

# Optimal Bidding Strategy of a Renewable-Based Virtual Power Plant including Wind and Solar Units and Dispatchable Loads

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## Abstract:

The accumulation of many production units with small capacities and transforming them into a larger entity will make them visible in electricity market. Renewable based virtual power plant (VPP) in this paper is a wide energy management system that incorporates probabilistic wind and solar units, non-renewable Distributed Generation (DG) units, and dispatchable loads. In an electricity market, a VPP optimizes its operating schedules in order to increase its economic efficiency. However, market uncertainties may influence the VPP's profit. In this paper, modelling the uncertainties is implemented by the proposed Information Gap Decision Theory (IGDT). The mentioned scheduling problem is formulated in three operation modes: risk-neutral, risk-averse and risk-seeker. The risk-neutral mode focuses on optimizing the VPP in the day-ahead market. In the risk-averse mode, the robustness function is used under low market prices. Moreover, in the risk seeker mode, an opportunity function is used under higher market prices towards higher profit results. The proposed model allows the VPP to decide on the scheduling of its components and the optimal bids to the day-ahead market. Another purpose is to investigate the role of the renewable-based VPP in minimizing emission and maximizing profit in a two-objective way. The IEEE 18-bus test system is utilized to simulate the proposed problem and analyse the results. The performance of the proposed problem is approved using different scenarios. Simulation results justify the advantages and necessities of the proposed problem.

**Keywords:** Bidding strategy, emissions, renewable energy, virtual power plant, IGDT, multi-objective

## Nomenclature

### Indices

$t$	Index for time period
$dg$	Index for distributed generation unit
$gsp$	Index for grid supply point
$m, n$	Index for buses
$ws$	Index for wind unit scenarios
$ss$	Index for solar unit scenarios

### Constants

$z(t)$	Day-ahead market forecasted price at period $t$
$z_G(gsp, t)$	Day-ahead market price at the Grid Supply Points (GSPs) at period $t$
$B_{mn}$	Susceptance of line $m - n$
$P_{Demand}(t)$	Power demand at period $t$
$RS$	Reserve of the system

$P_{max}(dg)$	Maximum units capacity limit
$P_{min}(dg)$	Minimum units capacity limit
$S^s(ss, t)$	Probability of solar unit scenarios in scenario $ss$ and at period $t$
$\chi(dg)$	Emission constant coefficient of units
$C(dg)$	Generation cost of units
$SUC(dg)$	Start-up cost of units
$SDC(dg)$	Shutdown cost of units
$W^s(ws, t)$	Probability of wind unit scenarios in scenario $ws$ and at period $t$
$RUP(dg)$	Ramp up limit for DG units
$RDP(dg)$	Ramp down limit for DG units
$WS$	Number of wind unit scenarios
$SS$	Number of solar unit scenarios
$T_{c,y}$	Cell temperature during state $y$ [ $^{\circ}\text{C}$ ]
$T_A$	Ambient temperature [ $^{\circ}\text{C}$ ]
$K_v$	Voltage temperature coefficient [ $V/^{\circ}\text{C}$ ]
$K_i$	Current temperature coefficient [ $A/^{\circ}\text{C}$ ]
$N_{OT}$	Rated operating temperature [ $^{\circ}\text{C}$ ]
$FF$	Fill factor

#### **Variables**

$P(dg, t)$	Cleared power for VPP in day-ahead market at period $t$
$P_G(gsp, t)$	Produced power by $b$ th block of unit $g$ in VPP at period $t$
$P^W(ws, t)$	Generated power of wind unit in scenario $ws$ and at period $t$
$P^S(ss, t)$	Generated power of solar unit in scenario $ss$ and at period $t$
$P_{DL}(t)$	Power of dispatchable loads at period $t$
$\delta(n, t)$	Voltage angle of bus $n$ at period $t$
$Revenue(t)$	Revenue of VPP at period $t$
$Cost(t)$	Cost of VPP at period $t$
$Profit$	Profit of VPP
$\sigma(dg, t)$	On/off status of units
$\mu(dg, t)$	Binary decision variable of start-up status of units
$\rho(dg, t)$	Binary decision variable of shut-down status of units
$I_{sc}$	Short circuit current
$V_{oc}$	Open circuit voltage
$I_{MPP}$	Current at maximum power point
$V_{MPP}$	Voltage at maximum power point
$s_{ay}$	Average solar radiation of state $y$
$P_{s,y}$	Output power of solar unit during state $y$

## 1. Introduction

These days, the increase of energy consumption, prevalent use of conventional fossil fuels as exhausting resources, and environmental issues are among major concerns in the world [1]. In recent years, renewable energy resources such as wind and solar have been used to address this issue. However, these resources are able to make some problems for power systems because of their intermittent energy output that would be a significant challenge for power system operation and corresponding owners. In other words, there are valuable benefits and costs for the electricity market when intermittent DERs are integrated into the electricity systems. In addition, the effects of renewable energy technologies on future power systems are much more important. Also, when intermittent DER is introduced to the rough market environment, a serious challenge is proposed for their owners. The first reason which deserves to be mentioned here is that this DER's forecasted power outputs consist of uncertainty. To illustrate clearly, under the natural influence of wind and solar irradiation and clouds, Wind Power Plants (WPPs) and Photovoltaic (PV) power plants' output are not naturally permanent [2,3]. In this case, the possibility of an interruption in energy delivery is being concerned. In order to address the above concerns, VPPs are introduced. The concept of VPP as a multidimensional heterogeneous entity is based on the integration of several dispersed units and making use of their aggregated capacities [4]. According to the FENIX project, a VPP aggregates the capacities of several distribution energy resources (DERs), which can provide distinct performance characteristics associated with each DER [5]. The VPP can also make contracts in the wholesale market and provide services to the system operator. An important feature of the VPP is its ability to participate in the energy market. Thus VPP owners can move toward maximizing their profits by determining optimal bidding strategies. The VPP concept as a multi-technology and multi-location heterogeneous entity is based on the sum of DERs capacities (generation, storage, or demand) to create a single operating profile like a generator at the transmission level. Within the scope of the mentioned VPP, not only can the producers make sure that their generators are properly and optimally operated, but also they can raise the value of the non-dispatched generation technologies by getting VPPs committed to a much more robust generation profile. In general, the VPP is classified into the Commercial and Technical type, CVPP and TVPP, respectively [6] in which the DER can be used as a part of both of them [7]. As it can be inferred from mentioned VPP types, the CVPP, which controls the DER portfolio(s) in order to make optimal decisions about involvement in the electricity market, plays the role of a competitive market actor. It deserves to be mentioned this delicate expression that the first objective of the VPP's optimal operation can be different from each other. As an illustration, economic optimization can either aim to minimize the expenses of producing energy and transmitting it to the loads or maximize the profits of the VPP owner. In this paper, a comprehensive model for a renewable-based VPP based on the probabilistic behaviour of the renewable energies (according to Weibull and Beta distribution functions, for wind and solar units, respectively), non-renewable energies, normal load, and dispatchable loads (demand response) has been stochastically implemented and the VPP acts as a single entity in the electricity market, and its aim is making all components visible and achieving the most profit in the electricity market. Many parameters in VPPs and the electricity market have uncertainties and there are many methods for modelling them. Two major kinds of this method related to power system problems are IGDT [8,9] and Robust Optimization (RO) [10]. Also, considering the uncertainties and managing the risk of decision at the same time can be modelled by these mentioned methods. However, specific embodying level of profit compared with introducing the probable measure of risk is the much more prevalent advantage of this method. The IGDT mentioned in [11] provides a method for Generation Companies (GenCos), while [12] and [13] are proposed for self-scheduling of non-renewable units and demand-side schedule, respectively. In order to investigate the self-schedule of hydrothermal GenCo in smart grids and decrease the probability of price uncertainty, the proposed RO is discussed in [14] and [15] respectively. The self-scheduling problem which is formulated in three categories, risk-neutral, risk-averse, and risk-seeker GenCos, is pursued in [16] by introducing a non-probabilistic information-gap model for investigating uncertainties in the short-term schedule of the

GenCos. Another subtle technique based on IGDT for providing various strategies for vast consumers is proposed in [17] which categorizes the supply sources into a mutual contract, self-generating facility, and pool market. Furthermore, in [17], the pool price and IGDT model are unstable around their estimated values in which the information gap between predicted and the real market is gained by factors such as market uncertainty with conventional methods. By considering this matter, trading strategy and GenCo's portfolio optimization method with using a non-probabilistic IGDT are proposed in Ref. [16], too. Large electric utilities, which consist of generation facilities with an associated demands' retailer in the presence of demand response programs are introduced and formulated as a new strategy in [18]. In this case, a price-taker generation company is needed to take part in the day-ahead electricity energy market. So, in addition to finding a bidding strategy for producers, some factors such as specifications of generators and market uncertain price, ought to be considered because they directly influence over target profits [19]. Besides, for modelling the day-ahead market uncertain price, the mentioned non-probabilistic IGDT is implemented in [18], too.

In recent years, reducing greenhouse gaseous emissions and increasing investors' profits have become more highlighted. Therefore, a solution that solely minimizes the total scheduling costs or maximizes the overall profit may not be appropriate for actual power systems. Accordingly, the bi-objective framework is used in many papers, such as [15] and [20] to minimize emissions and costs simultaneously. One of the essential challenges of the multi-objective meta-heuristic optimization methods is to find feasible and evenly distributed Pareto solutions throughout the decision space. Indeed, it is an important aspect of the optimization tool to ensure its ability to pass the local optimal points and move towards the global optimal point. Although a high number of researches have been studied to find an efficient approach to achieve this aim, none of the methods have been justified to have better performance compared to all other techniques in all the situations. Based on the existing knowledge in this field, the Epsilon Constraint (EP) has a good and acceptable performance in most of the situations to search all the decision space and find the solutions that yield toward the global optimum solution of the problem. Hence, the EP is developed in this paper in order to solve the proposed multi-objective problem by considering the emission criterion, as well as the profit function as the main objectives.

