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Energy Management of Virtual Power Plant to Participate in the Electricity Market Using Robust Optimization

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Abstract- *Virtual power plant (VPP) can be studied to investigate how energy is purchased or sold in the presence of electricity market price uncertainty. The VPP uses different intermittent distributed sources such as wind turbine, flexible loads, and locational marginal prices (LMPs) in order to obtain profit. VPP should propose bidding/offering curves to buy/sell from/to day-ahead market. In this paper, robust optimization approach is proposed to achieve the optimal offering and bidding curves which should be submitted to the day-ahead market. This paper uses mixed-integer linear programming (MILP) model under GAMS software based on robust optimization approach to make appropriate decision on uncertainty to get profit which is resistance versus price uncertainty. The offering and bidding curves of VPP are obtained based on derived data from results. The proposed method, due to less computing, is also easy to trace the problem for the VPP operator. Finally, the price curves are obtained in terms of power for each hour, which operator uses the benefits of increasing or decreasing market prices for its plans. Also, results of comparing deterministic and RO cases are presented. Results demonstrate that profit amount in maximum robustness case is reduced 25.91 % and VPP is resisted against day-ahead market price uncertainty.*

Keyword: Virtual power plant, Electricity market uncertainty, Robust optimization approach, Bidding and offering curves, Distributed energy resources.

NOMENCLATURE

DERs	Distributed energy resources
DGs	Distributed generators
EMS	Energy management system
LMP	Locational marginal prices
MILP	Mixed-integer linear programming
ODS	Optimal dispatch strategy
RO	Robust optimization
RES	Renewable energy sources
SG	Stochastic generation
VPP	Virtual power plant

1. INTRODUCTION

Nowadays, due to the climate change and environmental issues caused by the using fossil fuels, as well as the depletion and cost of non-renewable resources, the electric power industry is driven towards using renewable energy sources (RES) such as wind, solar and other renewable energy resources [1]. This issue in the electric power industry provides the intelligent power system with more utilization of renewable sources which results as following; reduction in energy losses, improved reliability, optimal control and utilization of the power system [2]. With the proliferation of RERs, despite the advantages of conventional power plants, there are problems with exploiting these resources in the power system [3]. These problems, which are caused by high volatility production, have created technical and commercial problems [4]. Technical problems indicate that the dynamic behavior of the power system and commercial problems are also seen in the electricity market participation segment. Today, one of the challenges facing the world of electricity in controlling and operating the distributed energy resources (DERs) is with problems raised, so it is essential to consider system performance improvements. Therefore, developing new approaches is essential in order to manage production and creating the right infrastructure for participation in the electricity market.

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1.1. Literature review

Smart distribution systems use a combination of distributed generators (DGs) and energy storage devices that are effective at the peak demand. Also, these systems utilize renewable sources which can be different as geographic location changes [3]. To create a sustainable power system with combination of distributed energy resources (DERs) and RESs, several strategies are presented by considering the current system with conventional units [4]. Virtual power plant (VPP) is defined as a management part of the distribution system which includes DER, storage, flexible loads, plug-in hybrid electric vehicle (PHEV) and electricity consumers by establishing energy management system (EMS) center with intelligent strategy [5]. Minimizing generation costs and greenhouse gas emissions, and maximizing profits or a combination of these purposes can be reached by using VPP [6]. The planning which takes place in EMS can be complicated with considering uncertainties, time constraints and non-linearity [7].

It is worth noting that another solution to address the above problems is the word microgrid. So that the microgrid, like VPP, is a program for integrating distributed generations (DGs) and storing energy in the smart grid. But the difference between VPP and microgrid is that the microgrid is a subset of VPP or inside VPP that can work as an island or connected to VPP [8].

The VPP is divided into two types of commercial VPP (CVPP) and technical VPP (TVPP) from two different perspectives of economic and technical aspects. Participation in the market and attaining maximum profits from different markets is the CVPP's goal while TVPP demodulates the technical limitations of the existing network to achieve these goals [9],[10].

