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Risk-Based Approach for Self-Scheduling of Virtual Power Plants in Competitive Power Markets

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Abstract- *Dispersed energy resources and storage devices may be grouped as a Virtual Power Plant (VPP). In a competitive electricity market, VPP can exchange energy through a pool market or bilateral contracts. in order to maximize the profit, VPP needs to determine the optimal operating schedule. This paper provides a new decision-making framework based on information gap decision theory (IGDT) for robust self-scheduling of VPPs in power markets. In the proposed approach, the energy price is the uncertain parameter while the decision variables are the energy that needs to be exchanged in the pool market and through bilateral contracts, the reserve which should be provided, dispatch of distributed energy resources, the load which is needed to be curtailed, and the state of charging/discharging of energy storage devices. The proposed method specifies the self-scheduling considering the risk-taking level of the decision maker. A case study has been used to validate the proposed framework.*

Keyword: Decision making, Distributed energy resources, Power markets, Scheduling, Uncertain systems.

NOMENCLATURE

B_D	VPP's Profit with forecasted prices
B_O	VPP's Target profit in opportunistic bidding
B_R	Critical VPP's profit in robust bidding
$C(A,x)$	System model for IGDT
$\text{cost}(DG_{i,t})$	Cost of DG i in period t
$\text{cost}(ES_{j,t})$	Cost of electrical storage j in period t
$\text{cost}(US_{k,t})$	Cost imposed by curtailment of load k in period t
$E_{CB,t}$	The energy bought via contracts in period t
$E_{CS,t}$	The energy sold via contracts in period t
E_t	The energy exchanged with pool market in period t
L_t	VPP's supplied load in period t
$Load_t^E$	VPP's supplied load through pool market in period t
$Load_t^C$	VPP's supplied load through bilateral contracts in period t
$Loss_t^E$	VPP's power losses while exchanging power in energy market in period t
$Loss_t^C$	VPP's power losses while exchanging power through bilateral contracts in period t
$Loss_t^R$	VPP's power losses while exchanging power in reserve market in period t
MSR_i	The reserve ramp rate of unit i
N_{DG}	Set of DGs
N_{es}	Set of electrical storages
N_{us}	Set of curtailable loads
$P_{DG,i,t}^E$	Generation of DG i for energy market in period t
$P_{DG,i,t}^C$	Generation of DG i for bilateral contracts in period t
$P_{DG,i}^{\min}, P_{DG,i}^{\max}$	Minimum and maximum generation limits of DG i
$P_{es,j,t}^E$	Charged/discharged capacity of electrical storage j for energy market in period t
$P_{es,j,t}^C$	Charged/discharged capacity of electrical storage j for bilateral contracts in period t
$P_{es,j}^{\min}, P_{es,j}^{\max}$	Minimum and maximum generation limits of storage j
$P_{ij}^{\min}, P_{ij}^{\max}$	Minimum and maximum flow limits of line ij
$P_{ij}(t)$	Active power flow of the line between

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	node i and j in period t
P_j, Q_j	Active and reactive power injected to node j
$P_{loss-ij}$ $Q_{loss-ij}$	Active and reactive power losses of the line between node i and j
$P_{us,k,t}^{E}$	The curtailed load of load k in energy market in period t
$P_{us,k,t}^{C}$	The curtailed load of load k for bilateral contracts in period t
$P_{us,k}^{\max}$	Maximum limit for curtailment in load k
R_{Con}	Revenue of bilateral contracts
R_{Res}	Revenue of reserve market
R_{Ret}	Revenue of supplying loads
$R_{CH,j}$	Maximum charge/discharge rate of electrical storage j
$R_{DG,i,t}$	Generation of DG i in reserve market in period t
Res_t	VPP's supplied load when reserve is called on in period t
R_t	VPP's total reserve bid in period t
$R_{us,k,t}$	Curtailed load in reserve market in period t
$RLoss_t$	VPP's power losses while reserve is called on in period t
r_{ij}, x_{ij}	Resistance and reactance of the line between nodes i and j
T	Scheduling horizon
$T^{on}(i), T^{off}(i)$	Minimum up and minimum down times of unit i
$U(\alpha, \hat{x})$	Uncertainty model for IGDT
V_i	Voltage of node i
$V_i^{\min}, V_i^{\max}$	Minimum and maximum voltage of node i
P_j, Q_j	Active and reactive power injected to node j
x	Uncertain parameter
$\hat{x}$	Predicted amount for uncertain parameter
$X^{on}(i,t)$	The duration of being on for unit i before period t
$X^{off}(i,t)$	The duration of being off for unit i before period t
$y(i,t)$	On/off status for unit i in period t
$Z_{down}^{(it)}, Z_{up}^{(it)}$	Down and up bounds of solution at iteration it
α	Uncertainty horizon
$\hat{\alpha}$	Robustness function
$\hat{\beta}$	Opportunity function
$\lambda_{CB,t}$	Price of buying contracts in period t
$\lambda_{CS,t}$	Price of selling contracts in period t
$\lambda_{E,t}$	Energy price in the market in period t
$\lambda_{L,t}$	Retail price for loads in period t
$\lambda_{R,t}$	Reserve price in the market in period t
$\hat{\lambda}$	Forecasted energy prices
δ_i	Voltage angle of node i
σ_O	Profit deviation factor for opportunistic bidding
σ_R	Profit deviation factor for robust bidding

1. INTRODUCTION

In recent decades, the growing trend of energy consumption, besides the environmental concerns, has motivated governments to utilize distributed energy resources (DERs) in power networks. Consequently, the future power system may have numerous DERs with different sizes and technologies. The existing technologies for the DERs can be categorized into fossil fuel-based and renewable-based resources. Using multiple energy resources has some advantages including reliability improvement, operating cost reduction, and carbon emission reduction [1].

