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Optimal Operation and Bidding Strategy of a Virtual Power Plant Integrated With Energy Storage Systems and Elasticity Demand Response

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ABSTRACT As an aggregator involved in various renewable energy sources, energy storage systems, and loads, a virtual power plant (VPP) plays a key role as a prosumer. A VPP may enable itself to supply energy and ancillary services to the utility grid. This paper proposes a novel scheme for optimizing the operation and bidding strategy of VPPs. By scheduling the energy storage systems, demand response, and renewable energy sources, VPPs can join bidding markets to achieve maximum benefits. The potential uncertainties caused by renewable energy sources and the demand response are considered in a robust optimization model. Moreover, the robust VPP optimization accounts for its influence on markets to ensure optimal energy and reserve capacity bidding transactions in the day-ahead market and deals balancing in the real-time market. To demonstrate the performance of the proposed scheme, markets comprising various participants and managed by the system operator are implemented using mathematical models. The proposed method is evaluated using an illustrative system and the practical Taiwan power (Taipower) system with diverse uncertainty levels. The numerical results demonstrate the promising performance and the efficiency of the proposed method. The results also verify the effectiveness of the proposed method VPP with various combinations of renewable energy sources, energy storage systems, and loads.

INDEX TERMS Virtual power plant, demand response model, ancillary service, energy storage system, electricity markets, renewable energy source, robust optimization, game theory, mixed integer programming.

ACRONYM AND NOMENCLATURE

ACRONYM

RES	Renewable Energy Source
PV	Photovoltaic
IPP	Independent Power Producer
VPP	Virtual Power Plant
ESS	Energy Storage System
DA	Day-Ahead
RT	Real-Time
DR	Demand Response
RO	Robust Optimization
WT	Wind Turbine
SoC	State of Charge
ToU	Time 0f Use
MO	Market Operator
MILP	Mixed Integer Linear Programing

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NOMENCLATURE

e_{tt}, $e_{tt'}$	Self-elasticity and cross-elasticity
d_t^0, d_t	Initial and modified demand response
c_{deg}^t	Degradation cost for ESS
μ_{cha}^t, μ_{dis}^t	The state of charging and discharging
η	ESS charge/discharge efficiency
SOC^t	State of Charge of ESS
e_{cap}	Capacity of ESS
C^{ESS}	Price for ESS
p_{cha}^t, p_{dis}^t	Energy charging/ discharging for ESS
m	Slope of battery life degradation
$c_{ope,VPP}^t$	The operating cost in the DA market
$r_{cap,VPP}^t$	The revenue obtained by selling reserve capacity
$r_{bal,VPP}^t$	The revenue of selling regulation energy in balancing market

p_{DA}^{t}	The buying or selling of energy in DA market
$\lambda_{ene,VPP}^{t}$	The bidding price for buying or selling energy in DA market
$r_{imp/exp,up}^{t}$, $r_{imp/exp,down}^{t}$	Reserve-up or reserve-down capacity selling in DA market at import or export state
$\lambda_{cap,VPP}^{t,up}$, $\lambda_{cap,VPP}^{t,down}$	The price for Reserve-up or reserve-down capacity selling in DA market
$p_{imp/exp,up}^{t}$, $p_{imp/exp,down}^{t}$	Reserve-up or reserve-down energy selling in RT market at import or export state
$\lambda_{bal,VPP}^{t,up}$, $\lambda_{bal,VPP}^{t,down}$	The price for Reserve-up or reserve-down energy selling in RT market
$p_{load,VPP}^{t}$	The RT energy consumption within VPP
$\lambda_{ToU,VPP}^{t}$	ToU price
c_{pen}^{t}	The penalty cost
$p_{netload,VPP,pre}^{t}$, $p_{load,VPP,pre}^{t}$, $p_{RES,VPP,pre}^{t}$	The predicted net load, load and RES generation
$r_{DR,VPP}^{t}$, $r_{dis,reserve}^{t}$	The regulation-up capacity offered from DR and ESS discharge
$r_{RES,VPP}^{t}$, $r_{cha,reserve}^{t}$	The regulation-down capacity offered from RES management and ESS charge
$\lambda_{bal,mp}^{t,up}$, $\lambda_{bal,mp}^{t,down}$	The marginal price of RT market
$e_{netload,VPP,pre}^{t}$	The prediction error
$c_{par,n}^{t}$	Cost for energy in DA market
$c_{par,res}^{t}$	Cost for reserve capacity in DA market
$\lambda_{eg,n}^{t}$, $\lambda_{cap,n}^{t,up}$, $\lambda_{cap,n}^{t,down}$	Bidding price for energy, reserve-up capacity, and reserve-down capacity provided by participant n in DA market
$c_{bal,n}^{t}$	The cost paid for the balancing power
c_{outage}^{t}	The outage cost
Λ_{VPP}	The bidding price matrix of VPP
Ψ_{VPP}	The bidding quantity matrix of VPP
$\Delta\Lambda_{step,VPP}$	The bidding price adjustment matrix
Λ_{MP}	The clearing price matrix of the markets

I. INTRODUCTION

RESs, mainly PV and wind power generation, are being increasingly integrated into power systems worldwide [1]. Because RESs exhibit the characteristic of uncontrollable power generation, they cause more inflexibility and uncertainty to power systems. The phenomenon of high RES penetration changes the operating patterns and quantities of energy as well as ancillary services needed by utilities and electricity markets [2]. In Taiwan, energy policy calls for a 20% RES penetration in the year 2025. An electricity market, including energy sources, reserves, and a balance of IPPs and a VPP, is thus imperative and put on the schedule.

Energy storage systems have been integrated with RESs in many studies to accommodate variability [3]–[5]. Doing so not only compensates for sudden variations in RES generation and maintains stable operating conditions, but also helps to provide increased flexibility. The aggregation of energy storage systems with a PV power plant [6] and a wind farm [3] improves the bidding efficiency of participating in energy and reserve markets, namely the DA market and RT market.

DR is one of most promising components to use to achieve system load balance management, benefits related to peak shaving, and RES efficiency enhancement with a short response period and relatively low cost. It has been proved to have the ability to compensate for the mismatch between short-term supply and demand in many studies [7]–[9]. DR will definitely play a progressively influential role in future grids.

Integrated with various RESs, energy storage systems, and types of loads, the framework of a VPP enables an operator to maintain a system's inner stability, while importing/exporting energy and services. As a market participant, a VPP operates as a "prosumer" (producer+consumer) in today's power system. References [10]–[16] propose various models and configurations for optimizing the control strategy of a VPP according to different roles of components. Reference [14] undertakes the most comprehensive consideration of controllable components of virtual power plants, as assessing the DR model, ESS model, and RES uncertainty. However, participation in DA or RT markets is not discussed in reference [14]; and it is described in [10] and [12].

A VPP, microgrid [17]–[18], RES [19]–[20], and hydropower system [2] are mostly treated as price takers, indicating that acceptance of the assumption that all participants' actions do not influence the price in the market and do not influence other participants' actions. However, when the amounts of energy and reserves provided by participants increase, bidding effects warrant consideration. Mathematical models have thus been proposed in some studies to imitate the operating modes in a real market that includes multiple agents, such as IPPs, multi-microgrid systems [21], and large-scale Energy storage systems [17].