In this paper, according to the IGDT model, the problem of uncertainty on the market price is modelled using the robust and opportunity functions. Besides the profit function of the renewable-based VPP, the emission problem has also been considered, and the model has been solved in two objectives by considering profit and emission using the Epsilon constraint method to investigate the effect of renewable-based VPPs in the emission and profit objective functions. A mixed-integer model is developed for the problem of the optimal bidding strategy of the VPP in the presence of different units, such as wind, solar and non-renewable DGs.

Recently, many papers have been published regarding the scheduling of VPPs. In [21], risk-constrained day-ahead scheduling strategies for a VPP integrating a Concentrating Solar Power Plant (CSPP) with some responsive residential and industrial loads are proposed considering some uncertainties. IGDT is utilized to hedge against the risk caused by these uncertainties. One of the deficits of this paper is that it does not model the network of the VPP and the VPP is connected to the upstream network only via one point and exchanges power. On the other hand, it can be pointed out that in this paper, despite the existence of pollutant resources, the issue of emission has not been considered and only the economic issue has been stated. Ref [22] presents a new robust self-scheduling strategy for VPPs considering the uncertainty sources of electricity prices, wind generations, and loads. IGDT as a non-probabilistic uncertainty modelling framework is proposed here to specifically model the uncertainty sources considering their various uncertainty horizons. One of the deficits of this paper is that the VPP is not connected to the upstream network via several points at different prices. In addition, a simple model for the wind unit has been obtained by predicting the amount of the wind speed, while in the present paper; the wind unit is modelled with a Weibull distribution function that has high accuracy for the wind units. In addition, while many pollutant units have been used in the VPP, no attention has been paid to the emission problem along with the profit of the VPP. Ref [23] outlines a novel bi-level decision-making framework for a price-maker

VPP to participate in both day-ahead and balancing oligopoly markets considering multiple forward contracts. In principle, VPP operator with having the possession of financial transmission rights can manage its financial risk through trading electricity among various markets. In this paper, the VPP with all its components is located on one bus and does not have a separate network. Whereas in real models, the VPP is part of the network structure. On the other hand, the problem has been solved as a single objective without considering the emission problem. In addition, a very simple model is considered for wind and solar units. In Ref [24], renewable power, market price, and load demand are classified as major factors of uncertainties. Based on the classification, the detailed mathematical descriptions are summarized. And then, optimization objectives and constraints, which are adopted to improve the running performance of the VPP with uncertainties, are summed up systematically. In this review paper, probability distribution functions are used to express uncertainty, which requires more information for modelling than IGDT. On the other hand, the reviewed papers are solved as a single objective problem and only on the basis of economic issues. In addition, the emission problem has not been considered, and finally, the VPPs have been modelled without a real network. Ref [25] combined interval and deterministic optimization together and adopted the combined approach to solving a VPP's dispatch problem. The combined optimization not only maximized VPPs' deterministic profits under forecasted scenarios to estimate the VPP's most likely profits but also maximized VPPs' profit intervals to manage uncertainties. One of the deficits of this paper is that it does not model the network of the VPP and the VPP is connected to the upstream network only via one point and exchanges power. On the other hand, it can be pointed out that, despite the existence of pollutant resources, the emission problem has not been considered and only the economic issue has been investigated. Finally, IGDT is not used in this paper to model uncertainty. Ref [26] introduces a framework that cooptimizes the VPP provision of multiple markets, system, and local network services with the aim of maximizing its revenue. To ensure problem tractability, while accommodating the uncertain nature of market prices, local demand, and renewable output and while operating within local network constraints, the framework is broken down into three sequentially coordinated optimization problems. Ref [27] proposed a comprehensive method for analysing the feasibility of using a VPP to benefit both the plant and demand sides. First, the energy-saving potential of a VPP composed of a PV and energy storage system (ESS) was explored, based on historical monitoring data in a Japanese smart community called Higashida District. Second, the economic performance of the VPP was evaluated based on a payback period and total life cycle cost analysis. In Ref [28], a stochastic scheduling problem for a VPP is modelled to meet the thermal and electrical load considering the network security constraints and uncertainties of electrical and thermal loads, wind speed, solar radiation, and market price. The VPP consists of conventional generators, photovoltaic panels, wind turbines, photovoltaic-thermal panels, combined heat and power, energy storage systems, and boilers. To model all uncertain parameters, a scenario reduction approach is used to decrease the number of possible scenarios. In [26-28] references, a network is considered for a VPP, but this network is connected to the upstream network only via one point. On the other hand, it can be pointed out that in these papers, despite the existence of pollutant resources, the issue has been seen as a single objective and the issue of emission has not been considered. These papers use probability distribution functions to model uncertainty parameters, whereas IGDT does not require probability distribution functions to model uncertainty.

In this paper, a comprehensive model for a renewable-based VPP based on the probabilistic behaviour of renewable energies (according to Weibull and Beta distribution functions, for wind and solar units, respectively), non-renewable energies, normal load, and dispatchable loads (demand response) stochastically has been implemented. The VPP is connected to the upstream network via three points. In this paper, according to the IGDT model, the problem of uncertainty on the market price is modelled using the robust and opportunity functions. Besides the profit function of the VPP, the emission problem has also been considered, and the model has been solved in two objectives by considering profit and emission using the epsilon constraint method. Such a comprehensive model for a VPP and attention to the emission and uncertainty has never been implemented before.

In order to demonstrate briefly the differences and advantages of the proposed method of this paper compared to the existing studies, a comparison table has been prepared as shown in Table I.

Table I: Details of the proposed problem of this paper compared to other studies

Features		References								This paper
		[21]	[22]	[23]	[24]	[25]	[26]	[27]	[28]	
<b>Independent Network for VPP</b>		x	✓	x	x	x	✓	x	✓	✓
<b>Objective Function(s)</b>	<b>Single</b>	✓	x	✓	✓	x	✓	✓	✓	✓
	<b>Multi</b>	x	✓	x	x	✓	x	x	x	✓
<b>Objective Function</b>	<b>Emission</b>	x	x	x	x	x	x	x	x	✓
<b>Renewable Energy Resources</b>	<b>Wind</b>	x	✓	✓	✓	✓	✓	x	✓	✓
	<b>Solar</b>	✓	x	x	✓	✓	✓	✓	✓	✓
<b>IGDT</b>		✓	✓	✓	✓	x	x	x	x	✓
<b>Grid Connection status</b>	<b>1 GSP</b>	✓	✓	✓	✓	✓	✓	✓	✓	x
	<b>Multiple GSPs</b>	x	x	x	x	x	x	x	x	✓

The main contributions of this paper are summarized as follows:

- Employing the IGDT method to propose the robustness and opportunistic bidding strategy of the renewable-based VPP against the uncertainty of the forecasted parameter.
- Evaluating the effect of the renewable-based virtual power plant considering wind and solar units and their uncertainties on the emission problem in the form of a two-objective model. In this case, one of the contributions of this paper is to investigate the role of the renewable-based virtual power plant in maximizing the profit of the VPP and minimizing its emission.

The organization of the paper is as follows. The Information Gap Decision Theory is presented in Section 2. The problem formulation is stated in section 3. The case studies and simulation results are discussed in Section 4 and Section 5 provides the conclusion.

## 2. Information Gap Decision Theory

One of the best robust decision making methods for intense uncertain parameters is the Information Gap Decision Theory (IGDT). Unlike other uncertainty modelling methods, such as the point estimate method, Monte Carlo simulation (MCS), and other scenario based uncertainty modelling methods, this method does not need any probability distribution function of the uncertain parameters and this is one of the strengths of this method. Another strength is that this method does not need to determine the maximum radius of uncertain parameters, which takes the advantage of the bidding strategy of the VPP. In fact, the IGDT seeks to achieve the maximum uncertainty radius for uncertainty parameters in such a way that the objective function is assured in the pre-specified interval [29]. In IGDT, the uncertainty model, which maximizes the uncertainty bound when setting decision variables, is an interval around the predicted quantity. Also, the IGDT uses this confident uncertainty interval in order to provide optimistic and pessimistic solutions that guarantee a specific value of the goal. Furthermore, the maximum acceptable deviation from the estimated value will be introduced in the case of bidding strategy along with the day-ahead uncertainty price [12]. For dealing with each IGDT problem, they can be divided into three component-system models, uncertainty model, and performance requirement [31]. These mentioned components are described as follows:

## 2.1. System Model (Risk Constraint)

This criterion includes the input/output structure of the system. For the present problem, the main model of the system, which is the VPP profit, is denoted by  $M(a, z)$ , where  $z$  is the price of the market and the uncertainty parameter, and  $a$  is the other decision variables of the VPP.

## 2.2. Uncertainty Model

The envelope bound model with  $\tilde{z}$  as a function is implemented in this paper and is defined as Eq. (1) [31].

$$N(\xi, \tilde{z}) = \{z: \tilde{z}(t) - \eta(t)\xi \leq z(t) \leq \tilde{z}(t) + \eta(t)\xi, \xi \geq 0, \forall t \in T\} \quad (1)$$

$\eta(t)$  is a known function that specifies the shape of the envelope. Depending on the application,  $\eta(t)$  may take different forms such as  $\eta(t) = 1$  and  $\eta(t) = \tilde{z}(t)$ .  $\xi$  is the area of uncertainty parameter and a slight increase in its value causes the area of uncertainty to be larger.