According statistics, the penetration of renewable energy resources, mainly PV systems and wind turbines, has experienced a rapid growth over the last few years [2]. However, due to the intermittent nature of renewable-based DERs, high penetration of these kinds of generation makes the energy scheduling a challenging task.

The concept of virtual power plant (VPP) has been lately introduced to manage the DERs in an elegant manner. VPPs aggregate renewable as well as conventional power generation, energy storage devices, and demands [3]. Based on the FENIX's [4] definition, VPP is a flexible representation of a portfolio of DERs which enables the aggregator to make contracts in the wholesale energy/reserve markets and to offer services to the system operator. VPPs may also benefit from Demand Response (DR) programs. DR can be regarded as a source of operational reserve which can affect the energy and reserve scheduling [5, 6]. In general, the main goal for VPPs in the markets is to take advantage of exchanging energy with a power network [7-9].

According to the operation strategy, there are two types of VPPs: commercial VPP (CVPP) and technical VPP (TVPP). The main goal of the CVPP is to gain the maximum profit of VPP without considering the impact of the distribution network. On the contrary, the local network constraints are included in the offering strategy of TVPP [10].

To get the maximum outcome, the optimal bidding scheme for the VPP portfolio should be determined. Different sources of uncertainty may affect the profit of the VPP in energy/reserve markets. Pool market price, loads, and availability and performance of DERs, due to the intermittent nature of some DERs in VPP, all have some degree of uncertainty which may affect the operating profit of VPPs in the energy/reserve market [9]. Specifically, the uncertainty in the price of the pool market is an important factor in the self-scheduling problem for different market participants [11].

Stochastic programming and robust optimization are two main techniques for handling uncertainties in optimization problems [3]. In stochastic programming, the probability distribution function for uncertain parameters must be forecasted, which may be difficult to obtain. On the contrary, robust optimization uses uncertainty set and does not need to make any assumption on the probability distribution function.

Some investigations have been accomplished to provide schedules for different energy market players in the presence of pool market uncertainty. Bidding strategies for Gencos, considering uncertainty in market price, have been investigated in Ref. [12-17]. In Ref. [17-19], several frameworks have been introduced to help retailers make decisions considering uncertainties in the energy/reserve market. The self-scheduling problem known as the procurement strategy of large-scale consumers has been addressed in Ref. [20-24]. Ref.[25, 26] have also discussed the impact of energy price uncertainty on the energy scheduling of multi-carrier energy systems.

The decision-making problem of VPP, as a player in the energy/reserve market, in the presence of uncertain parameters has been investigated in some recent researches [27-37]. Ref. [27] have proposed a stochastic decision-making framework for a VPP considering price uncertainty. In this model, part or all of the demand can be supplied through a bilateral contract. This contract offers a strong opportunity to guarantee VPP income due to the volatility of the market price and possible constraints of the transmission system operator. In [28], a stochastic adaptive robust optimization model has been introduced for the offering problem of VPPs in the day-ahead energy market. The model considers the uncertainty in wind-power production and energy/reserve market prices. In Ref. [29], a robust optimization approach has been proposed in order to find the optimal bidding and offering strategy for participating in the day-ahead energy market. Price uncertainty has been considered in the paper and the results showed that VPP would be resisted against the uncertainty using the proposed method. The self-scheduling of VPP based on stochastic programming subject to long-term bilateral contracts and technical constraints has been presented in Ref. [28]. In this framework, the uncertainty of wind and solar powers are compensated by including pumped hydro storage resources in VPP. Ref. [30] has proposed a stochastic programming model to find the optimal bidding strategy of a VPP, which participates in the electricity market. In this model, the price uncertainty and stochastic renewable power generation have been considered. In [31-33], uncertainties induced by renewable generation resources and prices in the energy market have also been taken into account in the short-term scheduling of VPP. These uncertainties in Ref. [31-30] were modeled in a probabilistic approach using Point Estimate Method (PEM). This method solves probabilistic problems by using deterministic routines. Based on the historical data, Conejo et. al. [33] used historical records in a scenario-based approach to model the uncertain parameters. In Ref. [34], two risk management approaches have been implemented in the decision making problem of VPPs based on the conditional value at risk (CVaR) and second-order stochastic dominance constraints (SSD) to avoid profit variability caused by market price uncertainties.

Information gap decision theory (IGDT), developed by BenHaim [35], is a non-probabilistic decision technique that tends to maximize robustness to failure, or opportunity for success, under “severe uncertainty” [35]. It is an effective approach to support making decisions in uncertain environments. The main advantage of this theory is that it does not need any assumption of the nature and size of the uncertain data. Furthermore, the IGDT-based models have the ability to determine the optimal schedules to gain a predefined profit level. The IGDT-based model may help the determiners to evaluate risks and opportunities and make informed decisions [22]. For instances, in Ref. [36], a decision-making framework has been proposed to optimize the electricity purchasing strategies of load aggregators in the day-ahead electricity market. The authors used IGDT approach to handle real-time price uncertainty. Ref. [37] has addressed unit commitment problem in power network considering VPP and DR programs. In this paper, the VPP has uncertain output and the authors used IGDT to deal with the uncertainties.