Table 1 summarizes various perspectives covered by previous studies and our proposed method, where 'O' indicates for 'considered' and 'X' represents as 'not considered'.

TABLE 1. Features covered by related works.

Method	DR Model	ESS Model	RES Manageme	Uncertainty	Price Maker	DA Market	RT Market
[4]	X	O	O	X	X	O	O
[10]	X	X	X	O	X	O	O
[11]	X	X	X	X	X	O	X
[12]	X	O	X	X	X	O	O
[13]	X	O	X	O	X	O	X
[14]	O	O	X	O	X	X	X
[15]	O	X	X	X	O	O	O
[16]	X	O	X	X	O	O	O
[17]	X	O	X	O	O	O	O
[18]	X	O	O	O	X	O	O
[19]	X	O	O	O	X	O	O
[20]	X	O	X	O	X	O	O
Proposed	O	O	O	O	O	O	O

As clarified in the table, with the RES management, ESS model, DR model, and associated uncertainties considered, our strategy aims to maximize profits by bidding for energy and reserve capacities in DA and RT markets as a price maker. Moreover, the features as indicated in Table 1 are not comprehensively considered in previous works which are indeed needed to be counted for a more practical application. Comparatively, the overall contribution of the study consists of the following:

- *Market Mechanism Design:* To formulate a realistic situation in which the VPP can sufficiently supply energy and services to influence markets, the joint DA and RT markets are constructed using a two-level model. Instead of treating the VPP as a price-taker, each bidding action of participant in the markets is modeled mathematically. The structure ensures the realistic simulation of VPP operating scenarios and thus facilitates the derivation of a practical bidding strategy.
- *DR Model:* As one of the major resources in a VPP, DR is modified with self- and cross-elasticity to evaluate the real actions and load shifting taken by end-users according to various price signals. Despite using a simple value or ratio to represent the DR quantities, the proposed model achieves a great improvement by quantifying the load shedding and shifting.
- *Uncertainty Treatment:* Dealing with the uncertainties associated with loads and RES generation is one of the key issues in our approach. The employment of RO realizes a bidding strategy for the VPP by arranging ESS, RES, and DR based on the considered uncertainty margin.

This paper is organized as follows. The framework of the market and bidding rules employed is discussed in Section III. The models of the VPP and markets as well as the bidding actions are mathematically formulated in Section IV. Following is the evaluation of the performance of our proposed scheme in a test system and a practical system as presented in Section V. Finally, the conclusion is given in Section VI.

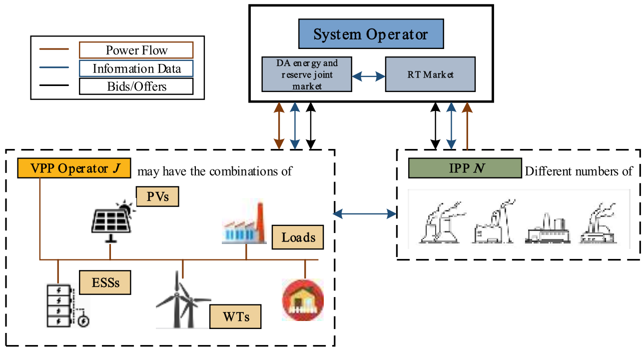

FIGURE 1. Overall framework of bidding system.

II. SYSTEM FRAMEWORK

Fig. 1 presents the overall framework of market and bidding actions considered in this study. VPPs are defined to have various combinations of PV, WT, ESS, and load. The distance between each generation unit and load is assumed to be short, and thus no power loss or congestion is considered. The VPP is treated as an aggregator to participate in the market held by the system MO. Various IPPs and other VPPs are also participants in the markets with the bidirectional information exchange on bidding.

The DA market opens between 4 p.m. and 6 p.m. in the day prior to the one on which energy will be consumed. All participants offer their bids and adjust the quantity and price during this duration. The competitors' bidding information is disclosed to all participants. The bidding in the RT market is assumed to begin every hour. The market is then cleared hourly [22]. The successful bid should be strictly followed. Otherwise, a penalty is levied on the supplier who does not follow the rules and dispatch.

This paper assumes the VPP has knowledge of other participants' bidding information. Considering other participants' bidding strategies in the market models, how the VPP optimizes its bidding strategy while operating each apparatus and is the key concern to be discussed.

III. PROBLEM FORMULATION AND PROPOSED METHODOLOGY

A. VPP BIDDING STRATEGY

The VPP aims to minimize the total cost by scheduling all the components, e.g. RES, ESS, and variable loads. The DR and ESS model are discussed individually in this section and the objective function of the bidding strategy is detailed as follows.

1) DR MODEL

Our proposed DR model imitates the real DR participants' bidding action. Two components are thus introduced that have an effect on the bidding capacity, namely self-elasticity and cross-elasticity. The percent change of demand reduction ∂d_t with respect to the percentage change in incentive price $\partial \lambda_t$ during the same time interval is self-elasticity e_{tt}, whereas the percentage change of demand reduction ∂d_t with respect to the percentage change in the price $\partial \lambda_{t'}$ of the other period t' is represented as cross-elasticity $e_{tt'}$ [9]. These two coefficients are expressed in

$$e_{tt} = \frac{\partial d_t / d_t}{\partial \lambda_t / \lambda_t}, \tag{1.1}$$

$$e_{tt'} = \frac{\partial d_t / d_t}{\partial \lambda_{t'} / \lambda_{t'}}, \tag{1.2}$$

where the e_{tt} denotes as the response modification when the price changes at time t, while $e_{tt'}$ refers to load shifting encouraged by price changes at other time except t. The incentive-based DR is thus described in

$$d_t = d_t^0 \times \prod\nolimits_t = 1^{24} (\frac{\lambda_{t'}}{\lambda_{t'}^0})^{e_{tt'}}. \tag{1.3}$$

The VPP operator considers the DR from the initial value d_t^0 to a modified level d_t during period $t$according to any price deviation [23]. Normally a 24 × 24 elasticity matrix is employed to quantify the elasticity within a 24-hour time interval. To simplify that, we divide a day into peak, semi-peak, and off-peak periods and list the elasticity value between the pairs as

$$E_{3\times3} = \begin{pmatrix} e_{op,op} & e_{sp,op} & e_{p,op} \\ e_{op,sp} & e_{sp,sp} & e_{p,sp} \\ e_{op,p} & e_{sp,p} & e_{p,p} \end{pmatrix}, \tag{1.4}$$

where peak, semi-peak, and off-peak are written as "p," "sp," and "op," respectively, as above.

A ratio α is employed to represent the percentage of DR participants among the total initial DR quantity. Equation (1.3) is thus accomplished to (1.5) as follows:

$$d_t = \alpha d_t^0 \prod_{t=1}^{24} \left(\frac{\lambda_{t'}}{\lambda_{t'}^0} \right)^{e_{tt'}}. \tag{1.5}$$

For example, after the modification, the adjusted DR quantities are compared with the original one represented in Fig. 2. Following the bidding price, it is simulated that the higher price encourages more DR participants to shift the quantity to this time period, while the quantity decreases at which the price is low. The adjustment shows the realistic effect of DR, and the corresponding operation of the VPP is made accordingly. Specifically, by adjusting the bidding price $\lambda_{t'}$, the VPP arranges the quantity d_t that is supplied by DR.