## 2.3. Performance Requirement

Based on the decision-maker strategy, two different performance functions can be defined for an IGDT model, risk-averse and risk-seeker [32, 33]. The robust function  $\hat{\xi}(a, F_e)$  is defined as the maximum value of  $\xi$ , so that it satisfies the minimum value of  $F_e$ , ie:

$$\hat{\xi}(a, F_e) = \max_{\xi} \{ \xi : \text{minimum requirement } F_e \text{ is always satisfied} \} \quad (2)$$

$F_e$  guarantees that VPP profits will never be less than the predetermined critical value. The opportunity function, denoted by  $\hat{t}(a, F_y)$ , is modeled as follows:

$$\hat{t}(a, F_y) = \min_{\xi} \{ \xi : \text{target performance } F_y \text{ may be achieved} \} \quad (3)$$

VPP profit ( $F_y$ ) will be obtained if the uncertainty parameter deviates from the predicted value by at least  $\hat{t}$ . In fact,  $\hat{t}(a, F_y)$  is the minimum value of the uncertainty parameter change that guarantees a certain value of  $F_y$ .

## 3. Problem Formulation

The objective function (maximizing profit) is as follows:

$$f_1 = Profit = \sum_{t=1}^T (Revenue(t) - Cost(t)) \quad (4)$$

$$Revenue(t) = \left( \sum_{dg=1}^{DG} P(dg, t) + \sum_{ws=1}^{WS} W^s(ws, t)P^W(ws, t) + \sum_{ss=1}^{SS} S^s(ss, t)P^S(ss, t) \right) z(t) + \sum_{gsp=1}^{GSP} P_G(gsp, t) z_G(gsp, t) \quad (5)$$

$$Cost(t) = \sum_{dg=1}^{DG} (P(dg, t) C(dg)\sigma(dg, t) + SUC(dg)\mu(dg, t) + SDC(dg)\rho(dg, t)) + C_{DL}(t)P_{DL}(t) \quad (6)$$

Eq. (4) represents the profit of the VPP that is derived from income minus cost. Eq. (5) represents the revenue of the VPP. This equation is because of the sale of power to the VPP normal loads and also the sale of power to the upstream network. If the VPP purchases power from the upstream network, it enters the equation with a negative sign and indicates a cost. Eq. (6) also shows the cost of the VPP. This includes the cost of operation, start-up cost, shut-down cost of VPP units, and cost of dispatchable loads.

### 3.1. Probabilistic Wind Unit Modelling

The Weibull probability distribution function is used to model wind speed [34,35]. Fig. 1 shows the Weibull distribution function for the wind unit in 24 hours. Each curve is for one hour, and in order to avoid crowded figure, the legend is only placed for a few hours.

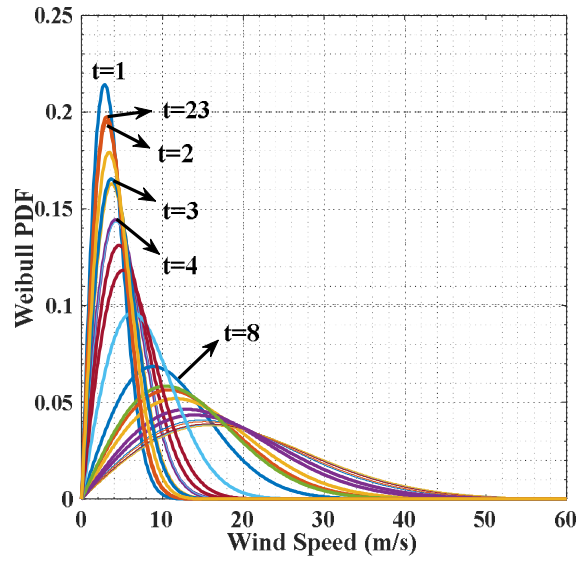


Fig. 1: Weibull probability density function

### 3.2. Probabilistic Photovoltaic Unit Modelling

For a specific hour of a sample day per year, the sunlight data usually have a beta probability distribution function (Fig. 2) that is calculated according to the following relationships. Each curve is for one hour, and in order to avoid crowded figure, the legend is only placed for a few hours.

$$f_b(s) = \frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha)\Gamma(\beta)} s^{(\alpha-1)}(1-s)^{(\beta-1)}, 0 \leq s \leq 1, \alpha \geq 0, \beta \geq 0 \quad (7)$$

It should be noted that  $f_b(s)$  for other  $s, \alpha, \beta$  is zero. In which  $s$  is the solar radiation,  $f_b(s)$  is beta distribution function, as well as  $\alpha, \beta$  are the parameters of the beta distribution function, as follows:

$$\beta = (1 - \mu) \left( \frac{\mu(1 + \mu)}{\sigma^2} - 1 \right) \quad (8)$$

$$\alpha = \frac{\mu\beta}{1 - \mu} \quad (9)$$

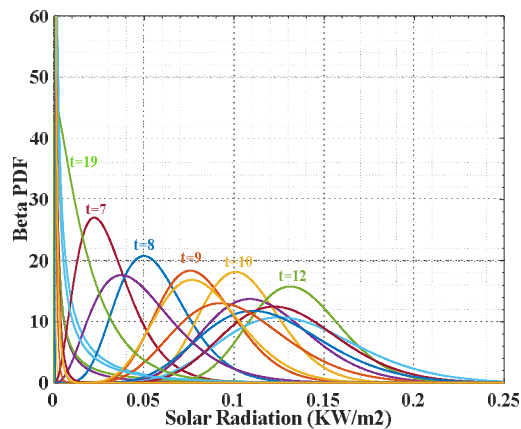


Fig. 2: Beta probability density function



The output power of the solar unit depends on the intensity of the sun radiation, the temperature of the environment, as well as its own technical characteristics. Therefore, when a beta probability distribution function is generated for a given period, the output power for different cases at that period is determined using the following equations:

$$T_{c_y} = T_A + s_{ay} \left( \frac{N_{OT} - 20}{0.8} \right) \quad (10)$$

$$I_A = s_{ay} [I_{sc} + K_i(T_c - 25)] \quad (11)$$

$$V_y = V_{oc} - K_v T_{c_y} \quad (12)$$

$$P_{s_y}(s_{ay}) = N \times FF \times V_y I_y \quad (13)$$

$$FF = \frac{V_{MPP} I_{MPP}}{V_{oc} I_{sc}} \quad (14)$$

### 3.3. Constraints

The problem constraints are represented as follows:

a) The power range of DGs:

$$P_{min}(dg)\sigma(dg, t) \leq P(dg, t) \leq P_{max}(dg)\sigma(dg, t); \quad \forall t \in T \quad (15)$$

b) The interconnection capacity is:

$$P(gsp, t) \leq P_{max}(gsp, t) \quad \forall t \in T \quad (16)$$

c) DC power flow equation:

$$P_{Gen}(n, t) - P_{Dem}(n, t) - \sum_k B_{kn} (\delta(k, t) - \delta(n, t)) = 0; \quad \forall t \in T \quad (17)$$

d) Power balance:

$$P_{DL}(t) + \sum_{dg=1}^{DG} P(dg, t) - \sum_{gsp=1}^{GSP} P_G(gsp, t) + \sum_{ws=1}^{WS} W^s(ws, t) P^W(ws, t) + \sum_{ss=1}^{SS} S^s(ss, t) P^S(ss, t) = P_{Demand}(t); \quad \forall t \in T \quad (18)$$

e) Ramp rate of DGs:

$$P(dg, t+1) - P(dg, t) \leq RUP(dg); \quad \forall t \in T \quad (19)$$

$$P(dg, t) - P(dg, t+1) \leq RDP(dg); \quad \forall t \in T \quad (20)$$

f) Minimum up and downtime constraints:

$$[T_{on}(dg, t-1) - MUT(dg)] \times [\sigma(dg, t-1) - \sigma(dg, t)] \geq 0; \quad \forall t \in T \quad (21)$$

$$[T_{off}(dg, t-1) - MDT(dg)] \times [\sigma(dg, t-1) - \sigma(dg, t)] \geq 0; \quad \forall t \in T \quad (22)$$

g) Reserve:

Amount of reserve is assumed as a percentage of the total generation of DG units and dispatchable loads (RS) (e.g. 2%).

$$\sum_{dg=1}^{DG} (P_{max}(dg) - P(dg, t))\sigma(dg, t) + P_{DL}(t) \geq RS \left( \sum_{dg=1}^{DG} P(dg, t)\sigma(dg, t) + P_{DL}(t) \right) \quad (23)$$

### 3.4. IGDT based model for VPP:

#### 3.4.1. Decision Variables

The considered variables are amounts of produced power of DGs, exchanged power between GSPs, curtailing power via DLs, and angles of buses:

$$a(t) = (P(dg, t), P_G(gsp, t), P_{DL}(t), \delta(n, t)); \forall dg \in DG, \forall gsp \in GSP, \forall t \in T, \forall n \in N \quad (24)$$

### 3.4.2. Robust Model:

The risk-averse VPP by using the robust function plans to reach a certain amount of profit in the face of unfavourable market price deviations from the predicted values. Hence, the robust function is given as:

$$\hat{\xi}(PP, A_e) = \max \left\{ \xi : \left( \min_{z \in N(\xi, \hat{z})} A(PP, z) \geq A_e = (1 - \alpha)A_0 \right) \right\} \quad (25)$$

