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Research Paper

An Information Gap Decision Theory Approach for Optimal Bidding of a Virtual Power Plant under System Uncertainties

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Abstract: Operation scheduling of a Virtual Power Plant (VPP) includes several challenges for the system according to the uncertain parameters, and security requirements, which intensify the need for more efficient models for energy scheduling and power trading strategies. Making suitable decisions under uncertainties, related to Renewable Energy Resources (RES), loads, and market prices impose extra considerations for the problem to make a clearer insight for the system operators to participate in local markets. This paper proposes a new risk-based hybrid stochastic model to investigate the effects of wind turbine power fluctuations on profit function, energy scheduling, and market participating strategies. Also, an incentivized Demand Response Program (DRP) is used, to enhance the system's efficiency. The results of the study indicate that the proposed model based on Information Gap Decision Theory (IGDT) approach makes a clearer environment for the decision-maker to be aware of the effects of risk-taking or a risk-averse strategy on financial profits. The results show that a 30% of robustness and opportunity consideration would change the profit function from -12.5% up to 14.5%, respectively. A modified IEEE 33 bus test system is used to simulate a technical VPP considering the voltage stability and thermal capacity of line requirements.

Keywords: Virtual Power Plant, Uncertainty, Stochastic Programming, IGDT, Scheduling.

1 Introduction

1.1 Motivation and Aims

A Virtual Power Plant as a single plant in the electricity market plays a significant role in the technical and economic management of generation facilities in reducing the operating costs and maximizing the revenue function of the system. A VPP includes a cluster of distributed generation units, controllable loads, and Energy Storage Systems (ESS), which are integrated to operate as a single power plant without any direct physical connection or power lines [1]. The hybridization of multiple energy sources improves the system efficiency and the reliability of the supply in comparison to single-source generators [2]. In this regard, two different groups of VPPs are formed as commercial and technical models, which the technical category incorporates the actual location of Distributed Energy Resources (DER) in the network and considers the network operational constraints in

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Nomenclature

Indices	
t	Indices of time periods, hour
b, bp	Indices of buses
h	Indices of HSS units
g	Indices of TG units
wt	Sets of buses that are connected to DG
pv	Indices of PV units
d	Indices of DRP
e	Indices of ESS units
k	Indices of Step-wise DRP
s	Indices of scenario
π_b	Sets of connection for energy generation units and buses
Scalars	
λ^u	Electricity price to sell power to upstream grid ($/MW)
$\lambda^{PV/WT}$	Operation and maintenance cost of WT/PV unit ($/MW)
P_r	Rated power of wind turbines (MW)
$v_{ci/co}$	Wind speed of cut-in/cut-out for the WT unit (m/s)
v_r	Rated wind speed of WT unit (m/s)
F_r/F_o	Critical profits of Robustness/Opportunity function ($)
Parameters	
$X_{b,bp}$	Reactance between bus *b* and *bp*
ρ_s	Probability of each scenario
$\lambda_{t,s}$, $Q_{b,t}$	Expected market clearing price at time t and scenario s to trade energy with customers ($/MW)
$v_{t,s}$	Speed of the WT unit at time t and scenario s (m/s)
η_e^{ch}/η_e^{dch}	Charge/discharge efficiency of the ESS unit e
$\eta_h^{P2H}/\eta_h^{H2P}$	P2H/H2P efficiency of the HSS unit h
$P_e^{ch,max}/P_e^{dch,max}$	Maximum charge/discharge rate of the ESS unit e unit (MW)
$P_h^{P2H,max}/P_h^{P2H,min}$	Maximum/Minimum hydrogen generation of HSS unit h (MW)
$P_h^{H2P,max}/P_h^{H2P,min}$	Maximum/Minimum hydrogen consumption of HSS unit h (MW)
$P_g^{TG,max}/P_g^{TG,min}$	Maximum/Minimum power output of TG unit g (MW)
SOC_e^{max}/SOC_e^{min}	Maximum/Minimum state of charge value for the ESS unit e (MW)
A_h^{max}/A_h^{min}	Minimum/Maximum energy of HSS unit h (MW)
$A_{h,int,s}$	Stored hydrogen level of HSS unit h in initial state and scenario s (MW)
M_h^{max}	Maximum energy conversion of hydrogen to other type of energy (MW)
$P_{b,bp}^{l,max}$	Maximum thermal capacity of line connecting bus b and bp (kW)
RU_g/RD_g	Ramp-up/ramp-down rate of TG unit g (MW/h)
$T_g^{on/off}$	Minimum up/down time of TG unit g (h)
SU_g	Start-up cost of TG unit g ($)
a/b/c	Cost function coefficient of energy generation units ($/MWh)
$\Delta\delta_b^{max}/\Delta\delta_b^{min}$	Maximum/Minimum phase angel deviation of bus b (Degree)

Variables	
α/β	Robustness/Opportunity
R_s	Total revenue of the VPP in scenario s ($)
C_s	Total cost of the VPP in scenario s ($)
$C_{t,s}^{Buy}$	Total cost of Buying energy at time t and scenario s ($)
$C_{t,s}^{DRP}$	Total cost of DRP at time t and scenario s ($)
$C_{t,s}^{TG}$	Total cost of TG units at time t and scenario s ($)
$C_{t,s}^{WT}$	Total cost of WT units at time t and scenario s ($)
$C_{t,s}^{PV}$	Total cost of PV units at time t and scenario s ($)
$C_{t,s}^{HSS}$	Total cost of HSS units at time t and scenario s ($)
$P_{pv,t,s}^{PV}$	Output power of PV unit PV, at time t and scenario s (MW)
$P_{wt,t,s}^{WT}$	Output power of WT unit WT, at time t and scenario s (MW)
$P_{g,t,s}^{TG}$	Output power by TG unit g, at time t and scenario s (MW)
$P_{b,t,s}^{d}$	Electricity demand of bus b at time t and scenario s (MW)
$P_{d,t,s}^{DRP}$	Reduced amount of power by DR provider d, at time t and scenario s (MW)
$P_{t,s}^{sell/buy}$	Power selling/buying of VPP at time t and scenario s (MW)
$P_{e,t,s}^{ch}/P_{e,t,s}^{dch}$	Charged/discharge power of the ESS unit e, at bus b, time t and scenario s (MW)
$P_{h,t,s}^{H2P}$	Power consumption of HSS unit h, at time t and scenario s (MW)
$P_{h,t,s}^{P2H}$	Power generation of HSS unit h, at time t and scenario s (MW)
$P_{b,bp,t}^{l}$	Power flowing between branch of bus b and bp at time t, kW
$SOC_{e,t,s}$	State-of-charge of the ESS unit e, at time t and scenario s (MW)
$M_{h,t,s}$	Power conversion of HSS unit h, at time t and scenario s, as energy loss (MW)
$A_{h,t,s}$	Stored hydrogen level of HSS unit h, at time t and scenario s (MW)
$X_{g,t,s}^{off}/X_{g,t,s}^{on}$	Off/On time of TG unit g at scenario s
$\delta_{b,t}$	Phase angel of bus b at time t, (Degree)
Binary Variables	
$I_{e,t,s}^{ch}/I_{e,t,s}^{dch}$	Binary variable for charge/discharge modes of the ESS unit e at time t and scenario s
$I_{h,t,s}^{P2H}/I_{h,t,s}^{H2P}$	Binary variable for P2H/H2P modes of the HSS unit h,at time t and scenario s
$I_{g,t,s}$	Binary variable of TG units g, at time t and scenario s
Abbreviations	
DER	Distributed Energy Resources
DR/DRP	Demand Response/Demand Response Program
ESS	Energy Storage System
H2P	Hydrogen to Power
HSS	Hydrogen Storage System
P2H	Power to Hydrogen
PV	Photovoltaic
RES	Renewable Energy Source
TG/TGU	Thermal Generating/Thermal Generating Unit
VPP	Virtual Power Plant
WT	Wind Turbine