2) ESS MODEL

As charging and discharging actions are made by the ESS, the fraction of ESS capacity decreases due to degradation of

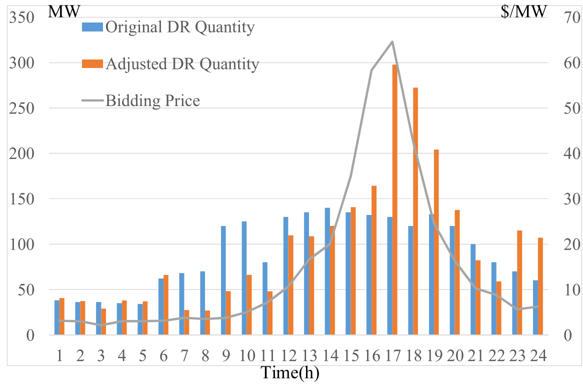

FIGURE 2. Example of DR model modification.

the battery. In this paper, the degradation cost of ESS c_{deg}^t is assumed to follow a linear pattern and to be sensitive only to the energy utilized per cycle. The model is described in (4.a) of reference [24], where the degradation cost is determined by

$$c_{deg}^t = \left| \frac{m}{100} \right| \frac{\sum_{t\in T} \max[0, SoC^{t-1} - SoC^t]}{e_{cap}} C^{ESS} e_{cap}. \tag{2.1}$$

The percentage of discharging energy is calculated by $\max[0, SoC^{t-1} - SoC^t]$ of an ESS and the total cost is determined by unit cost C^{ESS} and installation capacity e_{cap} for ESS. A linear approximation factor m of battery life is evaluated by the battery manufacturer's datasheets and is assumed to be −0.0017, according to current technology [25].

The state of charge value SoC^t at time t is calculated and restricted by equations below:

$$\mathrm{SoC}^t = \mathrm{SoC}^{t-1} + \eta p_{cha}^t - p_{dis}^t / \eta, \tag{2.2}$$

$$\mathrm{SoC}^1 = \mathrm{SoC}^{24} = 0.2 e_{cap}, \tag{2.3}$$

$$0.2 e_{cap} \le \mathrm{SoC}^t \le 0.8 e_{cap}, \tag{2.4}$$

where η refers to the efficiency of charging/discharging. The charging/discharging energy $p_{dis/cha}^t$ and reserve arrangement $r_{dis/cha,res}^t$ should follow the charging and discharging limit of battery $p_{dis/cha,limit}$:

$$0 \le p_{dis/cha}^t \le \mu_{dis/cha}^t \, p_{dis/cha,limit}, \tag{2.5}$$

$$0 \le p_{dis/cha}^t + r_{dis/cha,res}^t \le \mu_{dis/cha}^t \, p_{dis/cha,limit}. \tag{2.6}$$

where $\mu_{dis/cha}^t$ means μ_{cha}^t or $\mu_{dis.}^t$ The terms μ_{cha}^t and μ_{dis}^t refer to the state of ESS, the terms which are set to ensure either charging ($\mu_{cha}^t = 1, \mu_{dis}^t = 0$) or discharging state ($\mu_{cha}^t = 0, \mu_{dis}^t = 1$) is on and thus incur separately either charging or discharging limitation in Equations (2.5) and (2.6).

3) VPP MANAGEMENT METHOD

The bidding quantity and price are determined according to (3.1). The goal of the VPP operator is to maximize the benefit on any given day. The equation can be used for the

VPP consisting of various energy sources by calculating the associated cost and revenue.

$$\max \text{Benefit} = \sum_{t=1}^{24} (r^t_{cap,VPP} + r^t_{bal,VPP} - c^t_{ope,VPP}). \quad (3.1)$$

The details of each cost or revenue within a time interval t can be calculated using

$$c^t_{ope,VPP} = \lambda^t_{ene,VPP}{}^* p^t_{DA}{}^* - c^t_{deg}, \quad (3.2)$$

$$r^t_{cap,VPP} = \lambda^{t,up}_{cap,VPP} r^t_{imp/exp,up}{}^* + \lambda^{t,down}_{cap,VPP} r^t_{imp/exp,down}{}^*, \quad (3.3)$$

$$r^t_{bal,VPP} = \lambda^{t,up}_{bal,VPP} p^t_{imp/exp,up}{}^* + \lambda^{t,down}_{bal,VPP} p^t_{imp/exp,down}{}^* + \lambda^t_{ToU,VPP} p^t_{load,VPP} - c^t_{pen} - c^t_{deg,bal}. \quad (3.4)$$

The operating cost in the DA market $c^t_{ope,VPP}$ is calculated using the difference between the buying and selling of energy p^t_{DA} based on the bidding price $\lambda^t_{ene,VPP}$ and the degradation cost of ESS c^t_{deg}. The term $r^t_{cap,VPP}$ represents the revenue obtained by selling reserve-up $r^t_{imp/exp,up}$ and reserve-down capacity $r^t_{imp/exp,down}$ with the price $\lambda^{t,up}_{cap,VPP}$ and $\lambda^{t,down}_{cap,VPP}$, respectively, where the subscripts 'imp' and 'exp' refer, respectively, to the state 'import' or 'export' at time t.

Similarly, $r^t_{bal,VPP}$ denotes the revenue of selling regulation-up $p^t_{imp/exp,up}$ and regulation-down energy $p^t_{imp/exp,down}$ in the RT market with the price $\lambda^{t,up}_{bal,VPP}$ and $\lambda^{t,down}_{bal,VPP}$ as well. Moreover, the revenue of selling energy $p^t_{load,VPP}$ to consumers in VPP according to time-of-use prices $\lambda^t_{ToU,VPP}$, the penalty cost c^t_{pen} when the regulation requirement is not well supplied, and ESS degradation cost are also counted in $r^t_{bal,VPP}$.

By subtracting the predicted RES generation and load combined with the ESS schedule, the mentioned import or export state of the VPP operator is determined in

$$p^t_{netload,VPP,pre} = p^t_{load,VPP,pre} - p^t_{RES,VPP,pre}, \quad (3.5)$$

$$p^t_{DA} = p^t_{netload,VPP,pre} + p^t_{cha} - \eta p^t_{dis}, \quad (3.6)$$

where positive p^t_{DA} denotes import and negative p^t_{DA} denotes export. The predicted net load $p^t_{netload,VPP,pre}$ is first calculated with the load prediction $p^t_{load,VPP,pre}$ and RES generation prediction $p^t_{RES,VPP,pre}$. Combined with the arranged ESS charge and discharge energy, p^t_{DA} is obtained.