$A_e$  is the critical profit for  $F_e$  in Eq. (2).  $A_0$  is the maximum expected profit based on forecast prices.  $\alpha$  is the profit deviation coefficient. For risk-averse VPPs, the goal is to maximize the uncertainty parameter  $\xi$ , which is expressed according to Eq. (26).

$$\hat{\xi}(PP, A_e) = \max \xi \quad (26)$$

subject to:

$$\begin{aligned} \min \left\{ \left( \sum_{dg=1}^{DG} P(dg, t) + \sum_{ws=1}^{WS} W^s(ws, t)P^W(ws, t) + \sum_{ss=1}^{SS} S^s(ss, t)P^S(ss, t) \right) z(t) \right. \\ \left. + \sum_{gsp=1}^{GSP} P_G(gsp, t) z_G(gsp, t) - \sum_{dg=1}^{DG} (P(dg, t) C(dg)\sigma(dg, t) + SUC(dg)\mu(dg, t) \right. \\ \left. + SDC(dg)\rho(dg, t)) + C_{DL}(t)P_{DL}(t) \right\} \geq A_e \end{aligned} \quad (27)$$

$$(1 - \xi)\hat{z}(t) \leq z(t) \leq (1 + \xi)\hat{z}(t) \quad (28)$$

After applying the uncertainty parameter on the market price, the following equations will be obtained for VPP profit:

$$\hat{\xi}(PP, A_e) = \max \xi \quad (29)$$

subject to:

$$\begin{aligned} \left( \sum_{dg=1}^{DG} P(dg, t) + \sum_{ws=1}^{WS} W^s(ws, t)P^W(ws, t) + \sum_{ss=1}^{SS} S^s(ss, t)P^S(ss, t) \right) (1 - \xi)\hat{z}(t) \\ + \sum_{gsp=1}^{GSP} P_G(gsp, t) (1 - \xi)\hat{z}_G(gsp, t) - \sum_{dg=1}^{DG} (P(dg, t) C(dg)\sigma(dg, t) + SUC(dg)\mu(dg, t) \\ + SDC(dg)\rho(dg, t)) + C_{DL}(t)P_{DL}(t) \geq A_e \end{aligned} \quad (30)$$

The above optimization problem provides robust scheduling based on the defined value of  $A_e$ . In other words, solving the above problem guarantees the minimum profit  $A_e$ , and for this solution, the maximum amount of price deviation from the predicted price is obtained.

### 3.4.3. Opportunity Model:

The opportunity function is given by:

$$\hat{t}(PP, A_y) = \min \left\{ \xi : \left( \max_{z \in N(\xi, \hat{z})} A(PP, z) \geq A_y = (1 + \beta)A_0 \right) \right\} \quad (31)$$

$A_y$  is the final and guaranteed profit that the VPP will receive at prices higher than expected.  $\beta$  is the profit deviation coefficient.  $A_y$  target profit is generally higher than  $A_e$ . The formula for the opportunity function for a VPP is as follows:

$$\hat{t}(PP, A_y) = \min \xi \quad (32)$$

$$\text{subject to:} \quad (33)$$

$$\max \left\{ \begin{aligned} & \sum_{dg=1}^{DG} P(dg, t) + \sum_{ws=1}^{WS} W^s(ws, t)P^W(ws, t) + \sum_{ss=1}^{SS} S^s(ss, t)P^S(ss, t)z(t) \\ & + \sum_{gsp=1}^{GSP} P_G(gsp, t) z_G(gsp, t) - \sum_{dg=1}^{DG} (P(dg, t) C(dg)\sigma(dg, t) + SUC(dg)\mu(dg, t) \\ & + SDC(dg)\rho(dg, t)) + C_{DL}(t)P_{DL}(t) \end{aligned} \right\} \geq A_y$$

$$(1 - \xi)\hat{z}(t) \leq z(t) \leq (1 + \xi)\hat{z}(t) \quad (34)$$

After applying the uncertainty parameter on the market price, the following equations will be obtained for VPP profit:

$$\hat{t}(PP, A_y) = \min \xi \quad (35)$$

subject to:

$$\begin{aligned} & \left( \sum_{dg=1}^{DG} P(dg, t) + \sum_{ws=1}^{WS} W^s(ws, t)P^W(ws, t) + \sum_{ss=1}^{SS} S^s(ss, t)P^S(ss, t) \right) (1 + \xi)\hat{z}(t) \\ & + \sum_{gsp=1}^{GSP} P_G(gsp, t) (1 + \xi)\hat{z}_G(gsp, t) \\ & - \sum_{dg=1}^{DG} [(P(dg, t)]C(dg)\sigma(dg, t) + SUC(dg)\mu(dg, t) + SDC(dg)\rho(dg, t)) \\ & + C_{DL}(t)P_{DL}(t) \geq A_y \end{aligned} \quad (36)$$

Therefore, if prices are higher than expected in the future, more profit  $A_y$  will be obtained. Note that  $\hat{t}$  is the minimum price change that guarantees  $A_y$ .

The emission of the VPP units is modelled according to the linear Eq. (37). Nitrogen Oxide (NO<sub>x</sub>), Carbon Dioxide (CO<sub>2</sub>), and Sulfur Dioxide (SO<sub>2</sub>) are the most common emissions in thermal power plants. In this paper, NO<sub>x</sub> emission is considered. To obtain the total amount of emission, the production power of each unit of VPP is multiplied by the emission coefficient of the same unit. The emission coefficients of the units are shown in Table II [36].

*Minimize emission*

$$f_2 = \sum_{t=1}^T \sum_{dg=1}^{DG} \chi(dg) \times P(dg, t) \quad (37)$$

### 3.5. Epsilon Constraint Method (Bi-Objective)

The bi-objective optimization format of a problem with the epsilon constraint method is as follows [37].

$$\begin{aligned} & \text{Min } f_1(x) \\ & \text{subject to } f_2(x) \leq e_2 \end{aligned} \quad (38)$$

For the two-objective problem of profit and emission of dispatchable units,  $f_1(x)$  serves as the main objective function and another goal (here  $f_2(x)$ ) as a constraint in the problem. Furthermore,  $x$  is an array of decision variables, which in this problem are the generation power of units. In this method, the first objective function is considered as the main objective function, and the second to  $n$ -th objectives are limited to a maximum of  $e_i$ . By changing the value, there are various answers that may not be efficient. In the epsilon constraint method, efficient solutions are produced, first, and then the best solution is chosen [15].

### 3.6. Decision-Making Method

After solving the problem and obtaining all the Pareto solutions, the decision maker should choose one of Pareto's answers as the final solution to the problem, taking into account the priorities and the different uses of Pareto's answers. For this purpose, the proposed method for choosing the best answer is to use a fuzzy approach with a linear membership function for the decision maker. The membership function of the proposed fuzzy method is defined as Eqs. (39) and (40), which are used respectively for maximization and minimization. The best and worst amounts of each objective function are arranged in the order of the ideal point  $f_n^u$  and nadir point  $f_n^{SN}$ . In these equations,  $f_n^r$  shows the value of the objective function  $f_n$  in the  $r$ th Pareto solution number, and  $\mu_n^r$  is the membership function  $f_n$  in the  $r$ th Pareto solution number.  $\mu_n^r$  actually represents the optimality of the objective function in the  $r$ th Pareto solution number. The general membership function of the  $r$ th Pareto solution is called  $\mu^r$ , which is calculated according to Eq. (41), where  $\omega_n$  is the importance factor of the  $n$ th objective functions. The values of the importance coefficients are determined by the decision maker. For example, if economic issues are the top priority for the decision maker, a higher value is assigned to  $f_1$  and if emission is more important, a lower value is assigned to  $f_1$  [38].

3.6.1. Maximization:

$$\mu_n^r = \begin{cases} 0 & f_n^r \leq f_n^{SN} \\ \frac{f_n^r - f_n^{SN}}{f_n^u - f_n^{SN}} & f_n^{SN} \leq f_n^r \leq f_n^u \\ 1 & f_n^r \geq f_n^u \end{cases} \quad (39)$$

$n = 1$

3.6.2. Minimization:

$$\mu_n^r = \begin{cases} 1 & f_n^r \leq f_n^u \\ \frac{f_n^{SN} - f_n^r}{f_n^{SN} - f_n^u} & f_n^u \leq f_n^r \leq f_n^{SN} \\ 0 & f_n^r \geq f_n^{SN} \end{cases} \quad (40)$$

$n = 2$

$$\mu_r = \frac{\sum_{n=1}^P \omega_n \mu_n^r}{\sum_{n=1}^P \omega_n} \quad (41)$$

## 4. Case study

The renewable-based VPP in this paper includes non-renewable units, wind and solar units, and normal and dispatchable loads. The VPP is implemented on an 18-bus system extracted from the 30-bus IEEE standard system and is shown in Fig. 3. As it is clear from this figure, the VPP has 4 non-renewable units in buses 2, 7, 8, and 14, and the information of which are given in Table II. On the other hand, it has wind and solar units in buses 3 and 18, respectively. The VPP exchanges power through buses 1, 11, and 16 with the upstream network.