Coalition problem or DERs integration problem considering the VPP is studied in some researches which their results show the advantage of DERs aggregation in attaining maximum profit [11].

EMS in the VPP performs the optimal dispatch strategy (ODS) that is responsible for regulation and control of power dispatch. Maximizing the profit and minimizing VPPs cost are the ODS's goal, The ODS feature makes EMS a two-way communication between real-time data entry from DER to EMS and the output of simultaneous control signals from EMS to DER [12]. ODS should be able to predict the pricing schedule for the electricity market by considering the electricity market price, retail electricity price, the expected load, and an error [13]. Using the meteorological system with the new meteorological data measurements to better prediction of stochastic generation (SG) resources in order to boost profits is another VPP mechanism [14]. In [15], energy management of renewable-based microgrid based on information gap decision theory is studied. Furthermore, bidding strategy of energy hub system is provided in [16].

In practice, all the required information for the DER should be transferred to the EMS control center, which this process will meet telecommuting problems. By considering relation between small scale generation, storages and flexible loads with control center, EMS is known as a heart of the VPP [17]. The cost and benefits arising from the formation of the VPP and the penetration of flexible loads and PHEV on the network are shown through analysis in [18]. A new mechanism to incentivize and encourage DG owners is prediction report of their generation in VPP [19].

While estimates are doubtful, most researches acknowledge the benefits of combining DERs with the VPP help. However, risk management is necessary for VPP due to market prices and uncertainties which are caused by renewable energy resources. In order to self-scheduling of VPP, a robust optimization-based decision-making tool is applied in [20]. In [21], robust planning of smart distribution network in the critical situation considering the load and wind energy generation uncertainties in the presence of demand response programs for customers is investigated.

EMS has significant uncertainties due to the decisions made. Robust optimization (RO) approach is a non-probabilistic method which is used to obtain market price uncertainties. Considering the worst-case analysis, this approach is a safe procedure to resist against risk and shows a conservative state.

1.2. Novelty and contributions

Using the stochastic optimization model imposes more computational burden due to the high number of scenarios. Accordingly, a robust optimization-based model is proposed in this paper to manage the risk associated with market price uncertainty. Robust optimization technique is a new non-probabilistic method to control uncertainties. The VPP by using RO method can scientifically decide according to its contract with DG owners and how to buy or sell from or to the market due to uncertainties. The day-ahead market price knowledge is the key component to attain maximum revenue. Although VPP's profit is slightly reduced due to uncertainties in spite of using RO, but it resists against market price uncertainties. In this case, the bidding and the offering curves are proposed for each hour.

According to the mentioned explanation, the novelty and contributions of proposed work are provided as follows:

1. Virtual power plant (VPP) is scheduled in the presence of price uncertainty.
2. Robust optimization tool is proposed to model price uncertainty.
3. Locational marginal prices are used as an opportunity to increase profits.
4. Robust scheduling of VPP is obtained via robust optimization approach in comparison with deterministic method.
5. Bidding and offering curves of VPP are obtained to bid/offer to the market.

1.3. Paper organization

Rest of this paper is organized as follows: A deterministic formulation of the VPP is presented in Section 2. Robust optimization-based formulation of VPP is presented in Section 3. Required data are presented in Section 4. Comparison results between deterministic and robust optimization as well as optimal bidding and offering strategies are presented in Section 5. Finally, this paper is concluded in Section 6.

2. Deterministic formulation of VPP

The VPP is modeled by using the integration of different generation units such as DGs, SGs and flexible loads. VPPs should buy energy for VPP-affiliated customers and sell additional generation of DG sources to the market by using different LMPs to attain more revenue. All the taken decisions are based on the VPPs perspective in which the DG owners have not interfered on the decisions. In other words, uncertainties of wind and sunlight, besides other environmental factors are on the DG owners responsibility [20].