its decision makings process to avoid infeasibility in practical operation [3]. Wind turbine power as the most popular form of RESs is vastly utilized for clean energy generation [4]. However, uncertainty analysis should be properly considered in day-ahead unit commitment, optimal power flow, and economic dispatch models to avoid over and underestimation [5]. If the related uncertainty would not be properly addressed, several operational problems likely to occur, and economic energy scheduling will not be gained in real-time operation. So, a risk-based analysis must be executed for bidding and offering of a VPP, to make the operator aware of the effects of uncertainties. The risk-based IGDT approach is a suitable approach to deal with the risk of wind power uncertainty in scheduling analysis. According to the ownership concept and role of profit in the economic analysis of a VPP, it would be essential to consider the effects of uncertainty on bidding strategies to release the effects of fluctuations on the decision-making process and the gaining of financial profits.

1.2 Literature Review

Most of governments are currently pushing renewable growth policies to establish a secure, sustainable, and economical energy system while mitigating the consequences of climate changes [6]. According to the increasing rate of DER into the distribution system, several challenges related to technical, commercial, and regulatory requirements need to be considered in the scheduling procedure. Many researchers try to solve some of the barriers each of which study the problem from a specific point of view. Finding good strategies that deal with the uncertainties of daily operations requires the solution of a complex optimization problem to consider several uncertain quantities. Ref. [7] presents a review of optimization models for DGs under uncertainty. Ref. [8] proposes a multi-stage stochastic programming approach for the bidding strategy of a commercial VPP on the Spanish spot electricity market. The uncertain parameters include electricity prices and wind energy production neglecting the uncertainty of loads of the system. Although the proposed models incorporate the role of lower-level operators, under the final centralized solution approach the privacy of market participants would be influenced [9]. Ref. [10] presents the optimal bidding strategy of a VPP in the day-ahead market for energy, reserve, and regulation markets. But the uncertainty of loads is ignored in this paper. Ref. [11], proposes bidding strategy and profit allocation for energy storage participating in joint energy and regulation markets. To investigate the effects of load model and demand response programs, Ref. [12] proposes a bidding strategy for the electricity market considering the exact capacity of loads to accurately bid on market transactions. Ref. [13] presents a day-ahead and real-time market bidding and scheduling strategy for wind power participation based on shared energy storage. But risk-based analyses are ignored in this study. The machine learning models are also an efficient instrument for complex uncertainties with large-scale datasets compared to traditional approaches. Artificial intelligence-based methods and, in particular, deep learning have been widely applied in big data problems to forecast uncertain parameters. By predicting the uncertain parameters according to the neural networks, the stochastic problem can be solved in a deterministic manner. Ref. [14] has reviewed the methods of uncertainty forecasting for energy systems considering the MG structures. A forecasting procedure based on multi-task learning to predict the consumption load is proposed in Ref. [15]. The power generation uncertainty of a wind farm is predicted using machine learning methods in Ref. [16]. Deep learning methods have demonstrated good performance in different aspects, which can be employed in new structures [17]. Ref. [18] considers distributed generation units and DRP as VPP units. In this reference, the operators can select the best DRP in a scheduling procedure, but the scope of the paper does not include the technical VPPs. Ref. [19] investigates incentive-based DRP for VPP connected with wind, photovoltaic, and ESSs with uncertainties analysis. According to the risk aversion attitude of the problem structure, the objective function is defined based on the maximum procedure for the revenue function. Ref. [20] maximizes the VPP profit to make the best decisions on bidding/offering of VPPs to participate in the day-ahead, real-time, and spinning reserve market. The uncertainty lies in the energy and reserve prices, RESs production, and load consumption. This paper has ignored the risk analysis for uncertain parameters. Ref. [21] proposes a bidding strategy for VPPs to participate in the day-ahead and real-time market according to DRPs. The uncertainties related to RES and the DRPs are considered in a robust optimization model. Refs. [22], [23], and [24] also used robust optimization approaches to face uncertainty. Under robust hourly economic bidding strategies the optimal energy bids would be determined under the pessimistic attitude to cover the uncertainty. Ref. [25] uses a novel two-stage robust Stackelberg game for energy management and reserve scheduling considering the uncertainty of intermittent RES output and market prices. The proposed two-stage game model is linearized and solved by a column-and-constraint generation algorithm which makes a high computational burden for the problem of generating new variables in each iteration. Robust optimization as a general methodology includes a concept of robustness against optimization [26]. Risk analysis is a good complementary approach to fade the rigid and pessimistic attitudes of robust optimization. Although, the scenarios generation method using distribution functions is most widely used to model uncertainty in power system problems, using this method is not appropriate for short-term studies of wind power generation units [27]. IGDT approach can be considered along with risk analysis to make a Pareto attitude for the uncertain output power of a wind generation unit. Ref. [28] uses the IGDT approach to deal with wind power uncertainty in unit commitment problems. Ref. [29] uses the IGDT for optimal allocation of intelligent parking lots in distribution systems considering severe uncertainties. As the share of a stochastic energy generation unit is grown up in a model, the related effects need to be studied in more detail. Since the strong stochastic uncertainty of wind power brings challenges to the economic scheduling of a problem [30], the effects of uncertainty need to be considered in the model for rational bidding strategies. The ignorance of the uncertainty role in scheduling would influence the gaining of optimal profit for market participants.