Equations (3.7) and (3.8) indicate the up and down reserve quantities that are individually supplied by various VPP components. The regulation-up capacity is offered from DR $r^t_{DR,VPP}$ and ESS discharge $r^t_{dis,reserve}$, whereas the regulation-down capacity is offered from RES management $r^t_{RES,VPP}$ and ESS charge $r^t_{cha,reserve}$. Because the import and export modes do not occur simultaneously, $r^t_{imp,up}$ and $r^t_{exp,up}$ or $r^t_{imp,down}$ and $r^t_{exp,down}$ exist on the basis of which mode of VPP in the energy market at time t is.

$$r^t_{imp,up}, r^t_{exp,up} = r^t_{DR,VPP} + r^t_{dis,reserve} \quad (3.7)$$

$$r^t_{imp,down}, r^t_{exp,down} = r^t_{RES,VPP} + r^t_{cha,reserve} \quad (3.8)$$

As mentioned, based on the market rule, a penalty is levied if a successful DA bid is not strictly followed. The penalty cost c^t_{pen} is then calculated by multiplying the mismatch between the bid and the real contribution in the balancing market by the marginal price $\lambda^{t,up}_{bal,mp}$ and $\lambda^{t,down}_{bal,mp}$, as presented in

$$c^t_{pen} = \lambda^{t,up}_{bal,mp}((p^t_{imp/exp,up}{}^* - p^t_{imp/exp,up}) + \max\left(0, p^t_{imp/exp,DA}{}^* - p^t_{exp,DA}\right)) + \lambda^{t,down}_{bal,mp}((p^t_{imp/exp,down}{}^* - p^t_{imp,down}) + \max\left(0, p^t_{imp/exp,DA}{}^* - p^t_{imp/exp,DA}\right)). \quad (3.9)$$

All the preceding equations are constrained by power balance (3.10), ESS constraints, VPP import and export reserve capacity allowances, and RT energy import and export boundaries (limited by the reserve capacity bid in the DA market) (3.11). The constraints set by (3.12) and (3.13) ensure that the overall VPP can supply energy to two markets.

$$\left(p^t_{imp,DA} - p^t_{imp,up} + p^t_{imp,down}\right) - (p^t_{exp,DA}{}^* + p^t_{exp,up} - p^t_{exp,down}) = p^t_{load,VPP,real} - p^t_{RES,VPP,real} + \eta p^t_{dis} - p^t_{cha}, \quad (3.10)$$

$$0 \le r^t_{imp,up/down}{}^*, r^t_{exp,up/down} \le d_t + \mu^t_{dis/cha} p^t_{dis/cha}, \quad (3.11)$$

$$0 \le p^t_{imp,up/down}{}^*, p^t_{imp,up/down} \le r^t_{imp,up/down}{}^*, \quad (3.12)$$

$$0 \le p^t_{exp,up/down}{}^*, p^t_{exp,up/down} \le r^t_{exp,up/down}{}^*. \quad (3.13)$$

and constraints (1.1)–(1.5), (2.1)–(2.8).

4) FORMULATION WITH UNCERTAINTIES

Uncertainties associated with the load and RES are the key issues that induce the levying of a penalty to the VPP. The uncertain net load must be considered accordingly on the basis of Equation (3.5). To take into account the prediction error $e^t_{netload,VPP,pre}$, the equation is thus substituted in (4.1). The objective function (3.1) is further formulated to a max-min problem in (4.2).

$$p^t_{netload,VPP,pre} = p^t_{load,VPP,pre} - p^t_{res,VPP,pre} + \max e^t_{netload,VPP,pre}, \quad (4.1)$$

$$\max_{p^t_{\text{cha}}, p^t_{\text{dis}}} \min_{e^t_{netload,VPP,pre}} \sum_{t=1}^{24} (R^t_{cap,VPP} + R^t_{bal,VPP} - C^t_{ope,VPP}). \quad (4.2)$$

As an uncertainty-modeling scheme, RO is suitable for addressing conditions in which the range of uncertainty is well known but the distribution of the uncertainty is unknown [26]. The deviations of net load are modeled

$$p^t_{netload,VPP,pre} \in [p^t_{netload,VPP,pre,min}, p^t_{netload,VPP,pre,max}], \quad (4.3)$$

where

$$p^t_{netload,VPP,pre,max} = p^t_{netload,VPP,pre,min} + \Delta p^t_{netload,VPP,pre} \cdot \Delta p^t_{netload,VPP,pre} \quad (4.4)$$

$\Delta p_{netload,VPP,pre}$ is the largest expected variation in time t. On the basis of the RO model proposed in [27], Γ^{RO} is employed to determine the protection level against the uncertainty. The variation range of Γ is controlled within $[0, M]$, where $[M = t| \Delta p^t_{netload,VPP,pre} > 0]$. As the value of Γ^{RO} is adjusted to be equal to 0, no uncertainty is considered, and the solution is the same as the deterministic one. By contrast, $|M|$ is used to represent Γ^{RO}, and the most conservative solution is obtained. The employed RO model enables the selection of any Γ value in the range $[0, M]$ to ensure a tuned conservation level. The formulation of (4.5) can thus be remodified as

$$\max \sum_{t=1}^{24} (R^t_{cap,VPP} + R^t_{bal,VPP} - C^t_{ope,VPP}) - \Gamma^{RO} z^{RO}, \quad (4.5)$$

$$s.t.\ y^t_{RO} + z^{RO} \geq \Delta p^t_{netload,VPP,pre} \lambda^t_{bid,energy,VPP}, \quad (4.6)$$

$$y^t_{RO} \geq 0, \quad (4.7)$$

$$z^{RO} \geq 0, \quad (4.8)$$

and constraints (1.1)–(1.5), (2.1)–(2.8), (3.2)–(3.13).

Here, z^{RO} and y^t_{RO} are two positive RO variables that account for the known bounds of the net load combined with Γ^{RO}. The updated objective (4.5) is bounded by the original constraints (1.1)–(1.5), (2.1)–(2.8), and (3.2)–(3.13) as well as the new ones (4.6)–(4.8). The worst scenario is represented in (4.6) to constrain the variation in each time interval. The term z^{RO} represents the level of uncertainty considered. Using the equation, the worst Γ^{RO} periods are fully considered in the RO algorithm to worsen the objective function value.

Because most of the worse cases are considered in the model, almost no penalties (except for some extreme cases) are levied. Because of the RO formulation, the VPP operator may achieve the maximum benefit and flexible bidding strategy. Consequently, by becoming embedded in the following market structure, the VPP obtains the scheduling of ESS, RES, and DR along with the bidding price determined in the market through the objective function. The discussion of the VPP management solution and its interaction with other participants and market operator will be pictured in Subsection IV.C.

B. MARKET STRUCTURE

Market formulation is crucial for VPP operations in this research, with the participants' bidding considered. The MO schedules the operations in the DA market, which includes unit commitment and reserve arrangement, and RT market for real-time balance. Simultaneously, the marginal price is cleared in the markets.

1) DA MARKET

The objective function of the DA market is expressed in

$$\min \sum_{t=1}^{24} \sum_{n=1}^{N} (c^t_{par,n} + c^t_{par,res}). \quad (5.1)$$

The operating cost involves the cost for energy $C^t_{par,n}$ in (5.2) and that for reserve capacity $C^t_{par,res}$ in (5.3).

$$c^t_{par,n} = \lambda^t_{eg,n} p^t_{DA,n}{}^*, \quad (5.2)$$

$$c^t_{par,res} = \lambda^{t,up}_{cap,n} r_n{}^{t,up*} + \lambda^{t,down}_{cap,n} r_n{}^{t,down*}. \quad (5.3)$$

All the participants' bidding offers are considered in the optimization, where the bidding price for energy $\lambda^t_{eg,n}$, regulation-up reserve $\lambda^{t,up}_{cap,n}$ and regulation-down reserve $\lambda^{t,down}_{cap,n}$ serve as parameters in this optimization problem and vary for different suppliers. To be specific, n denotes the name or number of a participant. The power balance and reserve requirements, e.g. $r_{req}^{t,up/down}$, are ensured by constraints in

$$\sum\nolimits_{n=1}^{N} p^t_{DA,n}{}^* = p^t_{load,DA}, \quad (5.4)$$

$$\sum\nolimits_{n=1}^{N} r_n{}^{t,up/down*} = r_{req}^{t,up/down}. \quad (5.5)$$