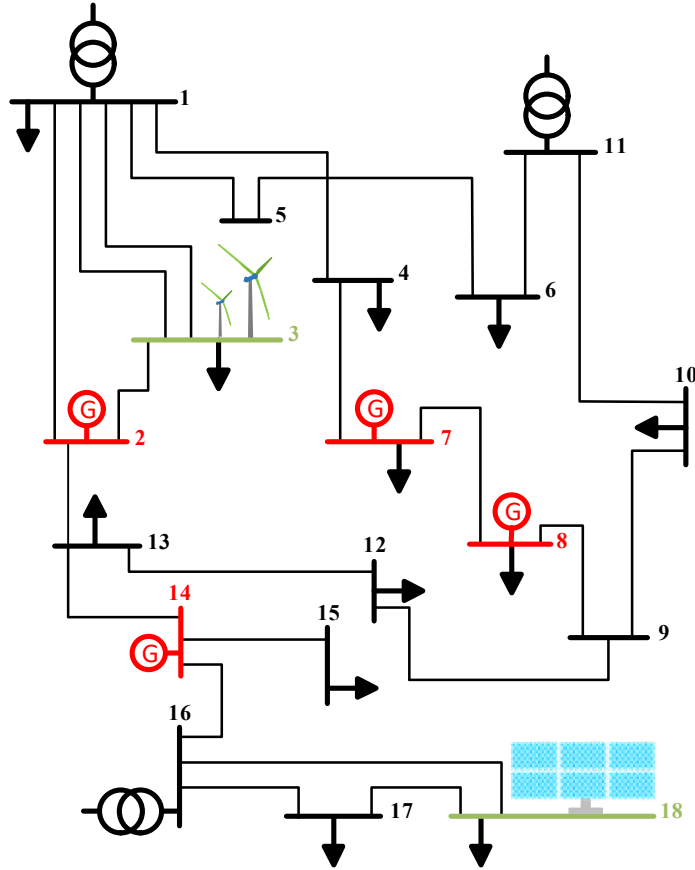


Fig. 3. Network of the VPP

The structure of the VPP is shown in Fig. 4. As can be seen from this figure, the VPP plans according to the data it obtains from the market and consumers. Non-renewable units have a bidirectional connection to the VPP controller. Since these units are controllable, they adjust their production with the controller command. Dispatchable loads are also controllable, but renewable units are not. Arrows in GSPs are bidirectional, which means the VPP can exchange power with them.

The VPP is connected to the upstream network through 1, 11, and 16 buses (Grid Supply Points) and exchanges power. The power exchange capacity with the upstream network in GSPs is assumed to be 12, 24, and 40 MW, respectively. The price of these GSPs is 95%, 105%, and 100% of the market price, respectively. The maximum amount of dispatchable loads is 5% of the normal load [36].

The original self-scheduling model is formulated and an IGDT-based operation model is proposed as a Mixed Integer Nonlinear Program (MINLP).

Table II: Main characteristics of VPP's DERs

DER No.	$P_{max}$ (MW)	$P_{min}$ (MW)	C (\$/MWh)	RUP (MW/h)	$\chi(dg)$ (Kg/MWh)
DG2	4	0	40	1	5.44
DG7	5	0	38	1.25	4.08
DG8	5.5	0	35	1.375	6.8
DG14	7	0	45	1.75	3.18

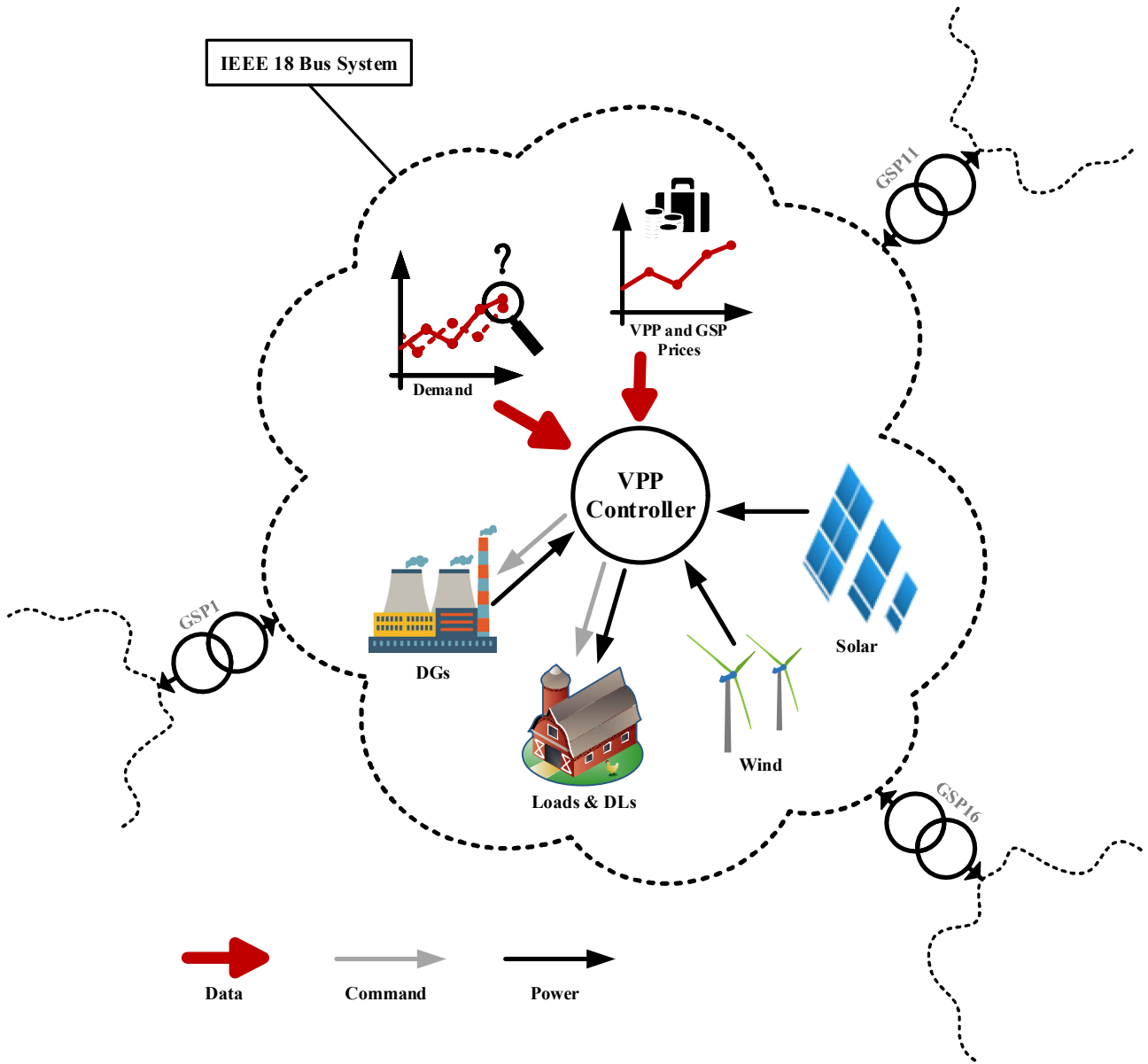


Fig. 4: Structure of VPP

#### 4.1. Risk-Neutral Case

For a typical day, forecasted price of day-ahead and the price for  $\alpha = 0.25$  which causes  $\xi = 0.142$  are shown in Fig. 5.

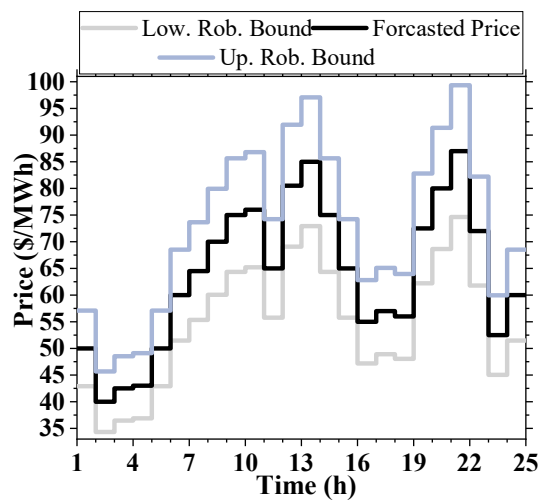


Fig. 5: Forecasted prices and the robustness region for  $\alpha = 0.25$  for an arbitrary 24-h period

In the risk-neutral case, forecasted prices are used and the problem is solved with respect to Eqs. (4)-(6) and (15)-(23). Production power in DG2 and DG8 is shown in Figure 6. DG8 has produced the most power in almost all scheduling hours. DG2 has produced less power than that. The main reason is that DG8 is cheaper than DG2. Since the price in GSP1 is lower than the market price (5%), the VPP tends to buy power through this bus. In GSP11 the situation is the opposite and the price in this GSP is 5% higher than the market price, so VPP tends to sell power through this point. In the early hours of scheduling, renewable units produce little power, so dispatchable loads curtailed a little of their own power. In this case, the final profit ( $A_0$ ) is equal to 13,385\$.

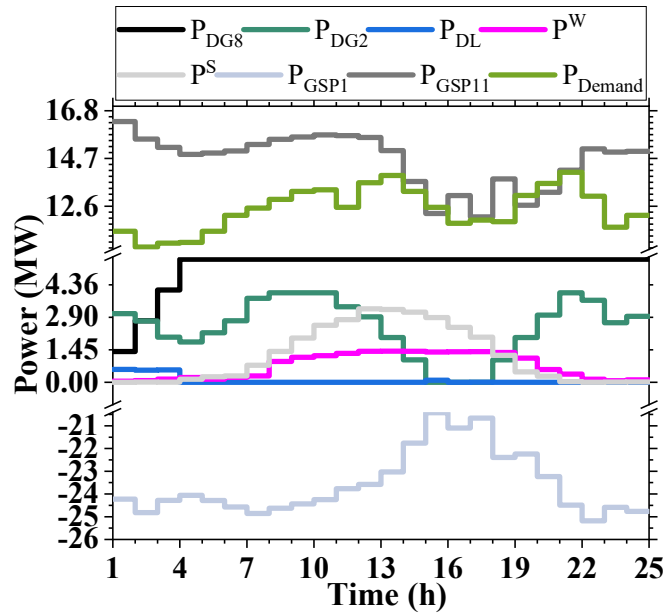


Fig. 6: Power generation in the risk-neutral case

#### 4.2. Robust Case

After solving the problem in the risk-neutral case, with respect to Eqs. (30)-(32), the problem is solved for different values of  $\alpha$  and different  $A_e$  is obtained. As an example for  $\alpha = 0.4$  guaranteed profit is  $A_e = 8030.96\$$  under the condition that  $\xi$  is not more than 22.4%. By solving the optimization problem Eqs. (30)-(31), for  $\alpha = 0.05 - 0.5$  values of robustness function for  $\xi$  are calculated and are shown in Fig. 7.