1.3 Contribution and Innovations

According to the recent studies it can be deduced that none of the recent papers have proposed a risked-based model for power trading of independent operators considering the system uncertainties. In this regard, this paper is devoted to the role of wind turbine output uncertainty on the bidding strategy of VPPs consisting of RES, ESS, Hydrogen Storage Systems (HSS), and thermal energy generation units. According to the more share of wind energy generation units in RES of the proposed VPPs, the IGDT approach is employed to consider the related uncertainty, and the scenario generation method is used to consider the uncertainty of Photovoltaic (PV) units, load, and price parameters. The prominent features of the current paper are summarized as follows:

i) A new mixed-integer linear formulation for a hybrid IGDT-stochastic strategy to consider the uncertainty of RES units, loads, and market prices
ii) A risk-based model for optimal bidding and offering of a VPP to participate in the day-ahead market with an uncertain environment
iii) An operation scheduling model for a technical VPP considering demand response programs for priced-based load controls under security constraints of the system

1.4 Paper Arrangement

This article is arranged as follows: Section 2 presents the system models for a VPP. This section includes system components and related constraints according to the operating constraints and security requirements of the system based on a stochastic problem model. To consider the effects of WT uncertainty, the IGDT approach is modelled for the uncertainty analysis in section3. Obtained results are provided and discussed in Section 4. Finally, the conclusion part reports the major findings of the current study.

2 Virtual Power Plant Model

The proposed virtual power plant is comprised of RES, Thermal Generating Unit (TGU), EES, and HES unit. Also, priced-based demand response programs are employed to enhance the system's flexibility. The related constraints are described for each component. In the proposed hybrid IGDT-stochastic method, all uncertain parameters for PV outputs, loads, and price parameters are modelled using normal probability density functions. The area below the probability distribution curve in every period indicates each scenario's probability, and each relevant scenario is considered to be the average amount of the period. By dividing the normal distribution function into five sections five scenarios are generated for each uncertain parameter, which creates 125 scenarios for the entire problem. To decrease the number of scenarios, the scenario reduction method is employed according to Ref. [31].

2.1 Objective Function

The objective function of the VPP operator is to maximize the expected profit comprised of market participation revenue and energy generation costs according to Eq. (1). Equation (2) describes the revenue formulation. The cost terms are formulated in Eq. (3). The first term of revenue function is related to the revenue of selling power to customers and the second one is related to the selling power to the upstream grid. Total operating cost is calculated by summing the cost of buying power from the upstream grid, DRP cost, operating cost of TG units, and operating and maintenance cost of WTs, PVs, and HSS.

$$OF = \sum_{s=1}^{N_s} \rho_s \times (R_s - C_s) \tag{1}$$

$$R_s = \sum_{t=1}^{T}\sum_{b=1}^{N_{Bus}} \lambda^u P^d_{b,t,s} + \sum_{t=1}^{T} \lambda_{t,s} P^{sell}_{t,s} \quad \forall s \tag{2}$$

$$C_s = \sum_{t=1}^{T} C^{Buy}_{t,s} + C^{DRP}_{t,s} + C^{TG}_{t,s} + C^{WT}_{t,s} + C^{PV}_{t,s} + C^{HSS}_{t,s} \quad \forall s \tag{3}$$

2.2 System Components

2.2.1 Photovoltaic System

Although most studies omit the operating cost of the PVs, the related cost of RES needs to be modelled in the problem [27]. Equation (4) describes the operation cost of the PV unit.

$$C^{PV}_{t,s} = \sum_{pv=1}^{N_{pv}} \lambda^{PV} P^{PV}_{pv,t,s} \quad \forall t,s \tag{4}$$

2.2.2 Battery Energy Storage

Energy storage systems act as load and energy generation units under the charging and discharging process. Equation (5) describes the State-of-charge (SOC) of an ES system. Equation (6) indicates the minimum and maximum values of SOC. To avoid the simultaneous charging and discharging process, binary variables are used in Eq. (9), which are defined in Eq. (7) and Eq. (8) to restrict the maximum values. SOC for the initial state and the final status is equalized by Eq. (10).

$$SOC_{e,t,s} = SOC_{e,t-1,s} + \eta^{ch} P^{ch}_{e,t,s} - \frac{P^{dch}_{e,t,s}}{\eta^{dch}} \tag{5}$$

$$SOC^{min}_e \le SOC_{e,t,s} \le SOC^{max}_e \tag{6}$$

$$0 \le P^{ch}_{e,t,s} \le P^{ch,max}_e I^{ch}_{e,t,s} \tag{7}$$

$$0 \le P^{dch}_{e,t,s} \le P^{dch,max}_e I^{dch}_{e,t,s} \tag{8}$$

$$I^{ch}_{e,t,s} + I^{dch}_{e,t,s} \le 1 \tag{9}$$

$$SOC_{e,1,s} = SOC_{e,24,s} \tag{10}$$

2.2.3 Hydrogen Storage System

A hydrogen storage system is considered a combination of an electrolyzer, hydrogen tank, and a fuel cell unit [32], which its figure is depicted in Fig. 1.

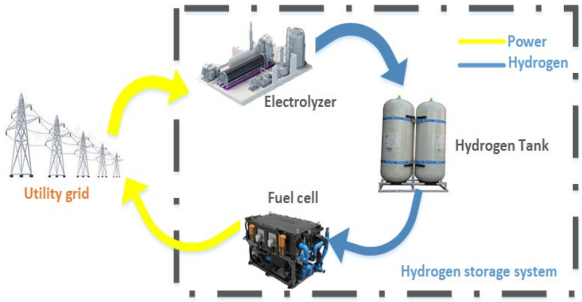

Fig. 1 Structure of the HSS.

Available hydrogen at each time step t in the HSS is determined by Eq. (11). The minimum and maximum capacity of HES is restricted by Eq. (12). Equation (13) determines an initial value for the SOC after the last charge or discharge process. Eq. (14) determines the maximum value of energy conversion. Eq. (15) and Eq. (16) indicates the maximum capacity of the electrolyzer and fuel cell as P2H and H2P value. Equation (17) prevents simultaneous P2H and H2P processes for HES. Eq. (18) indicates the total cost of HES. Details of calculations for the costs of an electrolyzer and fuel cell are formulated in Eq. (19) and Eq. (20) [32].