The variables with "*" indicate successful bidding that has a boundary set in the bid offer for both energy $p^t_{DA,n}$ in (5.6) and capacity $r_n^{t,up/down}$ in (5.7). When n refers to the VPP we managed, the $p^t_{DA,VPP}$ equals the p^t_{DA} obtained by the objective function (3.1), similarly hereinafter. The rest n-related variables are employed in the same manner to all participants.

$$0 \leq p^t_{DA,n}{}^* \leq p^t_{DA,n}, \quad (5.6)$$

$$0 \leq r_n{}^{t,up/down*} \leq r_n^{t,up/down}. \quad (5.7)$$

The bidding result is obtained by using equation (5.1) and the constraints described above. After the result is sent to the participants, they can choose whether an adjusted bid should be submitted before the market is cleared. The optimization is executed every time a new offer is submitted, while all the results are revealed to all participants.

2) RT MARKET

Similarly, the objective in the RT market is to minimize the cost of energy to balance the mismatch between RT demand and load prediction hourly. For each $t \epsilon [1, \ldots, T]$, the mathematical model of this market is represented by an objective function in

$$\min \sum_{n=1}^{N} c^t_{bal,n} + c^t_{outage}, \quad (6.1)$$

as well as the constraints

$$\sum\nolimits_{n=1}^{N} (p^t_{DA,n}{}^* + p_n{}^{t,up*} + p_n{}^{t,down*}) = p^t_{load,real} - p^t_{outage}, \quad (6.2)$$

$$c^t_{bal,n} = \lambda^{t,up}_{bal,n} p_n{}^{t,up*} + \lambda^{t,down}_{bal,n} p_n{}^{t,down*}, \quad (6.3)$$
$$c^t_{outage} = \lambda^t_{outage} p^t_{outage}, \quad (6.4)$$
$$0 \le p_n{}^{t,up/down*} \le r_n{}^{t,up/down*}. \quad (6.5)$$

Because only energy bidding occurs in this stage, the cost $c^t_{bal,n}$ is paid for increasing or decreasing power generation in IPPs[1] and for adjusting the import or export energy in the VPP to ensure system balance. System balance is guaranteed by (6.2), whereas the total cost of energy is determined on the basis of (6.3). Moreover, the outage cost c^t_{outage} is considered by (6.4).

According to the market rule that the quantity of energy is bound by the reserve capacity determined in the DA market, the bidding result in this market is optimized on the basis of constraint (6.5). The up and down balancing energy boundaries $r_n{}^{t,up/down*}$ are decision variables in the DA market. Once determined, these variables are treated as parameters in the RT market.

C. THE TWO-LEVEL GAME STRUCTURE AND METHODOLOGY

As observed in the objectives of the participants (3.1) and MOs (5.1) and (6.1), all participants aim to maximize the benefit, while MOs to minimize the cost. A two-level market gaming system [21] is introduced into the scheme to study the operating strategies of the participants and MOs. As presented in Fig. 3, the two-level structure is constructed to simulate the conditions. Using this structure, the objectives of the participants and MOs are finally achieved through bidding, price adjustment, and concessions in the two-level market gaming system in the light of the decision variables of lower level being the parameters of upper level, vice versa.

In the lower level, the VPP and IPP initiate the bidding prices according to the successful bidding of previous similar days. The DR quantity limitation can thus be determined through Equation (1.5). The optimal scheduling of DR, RES, and ESS is solved based on Equation (3.1). It should be noted that, from the mechanism of our proposed solution, to make Equation (3.1) solved by MILP, the prices $\Lambda_{VPP} \overset{\text{def}}{=} \left[\lambda^t_{ene,VPP}, \lambda^{t,up}_{cap,VPP}, \lambda^{t,down}_{cap,VPP}, \lambda^{t,up}_{bal,VPP}, \lambda^{t,down}_{bal,VPP}\right]$ all set as constant values at each iteration. Then for the calculation at each iteration, Equations (3.2), (3.3), and (3.4) are all linearized. Afterwards, the bidding is submitted to the upper level of the markets, which offers the prices, e.g. Λ_{VPP}, optimized schedule and quantity of energy, reserve capacity, and regulating reserve, e.g. $\Psi_{VPP} \overset{\text{def}}{=} [p^t_{DA}, r^t_{imp/exp,up}, r^t_{imp/exp,down}, p^t_{imp/exp,up}, p^t_{imp/exp,down}]$. These are given by other participants in the same manner and all employed as constant parameters in the upper level, a process which then leads to the decision of MO.

The upper level is a cooperative trading game and represents the MO costs that are minimized through an

[1]The objectives employed by the IPP, another type of participant, are described in the APPENDIX.

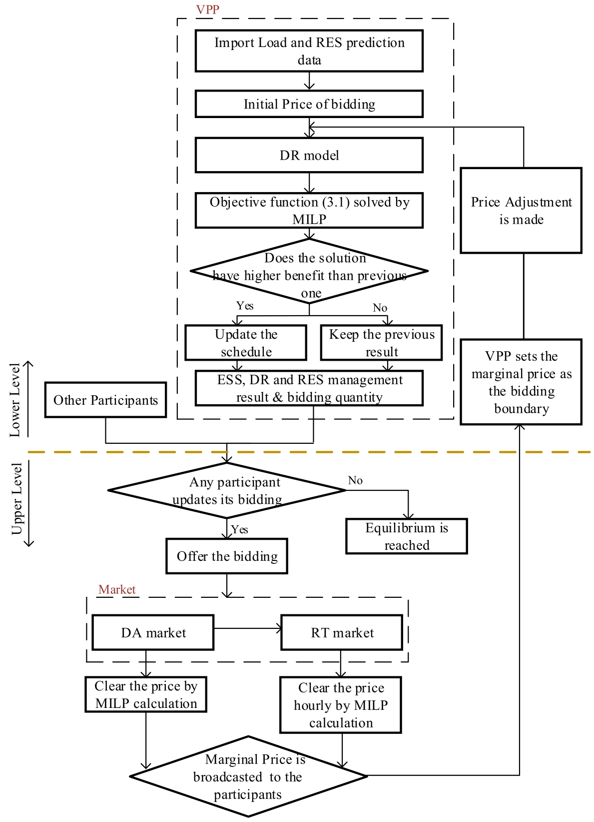

FIGURE 3. Two-level bidding structure and corresponding methodology in DA and RT markets.

interaction scheme. The DA market solves the joint problem (Equation (5.1)) accordingly and then broadcasts the result at each iteration. According to the result and bidding offers, the solution to the hourly RT market is achieved sequentially.