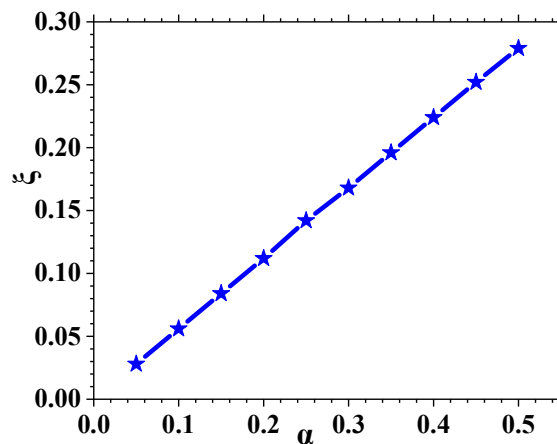


Fig. 7: Optimum robustness function value  $\xi$  versus profit deviation factor  $\alpha$

The answer to the problem for  $\alpha = 0$  is the same as the risk-neutral case which is explained. The value of the robustness parameter increases with increasing  $\alpha$  and it means that increasing forecasted error causes decreasing profit from what is expected. Scheduling of DG2, GSP1, GSP16, and  $P_{DL}$  are shown in Fig. 8. This program is shown for  $\alpha = 0.1$  and  $\alpha =$

0.5 by robust model. This shows that with increasing  $\alpha$ , the output power of units, for example, DG2 decreases. In GSP1 which prices are %95 of the market price, with increasing  $\alpha$ , purchased power decreases and in GSP16 which prices are equal to the market price, with increasing  $\alpha$ , the exchanged power decreases or doesn't change. On the whole, with increasing  $\alpha$ , produced power of units has decreased or has not changed. According to Eq. (25), with increasing  $\alpha$ , guaranteed profit decreases, hence the power generation in the VPP also diminishes.

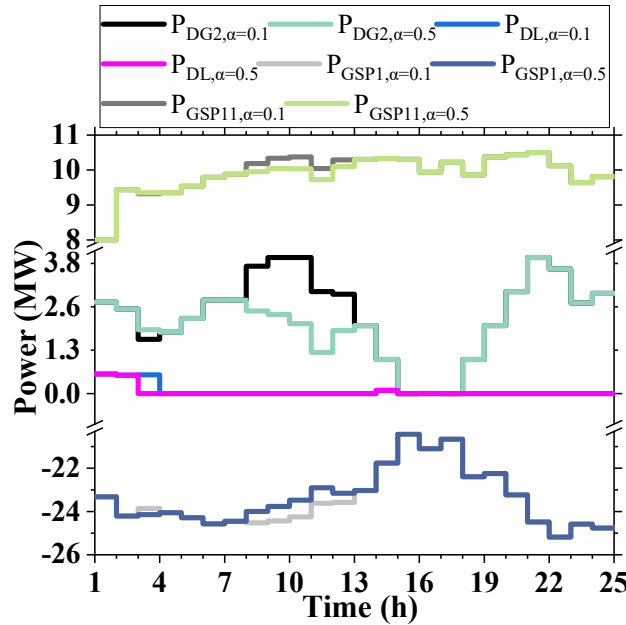


Fig. 8: Robust schedule of some component of VPP for two different critical profits

In GSPs according to their types, for those that their price is more than the market price, power does not change or increase, and for those that their price is lower than the market price, power decrease. In other words, as shown in Fig. 9, with increasing  $\xi$ , profit will decrease because with increasing  $\xi$ , price error becomes more than its forecasted value.

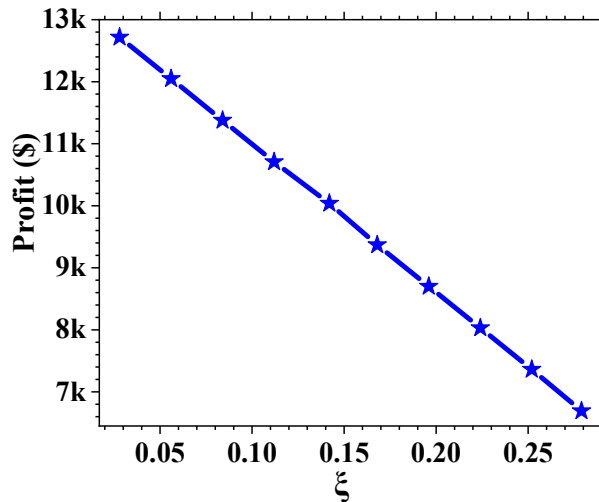


Fig. 9: Profit in Robust case versus  $\xi$

### 4.3. Opportunity Case

For obtaining profit in this case, from Eq. (31),  $\beta$  is being increased from 0.05 to 0.7 and from Eqs. (32)-(34) the optimization problem is solved. Values of target profit for different values of opportunity function are shown in Fig. 10. Compared to the neutral risk case, the profit is higher in this case, because the market price is higher than the forecasted price. Compared to figure 6 in the paper, the production of DG2 has increased. There are similar conditions in GSPs. In comparison between  $\beta = 0.1$  and  $\beta = 0.5$ , it should be noted that in case of increasing beta, the amount of profit will



increase according to Eq. (31). As can see in GSP1, with the increasing beta, the amount of purchases from the upstream network (with 95% price) has increased. In GSP11 it is reversed. In this GSP, the price is 105% of the market price, so with the increasing beta, the amount of sales has increased.

Fig. 12 shows different profits for different values of  $\tau$ . As an example, for having a minimum guaranteed a profit of 18738.91 \$, at least market price should be increased by 22.2% and vice versa.

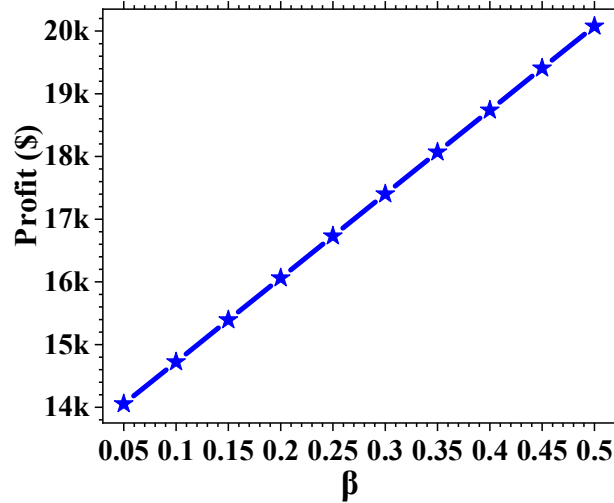


Fig. 10: Profit in opportunity case versus  $\beta$

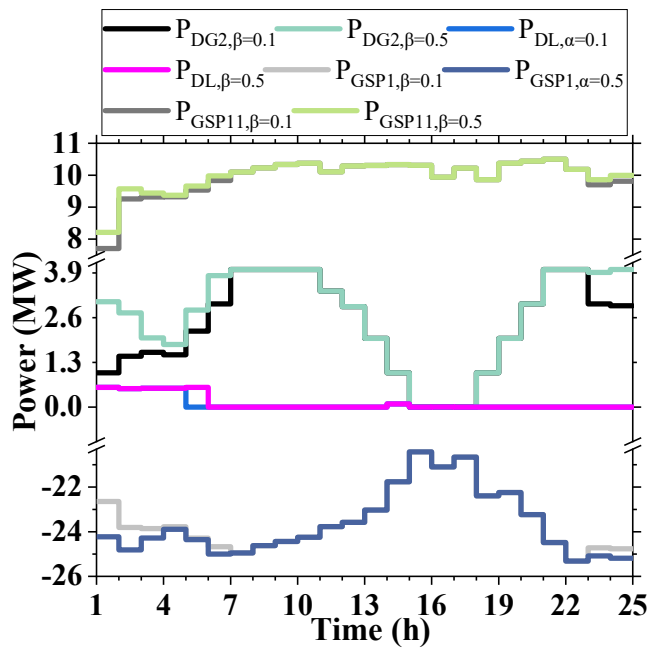


Fig. 11: Opportunity schedule of some component of VPP for two different critical profits

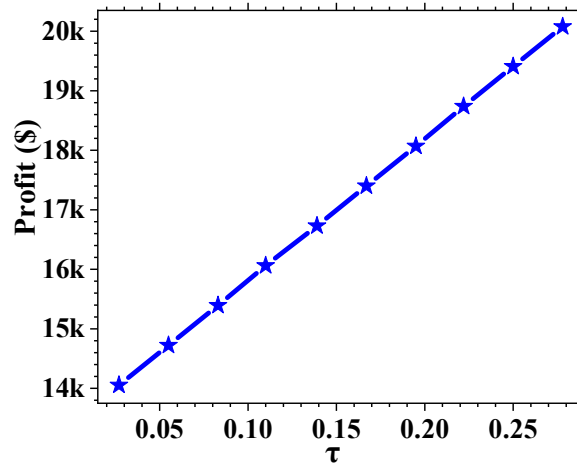


Fig. 12: Profit in Opportunity case versus  $\tau$

#### 4.4. Bi-Objective Case

In this case, in order to investigate the effect of renewable-based VPPs on emission and profit, the problem is solved by a two-objective method. For this purpose, two-objective functions are required. The first objective function is considered as the main objective function ( $f_1$ ) and the gaseous emission is considered as a constraint or the second objective function ( $f_2$ ). Using Eqs. (4)-(6), (15)-(23), and (37)-(41), and with respect to the main objective function, the problem is solved in the two-objective method. The cumulative profit and emission of the VPP are shown in Figure 13. As can be seen from this figure, the amount of profit is higher in the presence of renewable resources. In the case of emission, it is the opposite, as it is clear from this figure, while the renewable resources are in the VPP, the amount of emission is less. The main reason is that part of the production contribution is provided by pollutant sources through renewable sources.