This paper introduces a new bidding strategy framework for robust decision making and self-scheduling of a VPP, in which the IGDT is utilized to deal with the uncertainty of prices in the energy market. Furthermore, to manage the risk of VPP owners, besides the pool-based contracts, the bilateral contracts are also modeled in the VPP's decision-making approach. In our proposed framework, the energy pool price is the uncertain parameter and the decision variables comprise the energy that needs to be exchanged in the pool market and through bilateral contracts, the reserve which should be provided, dispatch of DERs, the load which is needed to be curtailed, and charging/discharging scheduling of energy storage devices. Considering the risk-taking level of the determiner, this method guarantees the least critical outcome for the VPP by choosing decision variables in the presence of uncertainties. The main contributions of this paper are summarized as follows:

1. A comprehensive analysis, based on IGDT-based self-scheduling framework, is performed to evaluate different schedules under various market settlement conditions for opportunistic and robust self-scheduling of VPP. Furthermore, the long-term bilateral contracts, besides the pool-based contracts, is considered and investigated by its modeling in the VPP's decision-making problem.

2. Using the proposed IGDT-based model, the VPP owner can quantify the risk and caution in his/her self-scheduling with respect to the obtained profit. Therefore, it is possible for the VPP owner to decide based on the risk (caution) level.

The rest of the paper is structured as follows: Section 2 gives characteristics and formulation for the self-scheduling problem of VPP in energy/reserve markets. The IGDT-based self-scheduling for VPP as well as the modeling of uncertainties through information gap decision theory is given in Section 3. In Section 4 the simulation results and discussions are presented. Finally, Section 5 is dedicated to conclusions.

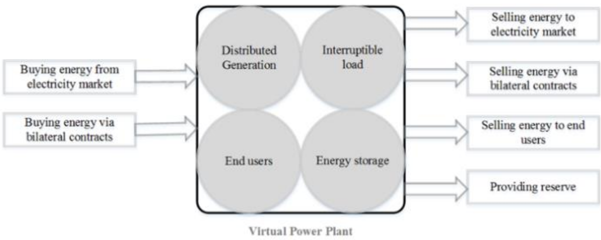

Fig.1. Potential energy/reserve transactions for VPP

2. VPP SELF-SCHEDULING PROBLEM

2.1. VPP in energy/reserve markets

A VPP, similar to other electrical market players, may take part in energy/reserve markets. Unlike typical power plants, VPPs may perform a dual role (seller or buyer) as a player in energy/reserve markets depending on parameters such as prices in the market, availability of DERs, or the demand of VPPs. Besides taking part in the pool market of energy, VPPs may enter a secondary market where producers and consumers can have bilateral contracts. The pool market is considered based on hourly bids. In the long term, on the other hand, bilateral contracts are concluded. Major reasons for bilateral contracting are the renewable energy resources uncertainties and possible system operator constraints. Accordingly, a VPP decides how much of its capacity should be contracted bilaterally in advance, and how much can be offered in the market. Moreover, similar to electricity retailers, VPPs need to satisfy their own small consumers by providing energy with a fixed price, which is known as the retail price. The potential energy/reserve transactions for VPP is illustrated in Fig.1.

2.2. The Formulation of self-scheduling problem for VPP

a. *Objective Function*

The purpose of self-scheduling for VPP is to gain maximum profit from selling energy to local loads, trading power in energy/reserve markets, and signing bilateral contracts. Therefore, the objective function indicating the self-scheduling problem of VPPs in the energy/reserve markets is expressed by (1) [38].

The first term in Eq. (1) implies the income gained by exchanging energy in the energy/reserve markets, signing bilateral contracts, and also supplying end consumers. The next terms in Eq. (1), respectively, stand for the costs of DGs, electromechanical storage, and load curtailment. In this framework, either pay-as-bid or uniform clearing mechanisms of the energy pool exchange market can be applied. The settlement of the reserve market is based on capacity bids. Similar to [39], the self-scheduling model is developed based on forecasted clearing prices of energy/reserve markets. The submitted capacities of participants whose bids are accepted are considered to be realized.

$$
\begin{aligned}
profit = &\sum_{t=1:T}\begin{pmatrix}\lambda_{E,t}\times E_t+\lambda_{CS,t}\times E_{CS,t}-\lambda_{CB,t}\times E_{CB,t}\\ +\lambda_{R,t}\times R_t+\lambda_{L,t}\times L_t\end{pmatrix}\\
&-\sum_{t=1:T}\left(\sum_{i\in N_{DG}}\text{cost}(DG_{i,t})\right)-\sum_{t=1:T}\left(\sum_{j\in N_{es}}\text{cost}(ES_{j,t})\right)\\
&-\sum_{t=1:T}\left(\sum_{k\in N_{us}}\text{cost}(US_{k,t})\right)
\end{aligned}
\tag{1}
$$

b. Equality constraints for supply-demand balancing

The constraints for the equality of supply and demand in the pool market and bilateral contracts are respectively given in Eq. (2) and Eq. (3). According to these constraints, VPP can determine the amount of energy that should be bought and sold through pool market and bilateral contracts for each time period of t in the scheduling horizon. The scheduling horizon in this paper is considered one week. Equation (4) shows the equality constraint for the operating reserve in the system. Equations (5) - (8) express the total scheduled power for DGs, storages, load curtailment, and served load in the pool market and bilateral contracts, respectively.