$$A_{h,t,s} = A_{h,t-1,s} + \eta^{P2H}_h P^{P2H}_{h,t,s} - \frac{P^{H2P}_{h,t,s}}{\eta^{H2P}_h} - M_{h,t,s} \tag{11}$$

$$A^{min}_h \le A_{h,t,s} \le A^{max}_h \tag{12}$$

$$A_{h,1,s} = A_{h,24,s} \tag{13}$$

$$0 \le M_{h,t,s} \le M^{max}_h \tag{14}$$

$$P^{P2H,min}_h I^{P2H}_{h,t,s} \le P^{P2H}_{h,t,s} \le P^{P2H,max}_h I^{P2H}_{h,t,s} \tag{15}$$

$$P^{H2P,min}_h I^{H2P}_{h,t,s} \le P^{H2P}_{h,t,s} \le P^{H2P,max}_h I^{H2P}_{h,t,s} \tag{16}$$

$$I^{H2P}_{h,t,s} + I^{P2H}_{h,t,s} \le 1 \tag{17}$$

$$C^{HSS}_{t,s} = C^{H2P}_{t,s} + C^{P2H}_{t,s} \tag{18}$$

$$C^{P2H}_{t,s} = \sum_{h=1}^{N_h} b^{P2H}_h \left(P^{P2H}_{h,t,s}\right) + c^{P2H}_h I^{P2H}_{h,t,s} \tag{19}$$

$$C^{H2P}_{t,s} = \sum_{h=1}^{N_h} a^{H2P}_h \left(P^{H2P}_{h,t,s}\right)^2 + b^{H2P}_h \left(P^{H2P}_{h,t,s}\right) + c^{H2P}_h I^{H2P}_{h,t,s} \tag{20}$$

2.2.4 Demand Response Program

In incentive-based DRP, the customers adjust their electricity consumption in response to the incentive payment. Figure 2 depicts the step-wise DRP model according to the price and quantity. Equation (21) formulates the minimum required response for DRP in the first step. Equation (22) indicates the related DRPs, which need to meet the principles of participating in the energy market schedule. Equation (23) calculates the DRP, and Eq. (24) indicates the cost of DRP to adjust the energy demands of users [33].

$$\mathrm{O}_{\min}^{\mathrm{d}} \le \mathrm{O}_{\mathrm{k}}^{\mathrm{d}} \le \mathrm{O}_{1}^{\mathrm{d}} \qquad \mathrm{k}=1 \tag{21}$$

$$0 \le \mathrm{O}_{\mathrm{k}}^{\mathrm{d}} \le \left(\mathrm{O}_{\mathrm{k+1}}^{\mathrm{d}} - \mathrm{O}_{\mathrm{k}}^{\mathrm{d}}\right) \ \forall \mathrm{k}=2,\dots,\mathrm{K} \tag{22}$$

$$\mathrm{P}_{\mathrm{d,t,s}}^{\mathrm{DRP}} = \sum_{\mathrm{k}} \mathrm{O}_{\mathrm{k}}^{\mathrm{d}} \tag{23}$$

$$\mathrm{C}_{\mathrm{t,s}}^{\mathrm{DRP}} = \sum_{\mathrm{d}} \sum_{\mathrm{k}} \lambda_{\mathrm{k}}^{\mathrm{d}} \, \mathrm{O}_{\mathrm{k}}^{\mathrm{d}} \tag{24}$$

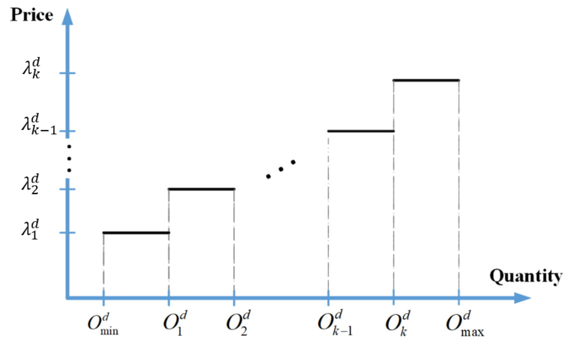

Fig. 2 Step-wise DRP [33].

2.2.5 Thermal Generating Units

Thermal generating units are included in the VPP structure as programmable units. Equation (25) describes generated power output of each TG unit according to the minimum and maximum restrictions. Ramp-up and ramp-down limit rates of the TGUs are modelled by Eqs. (26)-(27). Equations (28)-(29) model minimum up and down time constraints of the TGUs, respectively. Equation (30) considers the start-up cost value for TGUs. Equation (31) indicates the total operating cost of TGU.

$$\mathrm{P}_{\mathrm{g}}^{\mathrm{TG,min}} \mathrm{I}_{\mathrm{g,t,s}} \le \mathrm{P}_{\mathrm{g,t,s}}^{\mathrm{TG}} \le \mathrm{P}_{\mathrm{g}}^{\mathrm{TG,max}} \mathrm{I}_{\mathrm{g,t,s}} \tag{25}$$

$$\mathrm{P}_{\mathrm{g,t,s}}^{\mathrm{TG}} - \mathrm{P}_{\mathrm{g,t-1,s}}^{\mathrm{TG}} \le \mathrm{RU}_{\mathrm{g}} \tag{26}$$

$$\mathrm{P}_{\mathrm{g,t-1,s}}^{\mathrm{TG}} - \mathrm{P}_{\mathrm{g,t,s}}^{\mathrm{TG}} \le \mathrm{RD}_{\mathrm{g}} \tag{27}$$

$$(\mathrm{X}_{\mathrm{g,t-1,s}}^{\mathrm{on}} - \mathrm{T}_{\mathrm{g}}^{\mathrm{on}})(\mathrm{I}_{\mathrm{g,t-1,s}} - \mathrm{I}_{\mathrm{g,t,s}}) \ge 0 \tag{28}$$

$$(\mathrm{X}_{\mathrm{g,t-1,s}}^{\mathrm{off}} - \mathrm{T}_{\mathrm{g}}^{\mathrm{off}})(\mathrm{I}_{\mathrm{g,t,s}} - \mathrm{I}_{\mathrm{g,t-1,s}}) \ge 0 \tag{29}$$

$$\mathrm{SUC}_{\mathrm{g,t,s}} \ge \mathrm{SU}_{\mathrm{g}}(\mathrm{I}_{\mathrm{g,t,s}} - \mathrm{I}_{\mathrm{g,t-1,s}}) \tag{30}$$

$$\mathrm{C}_{\mathrm{t,s}}^{\mathrm{TG}} = \sum_{\mathrm{g=1}}^{\mathrm{N_g}} \mathrm{a_g}(\mathrm{P}_{\mathrm{g,t,s}}^{\mathrm{TG}})^2 + \mathrm{b_g}\mathrm{P}_{\mathrm{g,t,s}}^{\mathrm{TG}} + \mathrm{c_g}\mathrm{I}_{\mathrm{g,t,s}} + \mathrm{SUC}_{\mathrm{g,t,s}} \tag{31}$$

2.2.6 Load-flow Model

According to the technical restrictions of a VPP, Eq. (32) determines the power flow of lines under the DC power flow model. Equation (33) restricts line loading to the thermal capacity of lines. Equation (34) indicates maximum voltage angle deviation.

