, and finally dispatching the flexible loads to respond to the demand. Scenarios 2, 3, 4, and 5 show that the virtual power plant strictly adheres to the principle of self-balancing between producers and consumers, and then calls the energy storage to supplement the energy supply during insufficient time. It finally schedules the flexible loads for demand response.

(2) Impact of Source Load Uncertainty on Internal Pricing

The effect of source and load uncertainty on the internal purchase (sale) price of the virtual power plant is shown in Fig. 5-8. In the source uncertainty (Scenario 2), most of the time the VPPO publishes the same trend as in the certainty scenario, except that it publishes a lower purchase price at 11:00-13:00 and 20:00-21:00 to increase its profit when it sells surplus electricity to the consumers and producers in the spot market; in the load uncertainty (Scenario 3), VPPO tends to publish a higher internal purchase price (0:00-14:00) to buy more electricity from producers and consumers. In the load uncertainty scenario (Scenario 3), VPPO tends to issue higher internal tariffs (0:00-14:00) to buy more electricity from consumers to meet the demand for flexible loads.

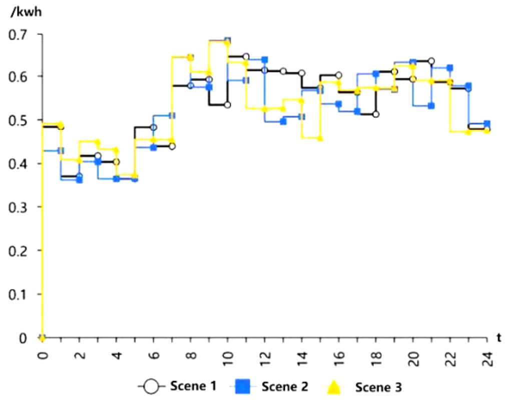

Fig.9 Change of internal purchase price of VPP under uncertainty of source and load

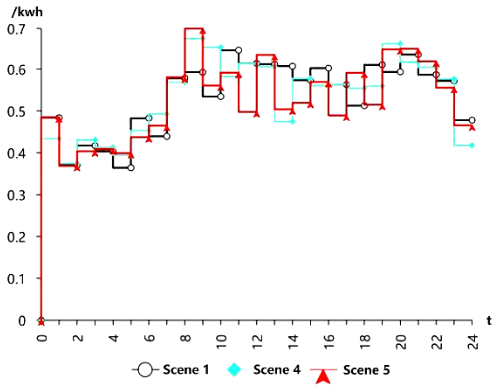

Fig.10 Change of internal sale price of VPP under uncertainty of source and load

B Comparative Analysis of the Revenue Situation of Various Subjects of Virtual Power Plants

(1) Revenue analysis of virtual operators

The total benefits of VPPO's participation in the day-ahead and real-time internal, as well as external markets under different scenarios are shown in Table 1. A comparative analysis reveals that:1) Source uncertainty has a greater impact on VPPO's benefits, with a reduction of $4,161.3, while load uncertainty is only $625.55. 2). In Scenario 5, even if VPPO dispatches the flexible loads and storage to participate in demand response, it cannot satisfy the internal energy supply. Even if the VPPO schedules flexible loads and storage to participate in demand response, it cannot satisfy the internal energy supply and needs to purchase power from the distribution grid several times, which results in negative revenue. 3) Flexible loads participate in demand response in Scenarios 2, 4, and 5, and it is found that if the VPPO does not schedule the flexible loads, the revenue will be reduced further, and the number of times of purchasing power from the power grid will increase, which is not conducive to the stabilization of the regional electric power system.

With relatively high revenue from 8:00-16:00, it is the period of high PV power output. Comparing the gains in Scenarios 3 and 4, we find that the VPPO's gain decreases from 0:00-2:00 due to the uncertainty of the source (wind power), and the gain is negative from 3:00-5:00 because the purchase price is also lower and the VPPO needs to buy some power to charge the storage. The VPPO makes a profit on the spot market by dynamically setting the internal purchase (sale) price and acquiring as much power as possible internally, especially at 13:00-15:00, because not only is there plenty of PV output at this time of day, but also the sale price in the internal market is high, and the combination of capacity and price contributes to the high profitability of the virtual power plant.

Table 1 Profits of the VPPO

Different scenarios	VPPO earnings/$	Not scheduling flexible load VPPO gains/$
Scene 1	6897.53	6897.53
Scene 2	2436.23	2503.37
Scene 3	6271.98	6271.98
Scene 4	2443.64	2251.11
Scene 5	-703.65	-1405.75

(2) Analysis of benefits to producers and consumers

1) Consumers and producers 1 and 3 can sell their surplus electricity in the electricity market to earn revenue on the premise of self-sufficiency by installing PV and wind turbines. 2) Comparing the revenue of each scenario, the installed PV capacity is not sufficient to fully support their load demand. They need to purchase electricity from the electricity market to meet their needs. Consumer 2 has a negative return, as its installed PV capacity is insufficient to fully support its load demand. It needs to purchase electricity from the electricity market to meet its own needs. A comparison of the returns under each scenario reveals that source uncertainty affects the returns of consumers to a greater extent, with 56.36%, 67.94%, and 11.04% of returns lost by each of the consumers under Scenario 2, respectively. 3) The overall return of consumer 3 is higher since the wind turbine has a higher return, which is because the wind turbine has a higher return. This is because wind power is available at all times of the day, and the load demand of CP3 is not high, but only during the period of 11:00-14:00. 4)The revenues of CP1-3 have decreased to different degrees when they trade with the grid independently, especially the positive revenues of CP1, which is the most important. In particular, the positive revenue of CP1 even becomes negative, which further proves the necessity for CPs to participate in VPP aggregation.

Table 2 Comparison of the prosumers' daily electricity purchase and sales income

	Net income from consumer producers1/$	Net income from consumer producers2/$	Net income from consumer producers3/$
Scene 1	3616	-1976	10564

Scene 2	1578	-3319	9398
Scene 3	3232	-2160	10742
Scene 4	1639	-3421	9575
Scene 4*	-567	-4597	7676
Scene 5	44	-6111	21937

(3) Flexible Load Benefit Analysis

The benefits of flexible loads under different scenarios are shown in Table 3. Among the five scenarios, the flexible loads participate in peaking in Scenario 2, Scenario 4, and Scenario 5, and carry out load interruptions, and the total costs are lower than those in the scenarios that do not participate in peaking because of the peaking benefits. On the other hand, the flexible load purchases power from the VPPO, and since the internal purchase and sale price set by the VPPO is lower than the grid retail price, the cost of the flexible load is reduced after participating in the VPP.

Table 3 Profits of the flexible load

Different scenarios	Power purchase costs/$	Peaking Value/$	Total cost/$
Scene 1	7063	0	7063
Scene 2	6953	1178	5775
Scene 3	6987	0	6987
Scene 4	7044	1435	5906
Scene 5	6950	3346	3604

5. Conclusion

Through the virtual power plant internal pricing method proposed in this paper, VPPO can make full use of the spot market to realize arbitrage and avoid the risk from the uncertainty of wind power and flexible load demand. It increases the benefit of participating in the electricity market. At the same time, flexible resources such as generators and consumers, flexible loads, and energy storage will increase their income by participating in the dispatch of VPP. The example analysis verifies the validity of the model. Source uncertainty has a greater impact on the internal pricing of virtual power plants. On the one hand, the load can realize its energy balance, but when the source is uncertain, it is necessary to make progress in scheduling flexible loads to participate in demand response. On the other hand, when there is source uncertainty, the VPPO will set higher internal power sales prices to compensate for its power purchases in the real-time market.

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