$$\begin{aligned} &-E_t + \sum_{i\in N_{DG}} P^E_{DG,i,t} + \sum_{j\in N_{es}} \left(\eta_{es,j} \times P^E_{ES,j,t}\right) \\ &+\sum_{k\in N_{us}} P^E_{US,k,t} = Load^E_t + Loss^E_t \end{aligned} \tag{2}$$

$$\begin{aligned} &E_{CB,t} - E_{CS,t} + \sum_{i\in N_{DG}} P^C_{DG,i,t} + \sum_{j\in N_{es}} \left(\eta_{es,j} \times P^C_{ES,j,t}\right) \\ &+\sum_{k\in N_{us}} P^C_{US,k,t} = Load^C_t + Loss^C_t \end{aligned} \tag{3}$$

$$\begin{aligned} &R_t + \sum_{i\in N_{DG}} R_{DG,i,t} + \sum_{j\in N_{es}} \left(\eta_{es,j} \times R_{es,j,t}\right) \\ &+\sum_{k\in N_{us}} R_{us,j,t} = \mathrm{Res}_t + Loss^R_t \end{aligned} \tag{4}$$

$$P_{DG,i,t} = P^E_{DG,i,t} + P^C_{DG,i,t} \tag{5}$$

$$P_{ES,j,t} = P^E_{ES,j,t} + P^C_{ES,j,t} \tag{6}$$

$$P_{US,k,t} = P^E_{US,k,t} + P^C_{US,k,t} \tag{7}$$

$$Load_t = Load^E_t + Load^C_t \tag{8}$$

c. DER constraints

In the following relations, Eqns. (9) to (14) represent constraints of DG units, Eqns. (15) and (16) show the limitation of storage devices, and Eq. (17) expresses the limitation of load curtailment. Constraint (9) represents that the sum of the scheduled generation of each DG unit in the energy and reserve market must be within its lower and upper production limits. The ramp rate for DG generation in the reserve market is constrained by Eq. (10) [39]. Equations (11) - (14) model the minimum up and down constraints for DG units.

$$P^{\min}_{DG,i} \le y(i,t)P_{DG,i,t} + y(i,t)R_{DG,i,t} \le P^{\max}_{DG,i} \tag{9}$$

$$\begin{aligned} &R_{DG,i,t} \times y(i,t) \le \\ &\quad \min\left\{\left(10\times MSR_i\right), \left(P^{\max}_{DG,i} - P_{DG,i,t}\right)\right\} \end{aligned} \tag{10}$$

$$\left[X^{on}(i,t) - T^{on}(i)\right] \times \left[y(i,t-1) - y(i,t)\right] \ge 0 \tag{11}$$

$$\begin{aligned} &\left[X^{off}(i,t-1) - T^{off}(i)\right] \times \\ &\quad \left[y(i,t-1) - y(i,t)\right] \le 0 \end{aligned} \tag{12}$$

$$X^{on}(i,t) = \left[X^{on}(i,t-1)+1\right] \times \left[y(i,t-1)\right] \tag{13}$$

$$X^{off}(i,t) = \left[X^{off}(i,t-1)+1\right] \times \left[1-y(i,t-1)\right] \tag{14}$$

$$P^{\min}_{es,j} \le P_{es,t,j} \le P^{\max}_{es,j} \tag{15}$$

$$\left|P_{es,t,j}\right| \le R_{CH,j} \tag{16}$$

$$0 \le P_{us,k,t} + R_{us,t,k} \le P^{\max}_{us,k} \tag{17}$$

d. Constraints for network security of VPP

The equations for considering the security of the network are given by Eqns. (18) to (23) [39]. Equation (18) and (19) denotes the power flow equations for a distribution network. The active and reactive power losses for the line connecting node i to j is calculated by equations (20) and (21), respectively. Equations (22) and (23) apply the upper and lower bounds for each line flow and node voltage, respectively.

$$\begin{aligned} V_j^2 = &-\left[r_{ij}P_j + x_{ij}Q_j - \frac{V_i^2}{2}\right] + \\ &\sqrt{\left[r_{ij}P_j + x_{ij}Q_j - \frac{V_i^2}{2}\right]^2 - [r_{ij}^2 + x_{ij}^2][P_j^2 + Q_j^2]} \end{aligned} \tag{18}$$

$$\sin(\delta_i - \delta_j) = \frac{x_{ij}P_j - r_{ij}Q_j}{V_iV_j} \tag{19}$$

$$P_{loss-ij} = r_{ij}\frac{(P_j^2 + Q_j^2)}{V_j^2} \tag{20}$$

$$Q_{loss-ij} = x_{ij}\frac{(P_j^2 + Q_j^2)}{V_j^2} \tag{21}$$

$$-P^{\max}_{ij} \le P_{ij}(t) \le P^{\max}_{ij} \tag{22}$$

$$V_i^{\min} \le V_i \le V_i^{\max} \tag{23}$$

3. IGDT-BASED SELF-SCHEDULING MODEL OF VPP IN ENERGY/RESERVE MARKETS

This section proposes an IGDT-based self-scheduling formulation for a VPP participating in the energy/reserve market in the presence of uncertain parameters. In the proposed approach, the energy pool price is the uncertain parameter while the decision variables are the energy that needs to be exchanged in the pool market and through bilateral contracts, the reserve which should be provided, dispatch of DERs, the load which is needed to be curtailed, and the state of charging or discharging of storage resources. The proposed model aims at maximizing the net profit of

VPP over the scheduling period, as expressed in Eq. (1).