$$\mathrm{P}_{\mathrm{b,bp,t}}^{\mathrm{l}} = \frac{\delta_{\mathrm{b,t}} - \delta_{\mathrm{bp,t}}}{\mathrm{X}_{\mathrm{b,bp}}} \tag{32}$$

$$-\mathrm{P}_{\mathrm{b,bp,t}}^{\mathrm{l,max}} \le \mathrm{P}_{\mathrm{b,bp,t}}^{\mathrm{l}} \le \mathrm{P}_{\mathrm{b,bp,t}}^{\mathrm{l,max}} \tag{33}$$

$$\Delta\delta_{\mathrm{b}}^{\mathrm{min}} \le |\delta_{\mathrm{b,t}} - \delta_{\mathrm{bp,t}}| \le \Delta\delta_{\mathrm{b}}^{\mathrm{max}} \tag{34}$$

2.2.7 Power balance

Equation (35) describes power equality constraints for energy generation and power demands.

$$\begin{aligned} &P_{t,s}^{buy} + \sum_{g} P_{g,t,s}^{TG} + \sum_{wt} P_{wt,t,s}^{WT} + \sum_{pv} P_{pv,t,s}^{PV} \\ &+ P_{e,t,s}^{ch} + P_{h,t,s}^{H2P} - P_{t,s}^{sell} - P_{e,t,s}^{dch} - P_{h,t,s}^{P2H} \\ &- P_{b,t,s}^{d} - \sum_{d} P_{d,t,s}^{DRP} \\ &= \sum_{bp} P_{b,bp,t}^{l} \qquad \forall t, \forall s, \forall b\colon \{g, wt, pv, e, h, d\} \\ &\in \pi_b \end{aligned} \tag{35}$$

2.2.8 Wind Turbine

The maximum value of power output of wind turbines is formulated as a function of wind speed in Eq. (36). Equation (37) indicates the output power of WT to the maximum valid values. The operating cost of WT units is modeled in Eq. (38) [27].

$$P_{wt,t}^{WT,max} = \begin{cases} P_r \times \dfrac{(v_t - v_{ci})}{(v_r - v_{ci})} & v_{ci} \le v \le v_r \\ P_r & v_r \le v \le v_{co} \\ 0 & otherwise \end{cases} \tag{36}$$

$$P_{wt,t}^{WT} \le P_{wt,t}^{WT,max} \qquad \forall wt, t \tag{37}$$

$$\mathrm{C}_{\mathrm{t}}^{\mathrm{WT}} = \sum_{\mathrm{wt=1}}^{\mathrm{N_{wt}}} \lambda^{\mathrm{WT}} \mathrm{P}_{\mathrm{wt,t}}^{\mathrm{WT}} \tag{38}$$

2.2.9 Bidding Offering Curves

VPPs strategies on market participating is modelled in Eq. (39) and Eq. (40).

$$P_{t,s}^{sell} - P_{t,\tilde{s}}^{sell} \geq 0 \text{ if } \lambda_{t,s} \geq \lambda_{t,\tilde{s}} \quad (39)$$

$$P_{t,\tilde{s}}^{buy} - P_{t,s}^{buy} \geq 0 \text{ if } \lambda_{t,s} \geq \lambda_{t,\tilde{s}} \quad (40)$$

2.2.10 Linearization of Model

According to the HSS and TGUs, the non-linear equations need to be linearized to give the optimal global solution for the problem. Ref. [34] determines the linearization process to achieve linear cost function and operating constraints.

3 Proposed Hybrid IGDT-based Risk-Constrained Approach

IGDT does not just analyze the worst strategies like robust optimization, which only deals with the worst case. This technical analysis of the worst and the best strategies. The IGDT works based on error adjustment attitudes for actual and forecasted parameters to consider the effects of the worst and the best case. It addresses both conflicting issues of profit reduction under risk-averse behaviors of prosumers and probable increases in profit under a risk-taking procedure. Using two immunity functions of robustness and opportunity, the two conflicting issues can be studied in the problem [35]. Ref. [36] describes the maximum WT power output fluctuation in the scheduling process. The IGDT method is composed of three main parts system model, operation requirements, and uncertainty modeling. The objective function of the problem to maximize the total profit of the VPP is formulated as $OF(X, P^{WT})$, which X is related to the decision variable and P^{WT}, is the uncertain parameter [31]. Equation (41) indicates the maximum fluctuation interval for the wind turbine power output.

$$U(\alpha, \tilde{P}^{WT}) = \left\{ P^{WT} : \frac{|P^{WT} - \tilde{P}^{WT}|}{P^{WT}} \leq \alpha \right\}, \alpha \geq 0 \quad (41)$$

3.1 Risk-averse Strategy Based on Robustness Function of IGDT

In order to be immune to decreasing the WT output power, $\hat{\alpha}(F_r)$ determines the maximum resistance against any decrease of WT power output. The robust optimization of the IGDT technique is modeled in Eq. (42). In this equation the parameter F_r is related to the predetermined amount of objective function, which is determined system operator. Also, μ is related to the setting parameter for the percentage of increasing cost due to the uncertain parameter.

$$\begin{aligned} &\hat{\alpha}(F_r) = \max_{\alpha} \{ \alpha : \min(OF(X, P^{WT})) \} \\ &s.t. \\ &OF(X, P^{WT}) \geq F_r \\ &F_r = OF(X, \tilde{P}^{WT}) \times (1 + \mu) \\ &0 \leq \mu < 1 \end{aligned} \quad (42)$$

3.2 Risk-taker Strategy Based on Robustness Function of IGDT

In contrast to the RO, in opportunity function provides the maximum amount of the objective function under an optimistic attitude for the energy generation of WT units. The opportunity function of IGDT is defined in Eq. (43). F_r is the predetermined value of the objective function as the least expected revenue of market participants. The ω is also determined by the operator.

$$\begin{aligned} &\hat{\beta}(F_o) = \min_{\beta} \{ \beta : \max(OF(X, P^{WT})) \} \\ &s.t. \\ &OF(X, P^{WT}) \geq F_o \\ &F_o = OF(X, \tilde{P}^{WT}) \times (1 - \omega) \\ &0 \leq \omega < 1 \end{aligned} \quad (43)$$

4 Case Studies

4.1 Parameters

IEEE 33-bus test system with four TG units located at buses 5, 12, 16, and 24, five PV units at buses 6, 20, 24, 26, and 32, three WTs at buses 13, 15, 30, an ES at bus 20, and finally an HSS located at bus 14 is considered for the case studyFig.3 depicts the related structure.

Figure 4 shows the predicted values of RES units Fig. 5 shows the Electricity demand of buses for VPP, which the share of hourly demand is depicted in Fig. 6. Fig. 7 reports the predicted market prices used for simulation. TG unit specifications are reported in Table 1. Wind turbine unit's specifications are reported in Table 2.