After each interval, the market clears the price, and the VPP and IPP adjust the price by setting the marginal price as the upper bound of the bidding price. Afterwards, the participants involved in the lower level are in a noncooperative state. The VPP determines the updated price with $\min\left(\Lambda_{VPP} + \Delta\Lambda_{step,VPP}, \Lambda_{MP}\right)$, where $\Delta\Lambda_{step,VPP}$ is a predetermined adjusted step matrix for various price categories. Once set, the value of $\Delta\Lambda_{step,VPP}$ is regarded as constant, while its sign (positive or negative) is determined based on the prices of the same category in Λ_{VPP} and Λ_{MP}. Take $\lambda^t_{ene,VPP}$ in Λ_{VPP} as an example, if $\lambda^t_{ene,MP}$ is higher than $\lambda^t_{ene,VPP}$, $\Delta\lambda^t_{ene,VPP}$ is set to be positive, vice versa. The updated price affects the operation strategy of related VPP power apparatuses, as the strategy is decided by the objective of VPP, due to the trade-off relationship among the participants with respect to revenue.

The proposed structure enables self-adaptability among participants. Any of them may adjust their bidding offers via cost recalculation after referring to others' bidding offers. Once the updated objective value is higher than the benefit gained from previous iteration, the participant offers the updated bidding; otherwise, it keeps the same one. In other words, the updated bidding needs to be ensured a better benefit gained. The proposed structure thus helps to finally achieve the equilibrium that is treated as the clearing price.

The proof of the equilibrium is as follows: In the proposed algorithm, the strategies of the lower-level parties always attain nonempty values for the price and quantity of energy, reserve capacity, and regulating reserve as the parameters of the upper-level problem. Conversely, in response to the lower level, the MOs solve their DA and RT problems in succession and provide the clearing price as the parameters to VPPs and IPPs. Therefore, the proposed methodology is guaranteed to reach the unique equilibrium.

IV. NUMERICAL RESULTS

The performance of the proposed method is investigated using an illustrative system and the Taipower system. The algorithm is developed using the MILP model of CPLEX in MATLAB. Monte Carlo simulations are employed to create various scenarios that a VPP may face for various prediction errors of load and RES generation in the VPP to evaluate the overall performance of the proposed method. The prediction errors are based on normal distribution function $p_{real,error} \sim N(0, \sigma^2)$. The proposed method is compared with two benchmarks (Benchmark 1 and Benchmark 2):

Benchmark 1. The research in [4] discusses how a PV power station containing ESS participates in the DA market, especially the reserve capacity market. The method used is modified to address an ESS-equipped, price-taker VPP joining the DA and RT markets.

Benchmark 2. In [17], the research considers a price-maker and ESS-equipped VPP joining the DA and RT markets. However, the risk caused by uncertainty due to load and RES is ignored. The method used is modified to address an ESS-equipped price-maker VPP joining the DA and RT markets.

The hourly maximum reserve capacity bidding supplied by RES management is assumed to be 10%, which means 10% of the total RES generation at time t is considered for regulation-down. The DR participant rate α is supposed to be 10% as well. The outage price λ_{outage}^{t} is assumed to be 10 times the ToU price. All this settings can be customized to fit the VPP's requirement.

A. ILLUSTRATIVE SYSTEM

The VPP in the test system considered in this study comprises one PV power station (installed capacity: 400 MW), two WT power plants (installed capacity: 100 MW + 50 MW), and one ESS (installed capacity: 120 MWh and 120MW having a charge–discharge cycle efficiency of 0.95) with a contract capacity of ±220 MW. The regional system contains 10 IPPs and various loads. Data for the PV, WT, and loads are modified from Elia [28], and data for the IPPs and ToU are

TABLE 2. RT market bidding strategies and corresponding reserve capacities of Benchmark 2 and the proposed method.

Market	Time	Benchmark 2				Proposed Method			
		RT Marginal Price	MG Bidding Price	MG bidding reserve capacity in DA market	MG successful RT supply	RT Marginal Price	MG Bidding Price	MG bidding reserve capacity in DA market	MG successful RT supply
Regulation Up	1	741	739	2	2	699	689	2	2
	2	699	739	19	0	739	679	25	19
	3	739	739	59	17	739	679	59	17
	4	739	739	74	37	739	679	74	37
	5	739	739	83	16	739	679	73	16
	6	739	739	80	12	739	679	85	12
	7	739	739	54	9	699	679	61	9
	8	739	739	97	36	739	679	97	36
	9	699	739	32	0	739	679	32	21
Regulation Down	10	1897	739	4	4	1280	1280	3	2
	11	1001	739	13	13	1270	1280	6	0
	12	1270	2139	5	0	1270	1280	0	0
	13	850	739	26	26	1001	1011	3	0
	14	1001	739	13	13	1826	1836	0	0
	15	1826	1267	27	27	1897	1907	0	0
	16	850	739	5	0	860	860	1	0
	17	2139	2139	22	0	2149	2149	3	3
	18	2139	2139	15	0	2149	2149	62	59
	19	2124	2139	3	0	2134	2134	30	25
	20	850	739	42	42	2134	2134	69	69
Regulation up	21	699	739	25	0	699	689	3	3
	22	699	739	20	0	739	679	47	17
	23	741	739	32	32	739	679	56	47
	24	699	739	29	0	699	679	32	25

modified from the generation units and three-phase electricity tariff structure in the Taipower system.

1) IMPORTANCE OF CONSIDERING UNCERTAINTIES

To demonstrate the importance of considering uncertainties due to load and RES, as both being the price-maker VPP, the proposed method is compared with Benchmark 2 rather than Benchmark 1 in this subsection. The reason is that the uncertainty consideration is not the sole difference between proposed method and Benchmark 1, but it is the key difference laying between proposed method and Benchmark 2. A typical day of the month in which the error of net load prediction varies between [−15%, +15%] is tested among the methods. No matter the prediction errors considered in these two methods, the VPP can obtain its bidding strategy individually.

However, performance can be easily evaluated by comparing the bidding strategies presented in Table 2. The bidding result in the RT market is examined to evaluate whether one of the compared methods is more robust than the other method. As observed, the upward regulation is initiated during 1:00–9:00 and 21:00–24:00, whereas downward regulation is initiated during 10:00–20:00. The corresponding RT marginal prices are listed. The RT bidding strategies provided by the two methods differ in terms of the prices and quantities.

The strategy of Benchmark 2 places great emphasis on bidding during 10:00–15:00 for the downward regulation in the DA market. However, it fails to provide a balance in the market because large prediction errors appear between 16:00 and 19:00, as marked in red. By contrast, by considering uncertainty through properly managing the DR, RES, and especially the ESS, the proposed method is assessed zero penalty while balancing the market.

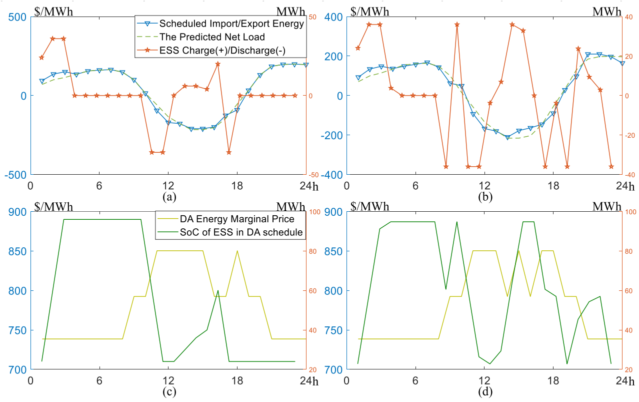

FIGURE 4. Scheduled ESS charging–discharging energy compared with the predicted net load and scheduled net load by using (a) benchmark 2 and (b) proposed method. SoC compared with DA energy marginal price in (c) benchmark 2 and (d) proposed method.