3.1. Uncertainty modelling through information gap decision theory

The IGDT helps the determiner to choose uncertain parameters based on its predefined aims such as maximizing robustness (defined as achievement of minimum requirements under any circumstances) or opportunity (defined as gaining maximum performance in the presence of desired deviations of uncertain parameters). Modeling errors between the exact and predicted values, IGDT supports the determiner to assess risk and to make risk-based decisions [22-24].

Uncertainties may be disadvantageous when they cause the profit to be decreased or may be advantageous when it leads to a higher profit. IGDT uses robustness and opportunity functions to manage this, considering the level of risk-taking behavior of the determiner. Robustness function and opportunity function for uncertainty parameter are expressed as follows [22-24]:

$$\hat{\alpha} = \max_{\alpha}\{\alpha \mid B(\lambda) \geq B_R, \left|\frac{\lambda - \hat{\lambda}}{\hat{\lambda}}\right| \leq \alpha\} \tag{24}$$

$$\hat{\beta} = \min_{\alpha}\{\alpha \mid B(\lambda) \geq B_O, \left|\frac{\lambda - \hat{\lambda}}{\hat{\lambda}}\right| \geq \alpha\} \tag{25}$$

The robustness function (24) shows the maximum amount of uncertainty so that the desired minimal reward or demand is satisfied. In other words, the robustness function is the degree of resistance to uncertainty and immunity against less profit. This means that a large value of $\hat{\alpha}$ is desirable. Therefore, it can be defined mathematically through an optimization problem as Eq. (24).

On the contrary, the opportunity function (25) expresses the minimum amount of uncertainty so that the desired maximal target is achieved. This function is the immunity against windfall profit. Thus, a low value of $\hat{\beta}$ is desirable. A low value of $\hat{\beta}$ indicates a situation in which the profit is achievable. The corresponding mathematical formulation can be represented by the minimization problem (25). An IGDT decision-making framework comprises three elements as follows [20-22]:

a. System model

The system model $C(A,\lambda)$ gives the input/output behavior of the system, which needs decision making. Using the system model $C(A,\lambda)$, the result of choosing decision variables A and the uncertain parameter λ is defined. In this research, the system model presents the outcome of VPP from participating in energy/reserve markets.

b. Performance requirements

The performance requirement can be whether the least expected benefit of a firm or the maximum expected cost it should pay. It is important to state that due to uncertainties, the minimum requirements are risk dependent. IGDT guarantees the determiner to achieve the minimum requirements by choosing decision variables in the presence of uncertainties of parameters. These requirements can be evaluated through robustness and opportunity functions mentioned in equations (24) and (25).

c. Uncertainty model

The uncertainty model shows the distance between unknown and forecasted values. In the IGDT method, the envelope bound model is considered as the uncertainty model $U(\alpha,\hat{x})$. The uncertainty model $U(\alpha,\hat{x})$ presents a set for all values with deviations not more than α from x, as follows:

$$x \in U(\alpha,\hat{x})$$

$$U(\alpha,\hat{x}) = \left|\frac{x-\hat{x}}{\hat{x}}\right| \leq \alpha \tag{26}$$

In this research, IGDT has been applied to VPP self-scheduling problem to help the determiner gain a robust profit in the presence of uncertainties in market prices. The prices in pool-based market are considered to be forecasted as $\hat{\boldsymbol{\lambda}} = \{\hat{\lambda}_1,\dots,\hat{\lambda}_T\}$. An envelope bound model $U(\alpha,\tilde{\lambda})$ is assumed as the IGDT uncertainty model to define the uncertainty vector λ by:

$$U(\alpha,\tilde{\lambda}) = \left\{\lambda : \left|\frac{\lambda-\hat{\lambda}}{\hat{\lambda}}\right| \leq \alpha\right\}, \alpha \geq 0 \tag{27}$$

where, $\hat{\lambda}$ is the forecasted amount of the actual price λ. α shows the radius that the parameter can drift from the forecasted value which defines the opportunity value for the opportunity-seeking strategy and the robustness value for the risk-averse strategy. This model expresses an envelope-bound model in which the magnitude of deviation is proportional to the forecasted value.

3.2. Robustness function

Risk-averse VPPs tend to guarantee a critical profit, denoted as B_R, which is protected against unpleasant deviations of actual energy market prices from their forecasted amounts. Therefore, robust performance of a VPP in energy/reserve markets can be formulated as:

$$\hat{\alpha}(A, B_R) = \max \alpha \tag{28}$$

Subject to:

$$\min \{\sum_{t=1:T} \begin{pmatrix} E_t \times \lambda(t) + R_{Con}(t) \\ + R_{Res}(t) + R_{Ret}(t) - \text{cost}(t) \end{pmatrix}\} \geq B_R \tag{29}$$

$$B_R = (1 - \sigma_R) B_D \tag{30}$$

$$\lambda(t) \leq (1 + \alpha)\hat{\lambda}(t) \tag{31}$$

$$\lambda(t) \geq (1 - \alpha)\hat{\lambda}(t) \tag{32}$$

$$\text{Equations (2) – (23)} \tag{33}$$

It should be noted that Equations (2) – (23) are added into the above optimization problem as constraints in (33). The VPP schedule achieved from the above-mentioned optimization model is robust to the predefined amount of B_R which is the least expected outcome for VPP. To put it another way, if all absolute relative errors of forecasted prices are smaller than or equal to $\hat{\alpha}$, the profit of VPP will be greater than B_R. In this way, the maximum tolerable error for forecasting will be $\hat{\alpha}$.