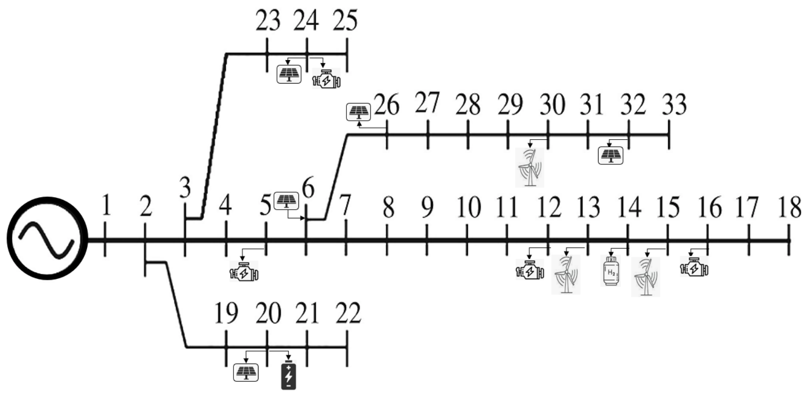

Fig. 3 A technical virtual power plant.

Table 1 Information of thermal generating units

	Pmax (MW)	Pmin (MW)	MUT (Hour)	MDT (Hour)	RU (MW)	RD (MW)	SU ($)	a ($/MW)	b ($/MW)	c ($/MW)
G1	3.5	1	2	2	1.8	1.8	15	0.002	87	27
G2	3	0.75	1	1	1.5	1.5	10	0.003	87	25
G3	3	0.75	1	1	1.5	1.5	10	0.003	87	25
G4	4.1	1	2	2	1.8	1.8	15	0.184	81	26

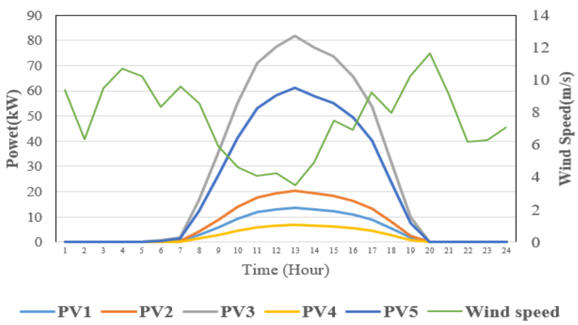

Fig. 4 Predicted values of RES units.

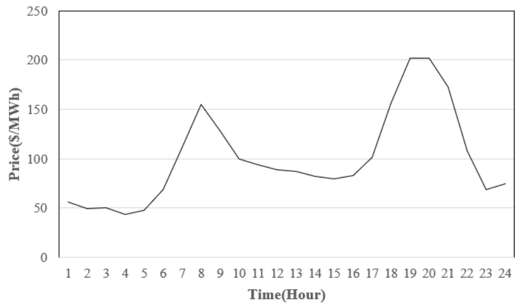

Fig. 7 Predicted market prices.

Table 2 Wind turbine unit's specifications

Rated power (kW)	Rated speed (m/s)	Cut-in speed (m/s)	Cut-out speed (m/s)
400	14	2	25

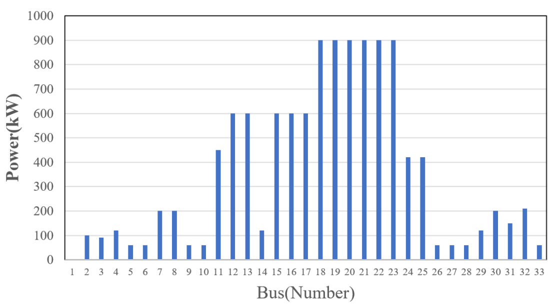

Fig. 5 Electricity demand of VPPs buses.

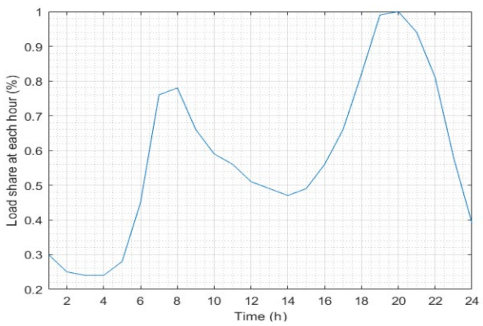

Fig. 6 Load share of each bus.

4.2 Numerical Result

According to the main scope of the current work to determine the effects of decision-maker strategy on energy scheduling, power trading, and optimal bidding curve to submit to the day-ahead market the results are provided in three different cases of risk-taker, risk-neutral, and risk-averse strategies, which are corresponded to opportunity, deterministic, and robustness functions of hybrid risk based IGDT technique. Also, optimal scheduling of the different components of the system is studied considering the uncertainty of RES generation, loads, and market price. In addition, to show the effectiveness of the DRP model, with and without DRP cases are considered to make a result comparison.

4.2.1 Profit Analysis

Obtained results for the case studies indicate that the behavior of the proposed VPP for output power fluctuation of the WTs is approximately linear according to the profit gain function, absolutely with different sensitivity and ramp rates. Figure 8 depicts the obtained results of profit functions against the robustness/opportunity parameters. Obtained results with zero values of robustness/opportunity parameters are considered risk-neutral strategies. The results show that, by increasing the robustness parameter, the total expected profit is considerably reduced, from \$2076.19 to \$1776.189, which indicates a 14.5% reduction in expected profit. Despite profit reduction, results show that under this circumstance robustness parameter is equal to 0.3, which means VPP is robust against a 30% fluctuation of WTs energy generation output. In contrast, under a risk-taker strategy and opportunity parameter of 0.3, the expected profit is increased from 2076.19 \$ to 2376.189\$. This means that a 30% increase in the generation output of WTs, will result in about a 15% increase in total profit. The results of the study show that for the proposed model it is not so recommended to have an intensive risk-averse strategy, because the target profit levels ramp shows that, under a specific robust/opportunity parameter the reduction in profit is more than the obtained profit of a certain value for opportunity parameter. The proposed structure would help the decision maker to gain a more clear insight into uncertain parameters before deciding on market participation.

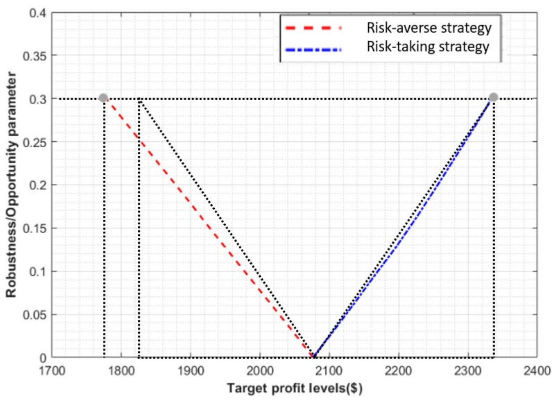

Fig. 8 Robustness/opportunity target profits against robustness/opportunity parameters.