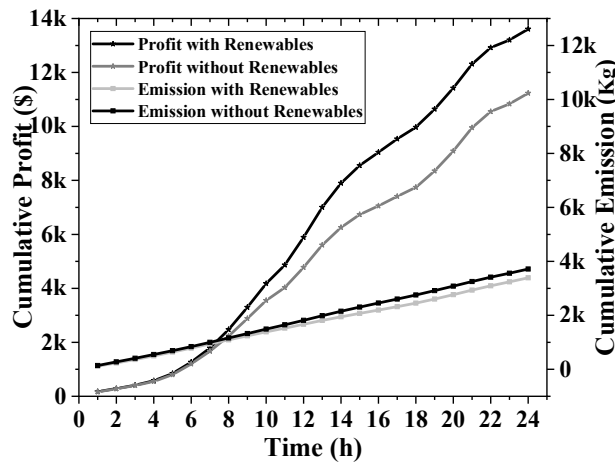


Figure 13: Cumulative profit and emission of the VPP with and without renewable resources

As shown in Fig. 14, the amount of emission is also increased by increasing the amount of profit, which is one of the most important reasons of that is the increase in the production of VPP units. To solve the problem using the epsilon constraint method, the problem is first solved with a single-objective approach with consideration of profit. In this case, the amounts of VPP profit and emission are 13,385\$ and 1565.08Kg, respectively. Then, the problem is solved in a single-objective manner and only with respect to the emission objective function. In this case, there is a significant decrease in the amount of emission, reaching 972.92Kg. However, the profit is also decreased to 8888.8\$. Finally, the problem was solved by using the two-objective epsilon constraint method, which resulted in a number of 10 Pareto solutions.

The fuzzy decision-making method, as described above, is used to select the best solution from the Pareto solutions. The choice of the best solution depends on the importance of the objective functions to each other. For this purpose, three different statuses are considered as below:

**Status I:** The importance of the profit objective function is considered to be triple of the emission one.

**Status II:** The importance of the emission objective function is considered to be triple of the profit one.

**Status III:** The importance of the profit objective function is considered to be equal with the emission one.

According to the expressed statuses and Eqs. (39)-(41), the best Pareto solution is obtained in each status. In the status I, the eighth Pareto solution is selected as the best solution. In statuses II and III, the second Pareto solution is selected as the best solution. Fig. 14 shows the profit and emission of these Pareto solutions and Fig. 15 shows the membership values of them.

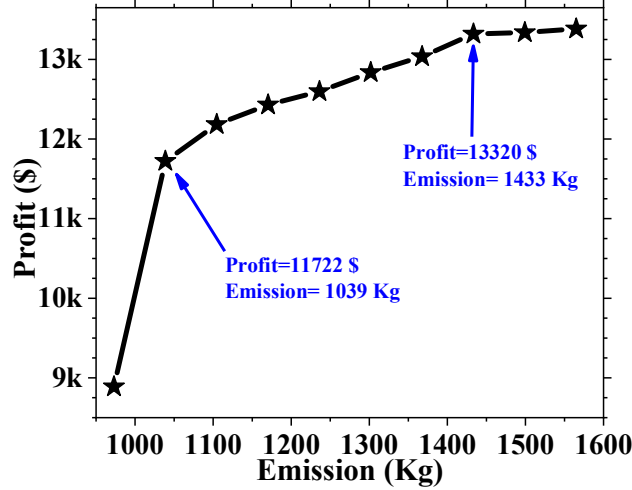


Fig. 14: Pareto optimal solutions, the profit versus emission

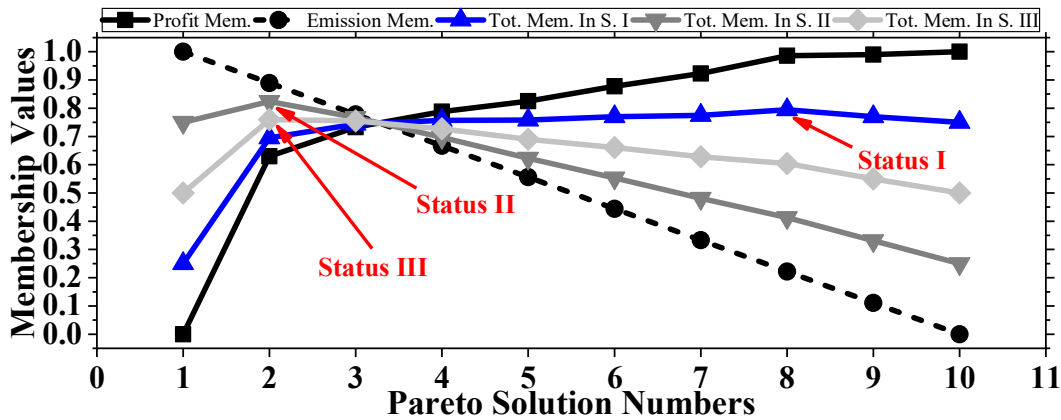


Fig. 15: Variation of the total membership, profit and emission functions versus Pareto optimal solutions

Table III provides the size of the optimization model. All models have been solved using Generalized Algebraic Modelling Systems (GAMS) software with DICOPT solver [39]. The system used to solve the problem is a Laptop with an Intel Core i-7 CPU with 2.5 GHz speed and 6 GB RAM on Win. 10 systems. In the risk-neutral (single-objective) case, we seek to maximize profit and there is no limit on the amount of emission objective function. In other words, in the single objective case, the value of the emission objective function is just calculated with no limitations. But in the case of two objectives, the emission objective function is limited to a certain interval. In other words, the problem-solving space is limited to find the maximum profit for the VPP. For this reason, the problem is solved in a lower number of iterations.

Table III: Execution time and size of the model

Cases	Execution Time (s)	Iterations	Single Equations	Single Variables	Discrete Variables
Risk Neutral	60.2	722	25795	9252	300
Bi-Objective (Status I)	68.9	660	25796	9252	300
Opportunity Case	136.6	744	25796	9253	300
Robust Case	103.3	728	25796	9253	300

Table IV shows the production power of renewable units, non-renewable units, dispatchable loads, and profit in risk-neutral and bi-objective cases. The production power of DGs in the bi-objective case differs greatly from the risk-neutral case. This limitation of production in these units is related to the emission problem. Among these, DG14 is the most expensive unit, but since it has less emission than the others, its production has increased compared to the risk-neutral case. The DG7 has similar conditions to the DG8. The total power required in the network in 24 hours is approximately 300 MW.

Table IV: Total generation and exchange power in the VPP

Cases	Generation Power (MW)					Exchanged Power (MW)			Curtailed Power (MW)	Profit (\$)	
	DG2	DG7	DG8	DG14	Wind	Solar	GSP1	GSP11	GSP16		PDL
<b>Risk Neutral</b>	58.9	90.74	123.75	1.75	17.528	29.134	-565.6	350.7	239.1	1.76	13384.93
<b>Bi-Objective (Pareto No. 7)</b>	89.99	112.5	46.80	25.32	17.528	29.134	-586.4	390.1	221	2.79	13036.69

## 5. Conclusion

This paper provided a method for the optimal bidding strategy of a renewable-based VPP, including conventional units, wind unit, solar unit, and dispatchable loads. The IGDT-based formulations for the VPP are proposed with an eye to the unspecified future electricity market prices. In the case of the risk-averse VPP, the proposed robust formulation could guarantee the minimum critical profit if the future prices fall into the maximized robustness region; while, for a risk-seeker VPP, the proposed opportunistic formulation enables the VPP to benefit from unpredicted spikes and reach to the desired profit. The proposed formulation has been applied to the 18-bus test system. By taking into account that the IGDT-based model does not require both probability distribution functions of the uncertain parameters and the capability of the method for modelling VPPs with different risk criteria, the IGDT-based model can attract much interest from the actual business. Another contribution of this paper was solving the problem in a two-objective approach using the epsilon constraint method, which aims to investigate the effect of renewable-based VPPs in maximizing the profit of the VPPs and minimizing their emission. Depending on the degree of importance of the profit and emission functions relative to each other, different final solutions will be obtained from Pareto solutions.