3.3. Opportunity function

Risk-seeker VPPs tend to make use of pleasant deviations of actual energy market prices from their forecasted values and reach the target profit, denoted as B_O. Hence, the opportunity function for risk-seeker VPP can be expressed as:

$$\hat{\beta}(A, B_O) = \min \alpha \tag{34}$$

Subject to:

$$\max \{\sum_{t=1:T} \begin{pmatrix} E_t \times \lambda(t) + R_{Con}(t) + R_{Res}(t) \\ + R_{Ret}(t) - \text{cost}(t) \end{pmatrix}\} \geq B_O \tag{35}$$

$$B_O = (1 + \sigma_O) B_D \tag{36}$$

$$\lambda(t) \leq (1 + \alpha)\hat{\lambda}(t) \tag{37}$$

$$\lambda(t) \geq (1 - \alpha)\hat{\lambda}(t) \tag{38}$$

$$\text{Equations (2) – (23)} \tag{39}$$

It should be noted that Equations (2) – (23) are added into the above optimization problem as constraints in (39). The above-mentioned optimization problem leads to a schedule that the owner is hopeful to gain a predefined target outcome of B_O when all absolute relative errors of forecasted prices are greater than or equal to $\hat{\beta}$. To put it another way, $\hat{\beta}$ is the least required error of forecasting which leads to the least expected target B_O.

Please note that any uncertain parameter might have negative or positive impacts on the system. Therefore, the IGDT method is utilized as a proper method to evaluate both negative and positive sides of uncertainty by considering robustness and opportunity functions, respectively.

4. NUMERICAL RESULTS

4.1. Case system

To evaluate the proposed self-scheduling model, the case study is chosen to be identical to the test system studied in [40-41]. In this test system, a VPP with eight DGs is considered to participate in energy/reserve markets. Figure 2 shows the network diagram of the case system. The network is connected to the main grid (infinite bus) at Bus 1.

Interruptible loads at buses 4 and 7, respectively, can be reduced up to 30 kW and 40 kW. The costs of curtailing loads at these buses are given in Eqns. (40) and (41), respectively.

$$c_{us}(P_{us}) = 0.01 \times P_{us}^2 + 3 \times P_{us} \tag{40}$$

$$c_{us}(P_{us}) = 0.01 \times P_{us}^2 + 1.5 \times P_{us} \tag{41}$$

In this study, similar to [23], the VPP's demand in each day has been divided into three load levels addressed as peak, shoulder, and valley. The retail rates for each load level are given in Table 1. Bilateral contracts are considered to be convenient for the scheduling horizon. Table 2 provides the data for bilateral contracts, including the type of the contract, the energy to be exchanged, the energy price, and available hours for the contract.

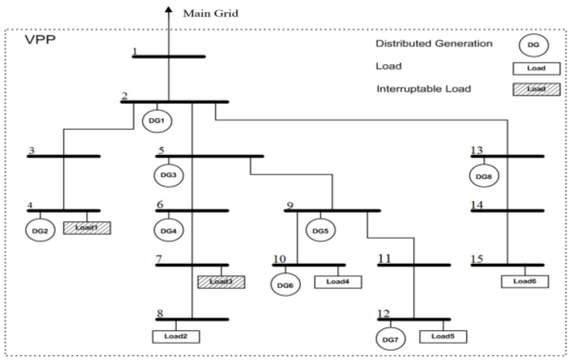

Fig. 2. The case system

Table 1. Retail rates at daily load levels

Load level	Hours of day	Retail rate (Monetary units/kW)
Valley	1,2,3,4,5,6,7,8	8
Shoulder	9,10,15,16,17,18,23,24	9
Peak	11,12,13,14,19,20,21,22	11

Table 2. Bilateral contracts specification

#	Type of contract	Amount (kW)	Price (Monetary units/kW)	Load Level

1	Bid to sell	40	6.2	Valley
2	Bid to sell	60	9.3	Shoulder
3	Bid to sell	80	14.7	Peak
4	Bid to buy	30	6.1	Valley
5	Bid to buy	50	8.9	Shoulder
6	Bid to buy	70	12.6	Peak

The net forecasted load over the scheduling horizon (1 week) and the forecasted clearing prices for energy/reserve markets are illustrated in Figures 3.a and 3.b, respectively. DG1, DG4, and DG8 besides interruptible loads in busses 4 and 7 are assumed as providers of reserve service. The proposed framework is modeled in GAMS 22.0.35 and solved using the BARON solver. It should be noted that the problem is a mixed-integer non-linear programming (MINLP) model. Therefore, to overcome the solution complexities, the Benders' cut decomposition has been utilized [38]. To establish simulations, the deterministic VPP's self-scheduling problem formulated in section 2 is solved according to the forecasted market prices. The desired optimal profit B_D is 126001.6 monetary units.