4.2.2 Operation Scheduling of TGUs

Four TG units are considered conventional energy-generating sources, and among them, G2 and G3 can be considered better cases in comparison to the others according to the lower operating cost and better specifications. So, two different TG units of G1 and G4 from different categories are chosen, for results illustrations. Figure 9 shows the generated output power of the G1 and G4 under different strategies. According to the result analysis, it can be deduced that risk-based analysis has more prominent effects on expensive TG units, which changes the optimal scheduling decision into a less operation of expensive units under risk-taking attitudes. In contrast, for a cheaper unit such as G4, the scheduling process is approximately the same for all scenarios. The opportunity for risk-taking would cover the high expense of operating for less efficient generating units. According to the G4 diagram, it can be deduced that the risk-based problem model does not influence dramatically the scheduling process of this unit under a low operating cost of energy generation.

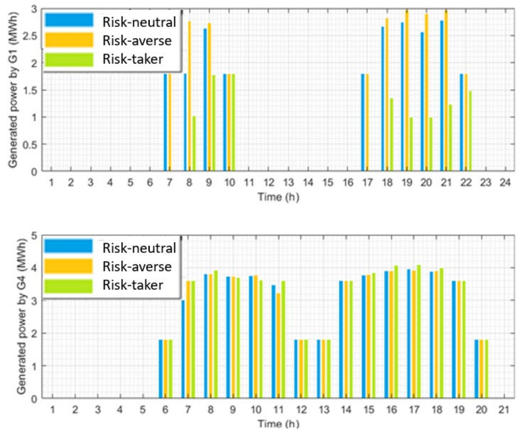

Fig. 9 Generated power by G1 and G4.

4.2.3 Demand Response Program

Figure 10 illustrates the results of the DRP schedule, which allows connected customers to buses 26-33 to be incentivized for demand reduction under participation in DRPs. Obtained results show that in a risk-taking strategy, the participation of prosumers between hours 17-22 is increased, which makes an opportunity for prosumers to participate in the energy trading market during the peak hours of demand with higher energy trading prices.

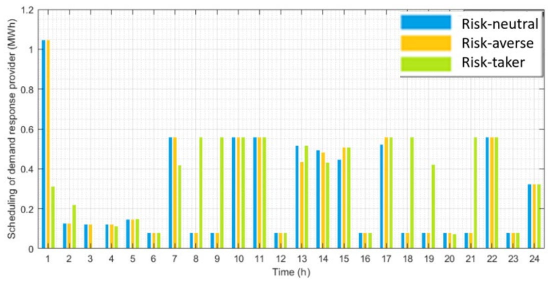

Fig. 10 Scheduling of the demand response program.

4.2.4 Operation Scheduling of Energy Storages

Figure 11 illustrates the SOC of the battery ES, which is located on bus 20. According to the obtained results of hours 1-8, more energy is stored in the battery energy storage in both risk-neutral and risk-averse strategies in comparison to the risk-taking strategy. Under a risk-taking strategy, the assumption is that generated power by the WTs would be increased in practical operation. So, there would be less energy storing need, which can be traded in the market to get financial profits. Between hours 12-16, when PVs generate power near their nominal capacity, the generated power is stored in ESS, which has been used between hours 18-24 to supply the peak load demand and satisfy the operational requirements of the ES. Hourly charged and discharged power of the energy storage is depicted in Fig.12. As expected, the discharging process took place under high market prices, and the charging and discharging processes of scheduling followed market prices. Figure 13 depicts the SOC results of the HSS. As it is shown in the related picture, the HSS in both risk-averse and risk-neutral strategies have the same behavior, while in the risk-taker strategy it is charged at hours 4-5, to store the excess generated power and discharged in higher price durations such as hour 7 to gain financial profit. According to the operating requirements, which determine the initial SOC of HSS for the final duration, another charging and discharging process is done at hours 20 and 22.

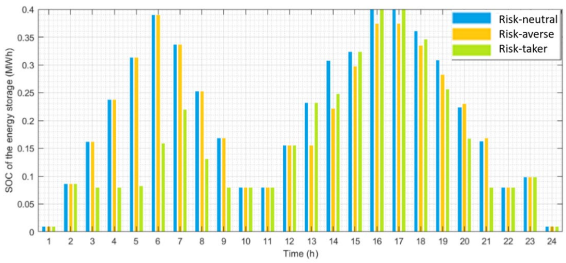

Fig. 11 SOC of the ES located in bus 20.

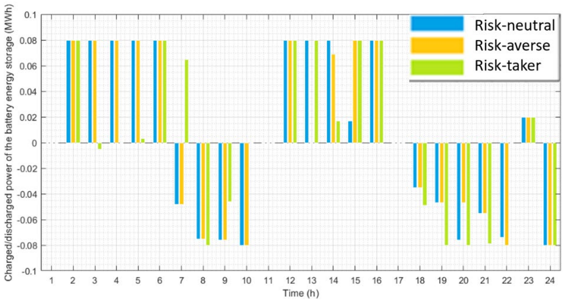

Fig. 12 Operation scheduling of battery energy storage system.

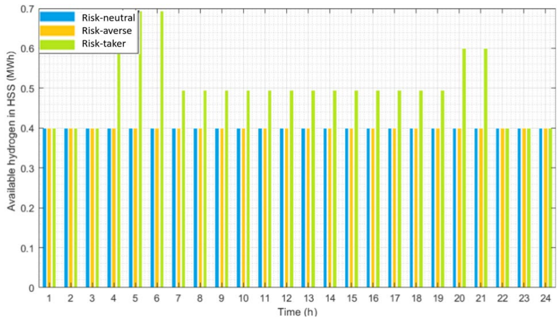

Fig. 13 SOC of the HSS.