## References

- [1] J. Samanes, A. Urtasun, E. Gubia and A. Petri, "Robust multi-sampled capacitor voltage active damping for grid-connected power converters," *International Journal of Electrical Power & Energy Systems*, vol.105, 741-752, 2019.
- [2] Ahmad, T., Zhang, D., & Huang, C. Methodological framework for short-and medium-term energy, solar and wind power forecasting with stochastic-based machine learning approach to monetary and energy policy applications. *Energy*, 231, 120911, 2021.
- [3] Nikpour, A., Nateghi, A., Shafie-khah, M., & Catalão, J. P. Day-ahead optimal bidding of microgrids considering uncertainties of price and renewable energy resources. *Energy*, 227, 120476, 2021.
- [4] Nguyen, H. T., Le, L. B., & Wang, Z. A bidding strategy for virtual power plants with the intraday demand response exchange market using the stochastic programming. *IEEE Transactions on Industry Applications*, 54(4), 3044-3055, 2018.
- [5] J. MartI. "Overview FENIX Findings and recommendations on LSVPP," [Online]. Available: <http://www.fenix-project.org/>.
- [6] M. Shafiekhani and A. Badri, "A Risk-Based Gaming Framework for VPP Bidding Strategy in a Joint Energy and Regulation Market," *Iranian J. of Science and Technology, Transactions of Electrical Engineering*, vol. 113, 208-219, 2019.
- [7] Shafiekhani, Morteza, Ali Badri, Miadreza Shafie-Khah, and João PS Catalão. "Strategic bidding of virtual power plant in energy markets: A bi-level multi-objective approach." *International Journal of Electrical Power & Energy Systems* 113, 208-219, 2019.

- [8] N. Rezaei, A. Ahmadi, A. Khazali, and J. Aghaei, "Multi-objective Risk-Constrained Optimal Bidding Strategy of Smart Microgrids: An IGDT-based Normal Boundary Intersection Approach," *IEEE Transactions on Industrial Informatics*, vol.15, n.3, 1532-1543, 2018.
- [9] Mirzaei, M. A., Sadeghi-Yazdankhah, A., Mohammadi-Ivatloo, B., Marzband, M., Shafie-khah, M., & Catalão, J. P. Integration of emerging resources in IGDT-based robust scheduling of combined power and natural gas systems considering flexible ramping products. *Energy*, 189, 116195, 2019.
- [10] S. E. Razavi, A. Esmael Nezhad, H. Mavalizadeh, F. Raeisi, and A. Ahmadi, "Robust hydrothermal unit commitment: A mixed-integer linear framework," *Energy*, vol. 165, pp. 593-602, 2018.
- [11] M. Saeedi, M. Moradi, M. Hosseini, A. Emamifar and N. Ghadimi, "Robust optimization based optimal chiller loading under cooling demand uncertainty". *Applied Thermal Engineering*, vol. 148, 1081-1091, 2019.
- [12] Nazari-Heris, Morteza, Behnam Mohammadi-Ivatloo, Gevork B. Gharehpetian, and Mohammad Shahidehpour. "Robust short-term scheduling of integrated heat and power microgrids." *IEEE Systems Journal* 13, no. 3, 3295-3303, 2018.
- [13] H. A. Bagal, Y. N. Soltanabad, M. Dadjuo, K. Wakil, and N. Ghadimi, "Risk-assessment of photovoltaic-wind-battery-grid based large industrial consumer using information gap decision theory," *Solar Energy*, vol. 169, 343-352, 2018.
- [14] Bahramara, S. "Robust Optimization of the Flexibility-constrained Energy Management Problem for a Smart Home with Rooftop Photovoltaic and an Energy Storage." *Journal of Energy Storage* 36, 102358, 2021.
- [15] H. Mavalizadeh, A. Ahmadi, F. H. Gandoman, P. Siano, and H. A. Shayanfar, "Multiobjective Robust Power System Expansion Planning Considering Generation Units Retirement," *IEEE Systems Journal*, vol. 12, no. 3, pp. 2664-2675, 2018.
- [16] Ben-Haim, Yakov. "Feedback for energy conservation: An info-gap approach." *Energy* 223, 119957, 2021.
- [17] Jordehi, A. Rezaee. "Information gap decision theory for operation of combined cooling, heat and power microgrids with battery charging stations." *Sustainable Cities and Society*, 103164, 2021.
- [18] M. Kazemi, B. Mohammadi-Ivatloo, and M. Ehsan, "Risk-constrained strategic bidding of GenCos considering demand response," *IEEE Transactions on Power Systems*, vol. 30. no. 1, pp. 376-384, 2015.
- [19] Lu, Xiaoxing, Kangping Li, Fei Wang, Zengqiang Mi, Rongfu Sun, Xuanyuan Wang, and Jingang Lai. "Optimal Bidding Strategy of DER Aggregator Considering Dual Uncertainty via Information Gap Decision Theory." *IEEE Transactions on Industry Applications* 57, no. 1, 158-169, 2020.
- [20] N. G. Paterakis, M. Gibescu, A. G. Bakirtzis, and J. P. Catalão, "A multi-objective optimization approach to risk-constrained energy and reserve procurement using demand response," *IEEE Transactions on Power Systems*, vol. 33, no. 4, pp. 3940-3954, 2018.
- [21] Zhao, Y., Lin, Z., Wen, F., Ding, Y., Hou, J., & Yang, L. Risk-constrained day-ahead scheduling for concentrating solar power plants with demand response using info-gap theory. *IEEE Transactions on Industrial Informatics*, 15(10), 5475-5488, 2019.
- [22] Yazdaninejad, M., Amjady, N., & Dehghan, S. VPP self-scheduling strategy using multi-horizon IGDT, enhanced normalized normal constraint, and bi-directional decision-making approach. *IEEE Transactions on Smart Grid*, 11(4), 3632-3645, 2019.
- [23] Gazijahani, F. S., & Salehi, J. IGDT-based complementarity approach for dealing with strategic decision making of price-maker VPP considering demand flexibility. *IEEE Transactions on Industrial Informatics*, 16(4), 2212-2220, 2019.
- [24] Yu, S., Fang, F., Liu, Y., & Liu, J. Uncertainties of virtual power plant: Problems and countermeasures. *Applied Energy*, 239, 454-470, 2019.
- [25] Liu, Y., Li, M., Lian, H., Tang, X., Liu, C., & Jiang, C. Optimal dispatch of virtual power plant using interval and deterministic combined optimization. *International Journal of Electrical Power & Energy Systems*, 102, 235-244, 2018.
- [26] Naughton, J., Wang, H., Cantoni, M., & Mancarella, P. Co-optimizing Virtual Power Plant Services Under Uncertainty: A Robust Scheduling and Receding Horizon Dispatch Approach. *IEEE Transactions on Power Systems*. 2021.
- [27] Y. Wang, W. Gao, F. Qian, Y. Li, "Evaluation of economic benefits of virtual power plant between demand and plant sides based on cooperative game theory," *Energy Conversion and Management*, vol. 238, 114180, 2021.

- [28] Rahimi, Mahdi, Fatemeh Jahanbani Ardakani, and Ali Jahanbani Ardakani. "Optimal stochastic scheduling of electrical and thermal renewable and non-renewable resources in virtual power plant." *International Journal of Electrical Power & Energy Systems* 127, 106658, 2021.
- [29] M. A. Mirzaei, M. Nazari-Heris, B. Mohammadi-Ivatloo, K. Zare, M. Marzband, M. Shafie-Khah, A. Anvari-Moghaddam, and J. P. S. Catalão, "Network-Constrained joint energy and flexible ramping reserve market clearing of power-and heat-based energy systems: A two-stage hybrid IGDT–stochastic framework," *IEEE Systems Journal*, 2020.
- [31] Kia, M., M. Shafiekhani, H. Arasteh, S. M. Hashemi, M. Shafie-khah, and J. P. S. Catalão. "Short-term operation of microgrids with thermal and electrical loads under different uncertainties using information gap decision theory." *Energy* 208, 118418, 2020.
- [32] N. Rezaei, A. Ahmadi, A. Khazali, and J. Aghaei, "Multiobjective Risk-Constrained Optimal Bidding Strategy of Smart Microgrids: An IGDT-Based Normal Boundary Intersection Approach," *IEEE Transactions on Industrial Informatics*, vol. 15, no. 3, 1532-1543, 2019.
- [33] A. Khazali, N. Rezaei, A. Ahmadi, and B. Hredzak, "Information Gap Decision Theory Based Preventive/Corrective Voltage Control for Smart Power Systems With High Wind Penetration," *IEEE Transactions on Industrial Informatics*, vol. 14, no. 10, 4385-4394, 2018.
- [34] M. Shafiekhani, A. Zangeneh, "Integration of Electric Vehicles and Wind Energy in Power Systems." *Electric Vehicles in Energy Systems*. Springer, Cham, 165-181, 2020.
- [35] M. Shafie-khah, E. Heydarian-Forushani, M. E. H. Golshan, M. P. Moghaddam, M. K. Sheikh-El-Eslami, and J. P. Catalão, "Strategic offering for a price-maker wind power producer in oligopoly markets considering demand response exchange," *IEEE Transactions on Industrial Informatics*, vol. 11, no. 6, 1542-1553, 2015.
- [36] M. Peik-Herfeh, H. Seifi, and M. Sheikh-El-Eslami, "Decision making of a virtual power plant under uncertainties for bidding in a day-ahead market using point estimate method," *International Journal of Electrical Power & Energy Systems*, vol. 44, no. 1, 88-98, 2013.
- [37] Pakdel, M. J. V., Sohrabi, F., & Mohammadi-Ivatloo, B. Multi-objective optimization of energy and water management in networked hubs considering transactive energy. *Journal of Cleaner Production*, 266, 121936, 2020.
- [38] S. Huang, Q. Wu, S. S. Oren, R. Li, and Z. J. I. T. o. P. S. Liu, "Distribution locational marginal pricing through quadratic programming for congestion management in distribution networks," *IEEE Transactions on Power Systems*, vol. 30, no. 4, pp. 2170-2178, 2015.
- [39] GAMS Web page [Online]. Available: [www.gams.com](http://www.gams.com).