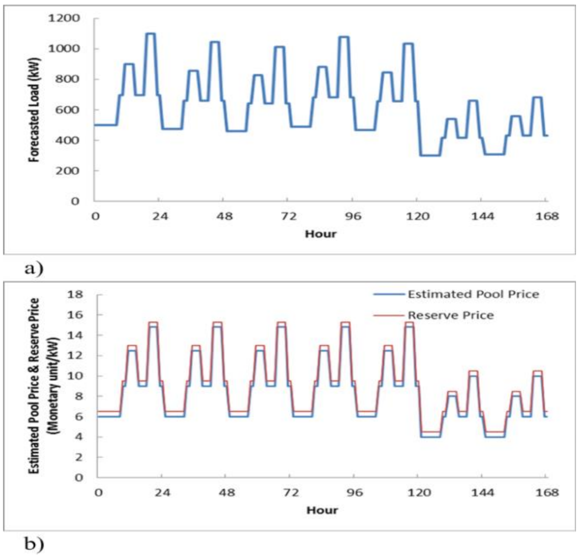

Fig. 3. The Forecasted a)load of VPP b)prices of energy/reserve markets over the scheduling horizon

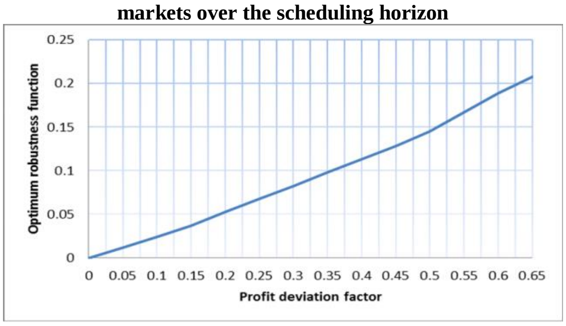

Fig. 4. The optimum robustness parameters over different profit deviation factors

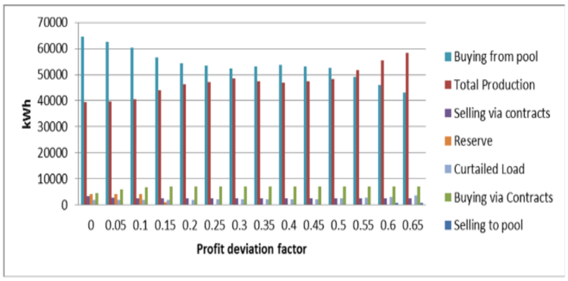

Fig. 5. The different robust schedules of VPP for various profit deviation factors

4.2. VPP's robust self-scheduling

The robust optimization problem (28)-(33) has been solved for different amounts of σ_R . The results in different optimum robustness functions depicted in Fig. 4. This figure reveals that, for example, a critical outcome of $B_R = 63000.787$ ($\sigma_R = 0.5$) is assured when none all hourly errors are not more than $\hat{\alpha} = 0.145$. It indicates that expecting smaller critical profits results in tolerability of larger errors in forecasting prices. However, the expected critical profit may not be obtained if real prices are not in the corresponding robust region.

Fig. 5 shows the robust schedules of VPP for different amounts of σ_R . The changes in the schedules of VPP over different values of $\sigma_R = 0$ to $\sigma_R = 0.65$ are to help VPP tolerate greater unfavorable price deviations. As can be seen in Fig. 5, for lower values of risk (higher σ_R), buying from the pool, with volatile prices, is decreased and buying via contracts and production are increased. Buying from the pool is decreased by 35.4 percent when σ_R is increased from 0 to 0.65. On the other hand, total production of the VPP is increased by 48.7 percent when σ_R is increased from 0 to 0.65. Due to high production of units in lower values of risk, the participation in reserve market is decreased.

4.3. Opportunistic self-scheduling of VPP

To assess the profit obtained through opportunistic self-scheduling, using equations (34) to (39), different opportunistic schedules for the operation of VPP are investigated with σ_O value ranging from zero to 0.65.

Fig. 6 depicts variations of opportunity parameter $\hat{\beta}$ over different profit deviation factors. This figure reveals that to obtain a greater desired target outcome, price mismatch from forecasted values should be desirable and high.

Fig. 7 shows the opportunistic schedules of the VPP for different values of σ_O. The changes in the schedules of the VPP over different values of σ_O are to help the VPP gain greater profits from desired price deviations. As it can be seen in this figure, with increasing σ_O, the VPP tends to increase buying from the energy market, with uncertain prices, and decrease local generation as well as buying energy via signing bilateral contracts. In this schedule, buying from the pool market is always more than total production for all different values of σ_O. Buying from the pool is increased by 30.7 percent when σ_O is increased from 0 to 0.65. On the other hand, total production of the VPP is decreased by 27.5 percent when σ_O is increased from 0 to 0.65.