4.2.5 Optimal Offering/bidding Curves

Figure 14 depicts the optimal offering strategies of the VPP for hours 5, and 11. The VPP power offer curve at 5 o'clock shows that this unit offers to sell the power in the neutral and risk-averse case is restricted to prices higher than 61 \$/MWh. With increasing caution, the amount of offered power for sale also has been reduced from 1.275 MW to 1.030 MW. On the other hand, with the increase in VPP's risk-taking, and under a more optimistic attitude, the energy selling prices have decreased from 61 \$/MWh in the neutral case to 25\$/MWh. Considering the low market prices at 5 o'clock, VPP has not shown much desire to sell power at this hour under a risk-taking strategy, and it has limited its offers to less than 0.6MW. At 11 o'clock, when the energy market prices increase, the power offer for VPP in the risk-taking case takes higher values in comparison to the others. This state indicates the role of optimistic attitudes in the power offering prices. VPP in a risk-neutral case, suggests higher prices for selling energy compared to the neutral and optimistic ones. The study of power offers shows that VPP has not made any power purchase requests in neutral and risk-averse states during off-peak hours, such as 1 o'clock. But in the risk-taking mode, according to the lower market prices, the risk-taker operator has bought power to benefit from the profit of its sale during the peak hours. The bidding strategies for hours 1, 12, and 15 are depicted in Fig. 15 at 12 o'clock, at the risk-taking strategy, the amount of energy generation is considered higher, which has reduced the request to purchase power from a 1MW power bid to a maximum of 0.8MW bid. Due to the higher demand at 12 o'clock, under a risk-averse strategy, the request for purchasing power has increased up to 1.3MW. At hour 15, the wind speed increased compared to hour 12, but the power demand also increased compared to 12. The results of using different risk-based strategies in changes in VPP profit are reported in Fig. 8 .

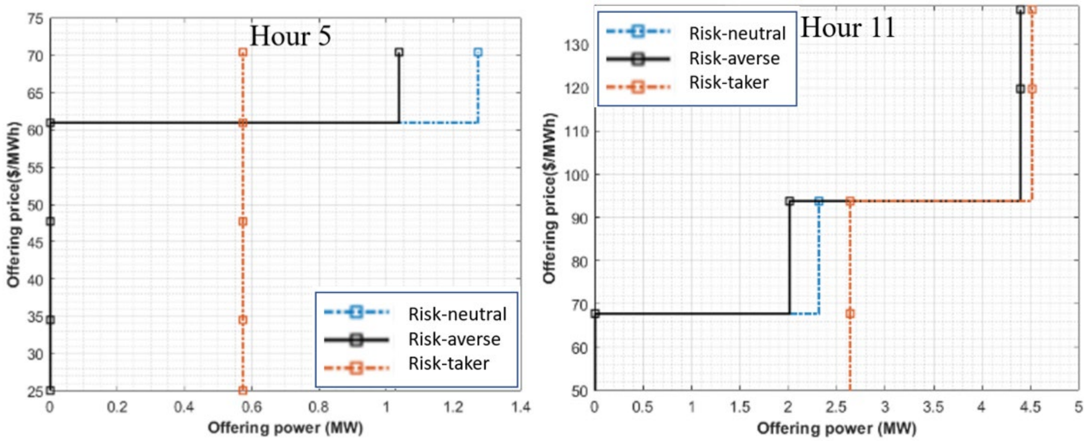

Fig. 14 Offering curves for hours 5, and 11.

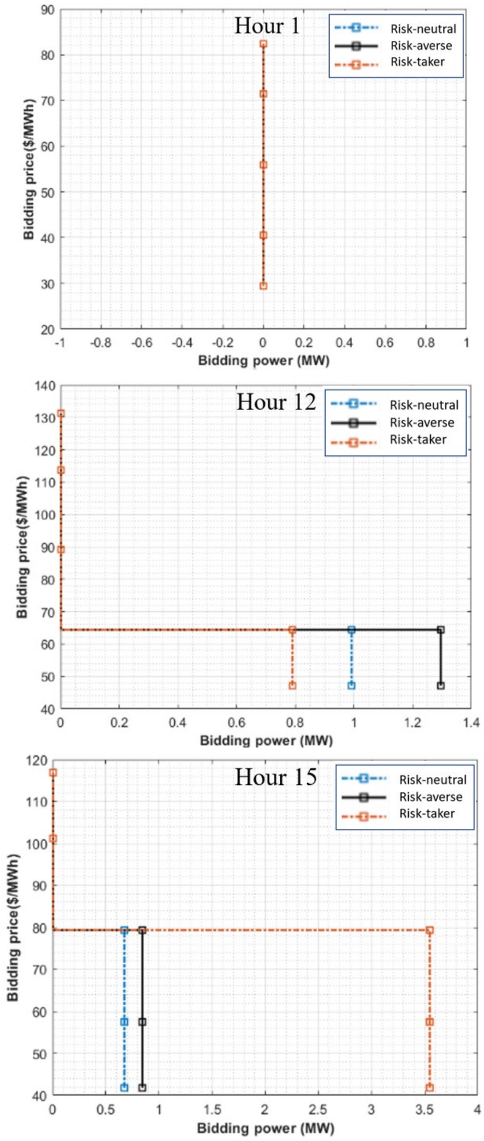

Fig. 15 Bidding curves for hours 1, 12, and 15.

As can be deduced under the result analysis, the operator's strategy has a great impact on the bid and offers strategies for each VPP.

5 Conclusion

In this paper, a risk-based hybrid IGDT model to consider the effects of WT output power fluctuation on the operating scheduling, power trading, and bidding strategy of the VPP is proposed. Also, the uncertainty of PV energy generation units, loads, and market price uncertainty is considered under a scenario generation and reduction model. The obtained result indicates that it would be so practical to use an uncertainty analysis, which makes a clearer environment for decision-makers under uncertain parameters. Results studies reported that a robustness parameter of 0.3, which means VPP is robust against a 30% fluctuation of WTs energy generation, would decrease the profit function by 14.5%. In contrast, under a risk-taking strategy, a 0.3 opportunity parameter would lead to a 12.5% increase in the profit function of the proposed model. So, the proposed method makes a suitable illustration of system behaviour against uncertain parameters for a decision-maker. According to the cost of a risk-averse strategy, in comparison to the profit increase of a risk-taker, it is not recommended to choose a rigid risk-averse strategy for the studied VPP. The proposed model makes a clearer insight for a VPP operator to make decisions under uncertainties. As a suggestion for the future, it is recommended to consider the effects of air pollution cost in analysis and make a multi-objective problem for Pareto solutions.

Intellectual Property

The authors confirm that they have given due consideration to the protection of intellectual property associated with this work and that there are no impediments to publication, including the timing to publication, with respect to intellectual property.

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A. Ghanuni: Idea & Conceptualization, Research & Investigation, Data Curation, Methodology, Software and Simulation, Original Draft Preparation, Revise & Editing. **R. Sharifi:** Methodology, Project administration, Supervision, Review & editing. **H. Feshki Farahani:** Methodology, Project administration, Supervision, Review & editing.

Declaration of Competing Interest

The authors hereby confirm that the submitted manuscript is an original work and has not been published so far, is not under consideration for publication by any other journal and will not be submitted to any other journal until the decision will be made by this journal. All authors have approved the manuscript and agree with its submission to "Iranian Journal of Electrical and Electronic Engineering".

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