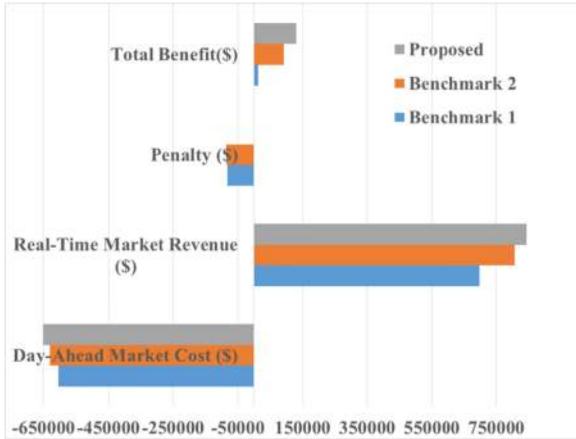

FIGURE 5. Average overall benefit with the corresponding components when various methods are used.

The schedules of energy import and export as well as ESS are presented in Fig. 4. The planned import–export energy of the two methods is compared with the ESS charge–discharge agenda and the predicted load profile, as separately shown in Fig. 4(a) and 4(b). The primary difference between these two schedules can be observed during 14:00–17:00. The export energy arranged by the proposed method during this time interval is less than that arranged by the reference to prevent the risk of penalty. To prevent the risk, the ESS is scheduled to charge at this time. Moreover, as illustrated in Fig. 4(c) and 4(d), the charge or discharge action is influenced by the price in the market.

In both schedules, the ESS is restrained to take as little action as possible yet nevertheless maintain the maximum benefit. Benchmark 2 is noted to set the ESS to charge when the price is low and discharge when the price is highest. However, because of the import/export limitation at PCC as given in (3.14), the ESS is managed to charge energy during the peak time to decrease export. In the meantime, the ESS in the proposed method is determined to cycle the charge and discharge operations more frequently than the schedule in Benchmark 2. The ESS of the VPP in the proposed method is also noted to be more flexible, because it allows a higher quantity to charge during the peak hours of export (12:00–14:00 and 20:00) and discharge during the import hours (15:00–17:00) because of the uncertainty margin consideration.

To conclude the performance in considering uncertainties, in the event of a high-capacity shortage in the system, the VPP in Benchmark 2 and proposed method may inevitably face a situation in which it cannot provide the quantity of generation needed, thus resulting in a penalty. Nevertheless, the VPP operation strategy optimized by using the proposed method can arrange more margin than Benchmark 2 by considering uncertainties. Moreover, as a price-maker, the operation strategy is able to avoid being dispatched by raising its RT bidding price when the prediction error is beyond consideration.

2) ECONOMIC PERFORMANCE

Whether with respect to the VPP or overall system, the standard deviation of prediction error σ is set to 15%. As can be found in the initial net load shown in Fig. 4 (a) and (b), the VPP in this case mostly imports energy rather than exports.

The average operating costs of the VPP obtained from 1000 scenarios using the mentioned methods are presented in Fig. 5. The DA costs, including the price for buying energy, the revenue for selling energy (including import and export), and reserve capacities are presented as histograms with the revenue earned and the penalties levied in the RT market. Different colored histograms signify the results from using various methods, with gray for proposed method, blue for Benchmark 1, and orange for Benchmark 2.

For Benchmark 1, the VPP sold the reserve capacity and energy on the basis of the market price. This situation entails the least VPP operating cost in the DA market. However, when bidding ability and risk are neglected, the VPP in Benchmark 1 has comparable DA costs and RT revenues because the effect of uncertainties cannot be avoided and the market price is simply considered. In this structure, penalties are directly levied on the VPP by Benchmark 1 on the basis of the prediction error of the net load.

By contrast, the VPP using Benchmark 2 gains higher revenues because of the price-maker ability. Moreover, when the bidding strategies in the RT market are adjusted, revenue is clearly increased to eliminate the influence of uncertainties. When the margins for preventing risks and selling are considered in the process of balancing the market, the VPP in the proposed method is determined to have a higher cost for DA market operation compared with those obtained from the other two methods. Nevertheless, the advantage of this conservative arrangement is observed in the RT market revenue and penalty proportion. When the proposed bidding strategy is used, the VPP gains more in a balanced market with considerably less penalty. The optimal performance of the proposed method is thus demonstrated by the overall benefits.

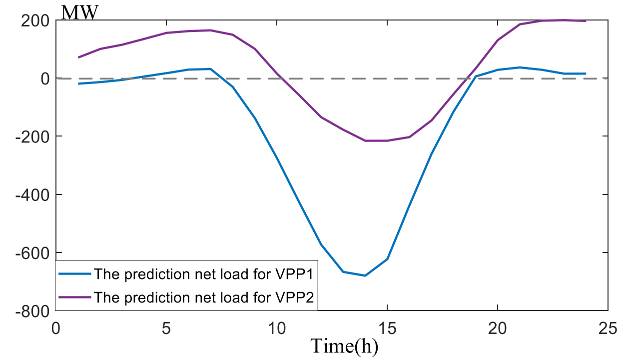

FIGURE 6. Predicted values of the net load profile in VPP1 and VPP2.

When the test time series is extended to a month on the basis of the data for July, 2016, overall benefits achieved by Benchmark 1, Benchmark 2, and the proposed method are \$13,149, \$94,481, and \$124,836, respectively, using the realistic corresponding data. Accordingly, the proposed method enabled the VPP to earn \$111,687 and \$30,355 more benefits relative to the ones that use the other two methods during the month. The overall model is calculated within 10.80 s using the proposed method.

B. TAIPOWER SYSTEM

Currently, no actual power markets exist in the Taipower system. However, separating the responsibilities of generation, transmission, and distribution of utilities is being planned by Taipower. To assess the ability of the proposed method to model bidding actions and the applicability of the proposed method to different VPPs, this study regards all existing generators as IPPs and two regional distribution systems as VPPs.

In the test market system, 84 IPPs and 2 VPPs are considered the market participants. They bid for energy, reserve, and balance on the basis of their capacity, generation cost, and ramp abilities. These two VPPs comprise ESS, PV power stations, and wind power plants, and all predicted and real data for loads and RES generation are obtained from Taipower. VPP1 comprises two PV stations (installed capacity: 400 MW + 600MW), one wind power plant (installed capacity: 100 MW), and one ESS (installed capacity: 200 MWh, 200MW). A 300-MW PV power station, a 150-MW wind power plant, and a 50-MWh (50 MW) ESS are included in VPP2.

Fig. 6 illustrates the initial predicted net load profiles of VPP1 and VPP2. As indicated in the profile, VPP1 mainly exports energy, especially during 10:00–18:00. By contrast, the net load for VPP2 appears to exhibit a relatively flat shape. VPP1 behaves more as an RES generation supplier, although it faces a high risk of prediction failure. VPP2 has a characteristic similar to a traditional microgrid—it occasionally consumes energy from or delivered energy to the utilities system. The advantage of the proposed method is adequately validated by these two VPPs which have different strategies but operating in the same markets.