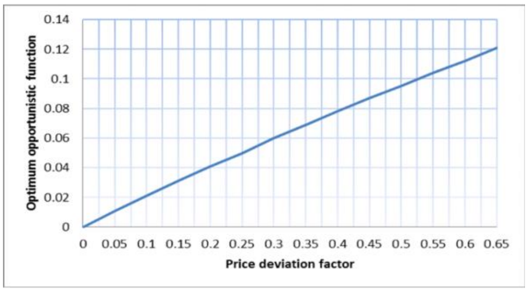

Fig. 6. Optimum opportunity parameters over different profit deviation factors

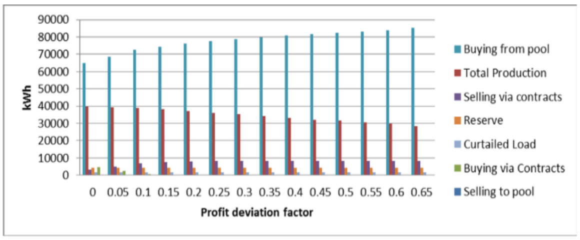

Fig. 7. The opportunistic schedules of VPP for different profit deviation factors

Table 3. Profits of the VPP in each scenario

Price Scenario	Benefit of Robust scheduling (Monetary Units)	Benefit of Opportunistic scheduling (Monetary Units)
Scenario 1	124000.12	126341.58
Scenario 2	104465.61	95656.36
Scenario 3	122220	123878.47
Scenario 4	94999.04	86546.63
Scenario 5	149471.9354	161633.75
Scenario 6	95954.86	85547.17

It should be noted that the main difference between the IGDT model with other uncertainty modeling systems is that the VPP can decide according to the risk or caution level, while other uncertainty modeling methods do not provide such an option for the decision-maker. In other methods, the self-scheduling is done without any predefined values for risk and caution. Therefore, any level of risk and caution illustrated in figures 5 and 7 may be the final solution, while in our model, the VPP can decide his/her desired scheduling based on the risk/caution level.

4.4. Evaluation of robust and opportunistic schedules in various market settlement conditions

In this part, we investigate the changes in the VPP's profit through different operating schedules under various market settlement conditions. To simulate various market-clearing conditions, different scenarios of real market prices have been considered. The robust regions for all of these scenarios correspond to $\sigma_R = 0.2$. These scenarios for energy/reserve market prices are presented below:

1. In scenario 1, real prices are randomly located in the corresponding robust region and they all are below the forecasted prices.
2. In scenario 2, all real prices are randomly located in the corresponding robust region and are above the forecasted prices.
3. In scenario 3, all real prices are distributed randomly in the corresponding robust region.
4. In scenario 4, real prices have some spikes over the forecasted prices.
5. In scenario 5, some negative spikes happen in real market prices compared with the forecasted prices.
6. In scenario 6, both negative and positive spikes happen in real market prices compared with the forecasted prices.

To evaluate different schedules under various market settlement conditions, the robust and opportunistic operating schedules expressed by $\sigma_R = 0.2$ and $\sigma_O = 0.2$ have been used. The critical outcome for the robust schedule and the target outcome for the opportunistic schedule are $B_R = (1-0.2)\times 126001.6 = 100801.3$ and $B_O = (1+0.2)\times 126001.6 = 151201.9$ monetary units, respectively. Considering the previously defined scenarios, the outcome of the opportunistic and the robust schedules in each scenario are determined. The gained profits of the VPP from these schedules for each scenario are given in Table 3.

Table 3 shows that while clearing prices of the first three scenarios are all located in the corresponding robust region, the critical outcome of $B_R = 100801.3$ will be guaranteed for the VPP. For scenarios 4 and 6, the achieved profits for the robust schedule are 94999.04 and 95954.86 monetary units, respectively.

The profits for these two scenarios are below the critical outcome. The reason is that the real prices are out of the corresponding robust region in some hours. The obtained profit from the robust scheduling in scenario 5 not only is more than the critical outcome but also is more than the profits obtained by the VPP in other scenarios. That is because the VPP can play a dual role (seller/ buyer) as a player in energy/reserve markets. Therefore, negative price spikes in the real market prices may lead to the higher outcome for the VPP by purchasing energy from the market. However, achieving such a profit has no conflict with the concept of robust self-scheduling.

On the contrary, due to a lack of satisfying price spikes in real market prices, the VPP's opportunistic schedule in each of the first three scenarios has not reached the predefined target profit. It is necessary to note that the opportunistic schedule in scenario 2 fails to reach the critical outcome either. The situation is similar for scenarios 4 and 6. In these scenarios, real market prices deviate undesirably from the VPP point of view. In the fifth scenario, the situation is a bit different. In this scenario, there are favorable differences between real and forecasted market prices. Due to these differences, the VPP will obtain higher profit in the time of purchasing energy from the market.

5. CONCLUSION

This paper proposed two new IGDT-based models for the risk-constrained self-scheduling problem of VPPs considering uncertain pool market prices. A VPP with risk-aversion behavior, using the proposed formulation, assures a least predefined profit called critical profit while the real prices are in the robust corresponding area. In contrast, a risk seeker VPP may reach a predefined target profit by using the proposed framework and with the help of desired sudden large price spikes that may happen in the markets.

For the purpose of illustrating the validity of the IGDT-based formulation, the proposed method was tested on a VPP case system. Robust and opportunistic scheduling of the VPP were determined through the method. Using this method, risk and caution in self-scheduling for the VPP were quantified with respect to the obtained profit. In the proposed robust formulation, the profit relies on how cautious is the VPP about considering tolerance for forecasted errors. On the contrary, in opportunistic self-scheduling, the profit relies on how ambitious is the VPP by choosing the targeted profit. Our future work will consider the impacts of uncertainties in loads and intermittent renewable resources.

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