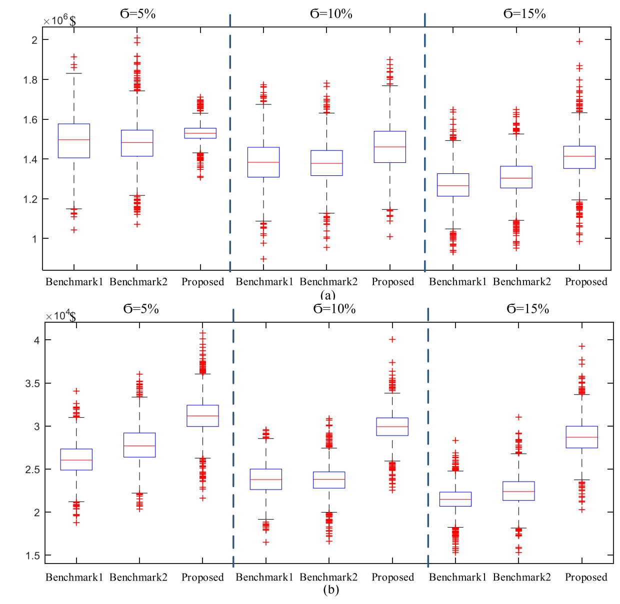

FIGURE 7. The benefits obtained by three methods for different prediction errors σ of 5%, 10%, and 15% for (a) VPP1 and (b) VPP2.

To demonstrate the advantage of the proposed method in diverse situations, three methods are tested by 1000 scenarios created by Monte Carlo simulations that vary σ from 5% to 10% and 15%. Joining in the RT market and selling balancing energy by the Benchmark 1, Benchmark 2, and proposed method yield profits for VPPs. The benefits obtained by the methods are represented as a box plot in Fig. 7. Because of uncertainties not considered, more penalties are levied on Benchmark 1 and Benchmark 2. The ESS helps to reduce the penalty amount by supplying some margins for VPP1 and VPP2 in all these methods.

Similarly, Benchmark 1 appears to have less flexibility without adjusting the bidding strategy function or considering uncertainties. Benchmark 2 can avoid some penalties by adjusting RT bidding, but the proposed method achieves overall better performance because of its consideration of uncertainties in advance.

The bidding strategy optimized by the proposed method enables VPP1 and VPP2 to contribute in the markets as price makers and consider uncertainty. The results indicate an apparent overall advantage whether in terms of average or whole stable performance with less benefit variation. Moreover, the most benefit is obtained from the proposed method when dealing with the high uncertainty situations. The results obtained using the proposed method are calculated within 147.30 s on average for each scenario.

V. CONCLUSION

VPPs are expected to become crucial components of electricity markets, chiefly DA and RT markets, in the future. This paper has described a method for determining the bidding strategy of VPP. The method enables the calculation of the optimization schedule of ESS, DR, and RES management. Uncertainties caused by RES and loads are also considered in the method to avoid penalties. Additionally, to construct a practical market environment, a bi-level multiagent model is employed to simulate the market structure by embedding bidding actions. Mathematical models of the VPP, IPPs, DA market, and RT market were embedded in this structure. Bids provided by different parties are continually calculated in the market model until convergence is achieved. A successful bid can thus be obtained, when the VPP generates the corresponding optimized bidding strategies under the price cleared by MO.

Two test systems—an illustrative system and the Taiwan power system—were evaluated in this study. Different types of VPPs were discussed under scenarios generated by Monte Carlo simulations based on realistic data. The results reveal that the proposed method can successfully solve the strategy determination problems irrespective of the RES penetration level. Moreover, even for various situations of uncertainty, the proposed method achieved superior economic solutions to the other methods. An evaluation of longer-term operation of up to one month in this study also reveals a clear improvement when the proposed method is employed with acceptable computational efficiency.

APPENDIX

IPP BIDDING STRATEGY

As the conventional generation, IPPs bid in the market to maximize their benefits. The benefit is calculated using (7.1), which is expressed as the revenue obtained by selling the energy $\nu^t_{ene,IPP}$ and reserve capacity $\nu^t_{cap,IPP}$ minus the cost of generation and penalty c^t_{pen}. As presented in (7.2), the cost of generation $c^t_{ope,IPP}$ differs from the values of a, b, and c, which correspond to the unit characteristic and fuel cost. The revenue $\nu^t_{ene,IPP}$ obtained by selling energy in the DA and RT markets is considered in (7.3), whereas the revenue for reserve capacity bidding $\nu^t_{cap,IPP}$ is considered in (7.4); moreover, the penalty cost c^t_{pen} is considered in (7.5). The energy contributed by generation is limited due to its capacity $P_{gen,n,capacity}$, as indicated in (7.6) and (7.7). The ramp ability is also considered in (7.8). Due to constraint (7.9), the energy quantity of RT bidding for the balance market is limited by the reserve capacity bid in the DA market.

$$\max \text{Benefit} = \sum_{t=1}^{24} (\nu^t_{cap,IPP} + \nu^t_{ene,IPP} - c^t_{ope,IPP} - c^t_{pen}) \tag{7.1}$$

$$\begin{aligned} c^t_{ope,IPP} = {} & a(p^t_{gen,n,DA} + p^t_{gen,n,realup} \\ & - p^t_{gen,n,realdown})^2 \\ & + b\left(p^t_{gen,n,DA} + p^t_{gen,n,realup} \right. \\ & \left. - p^t_{gen,n,realdown}\right) + c \end{aligned} \tag{7.2}$$

$$\begin{aligned} \nu^t_{ene,IPP} = {} & \lambda^t_{bid,ene,n} p^t_{gen,n,DA} \\ & + \lambda^t_{bid,bal,up,n} p^t_{gen,n,realup} \\ & + \lambda^t_{bid,bal,down,n} p^t_{gen,n,realdown} \end{aligned} \tag{7.3}$$

$$\nu^t_{cap,IPP} = \lambda^{t,up}_{cap,n} r_{gen,n}{}^{t,up*} + \lambda^{t,down}_{cap,n} r_{gen,n}{}^{t,down*} \tag{7.4}$$

$$\begin{aligned} c^t_{pen} = {} & \lambda^{t,up}_{bal,mp}(p^t_{gen,n,realup}{}^* - p^t_{gen,n,realup} \\ & + \max\left(0, p^t_{gen,n,DA}{}^* - p^t_{gen,n,DA}\right)) \\ & + \lambda^{t,down}_{bal,mp}(p^t_{gen,n,realdown}{}^* \\ & - p^t_{gen,n,realdown} \\ & + \max\left(0, p^t_{gen,n,DA} \right. \\ & \left. - p^t_{gen,n,DA}{}^*\right)) \end{aligned} \tag{7.5}$$

$$0 \le p^t_{gen,n,DA} \le P_{gen,n,capacity} \tag{7.6}$$

$$\begin{aligned} 0 \le {} & p^t_{gen,n,DA} + p^t_{gen,n,realup} \\ & - p^t_{gen,n,realdown} \le P_{gen,n,capacity} \end{aligned} \tag{7.7}$$

$$\begin{aligned} \Delta_{ramp-down,gen,n} \le {} & p^t_{gen,n} \\ & - p^{t-1}_{gen,n} \le \Delta_{ramp-up,gen,n} \end{aligned} \tag{7.8}$$

$$0 \le p^t_{gen,n,realup/down} \le r_{gen,n}{}^{t,up/down*} \tag{7.9}$$

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