The profit function of VPP is formulated in Eq. (1) which should be maximized.

$$\begin{aligned} Max\, Z_{profit} = \sum_{t=1}^{T} ((P_t^D + BC_t) \times \lambda_t^{DSO.charge} \\ + \sum_{k\epsilon GSP} P_{kt}^{Upstream} \times \lambda_{kt}^{LMP} \\ - \sum_{i\epsilon DG} (P_{it}^{DG} \times \lambda_i^{DG.cost} + y_{it}^{DG.start} \\ \times \lambda_i^{DG.startcost} + Z_{it}^{DG.shut} \\ \times \lambda_i^{DG.shutcost}) - \sum_{j\epsilon SG} P_{jt}^{SG} \times \lambda_j^{SG.cost} \\ - P_t^{FL} \times \lambda_t^{FL.cost}) \end{aligned} \quad (1)$$

where Z_{profit} is the expected revenue from whole system minus operational and maintenance costs or total profit for a specific period. The first term is total revenue from sold energy to ordinary and contracted customers where P_t^D is the total active power demand of VPP's customers in time period t (MW), BC_t is bilaterally contracted energy delivery in time period t (MWh), $\lambda_t^{DSO.charge}$ is power price that is charged to local VPP customers in time period t ($/MWh), and T is set of time periods. The second term is income/cost from selling/buying energy from/to the upstream grid with different LMPs with different market prices. In Eq.(1), $P_{kt}^{Upstream}$ is VPP's active power exchange with the day-ahead electricity market at the GSP k in time period t (MW), λ_{kt}^{LMP} is day-ahead market price at the GSP k (as LMP) in time period t ($/MWh), GSP is set of upstream grid supply points for transaction with the electricity wholesale market and K is index of upstream grid supply or transaction points. The third term shows generation, start-up and shut-down costs of DG units. where P_{it}^{DG} is generation of dispatchable DG unit i in time period t (MW), $\lambda_i^{DG.cost}$ is generation cost of dispatchable DG unit i ($/MWh), i is index of dispatchable DGs, $y_{it}^{DG.start}$ is a binary variable which is equal to 1 if unit i is started-up at the beginning of period t, $\lambda_i^{DG.startcost}$ is startup cost of dispatchable DG unit i ($), $Z_{it}^{DG.shut}$ is 0/1 variable which is equal to 1 if unit i is shut-down at the beginning of period t, $\lambda_i^{DG,shutcost}$ is shut down cost of dispatchable DG unit i ($) and DG is set of dispatchable DGs active in the VPP coalition. The forth section presents installing, starting and maintaining of SG units and the final term is related cost to limited flexible load or disconnection of the load. where P_t^{FL} is the curtailment value of flexible loads in time period t (MW) and $\lambda_t^{FL.cost}$ is cost of a flexible load to curtail its demand in time period t ($/MWh).

As the VPP does not have precise scheduling or prediction of uncertainty parameter, it is possible to face lack of generation which in this case, wholesalers of the market are one of variables for helping VPP to supply costumers load. This issue can be harmful to VPP due to bilateral contracts with appointed prices [22].

The objective function should be maximized subject to technical constraints which are presented as follows: The amount of VPP power exchange with the upstream grid is limited to required amount and maximum capacity of connected feeder to the upstream grid.

$$P_{kt}^{Upstream} \geq -\min\left\{\max\left\{0.\left(P^{D.max} - \sum_{i\epsilon DG} P_i^{DG.min} - \sum_{j\epsilon SG} P_j^{SG.min} - P^{FL.min}\right)\right\}.P_k^{SSmax}\right\} \quad \forall k.t \tag{2}$$

$$P_{kt}^{Upstream} \leq \min\left\{\max\left\{0.\left(\sum_{i\epsilon DG} P_i^{DG.max} + \sum_{j\epsilon SG} P_j^{SG.max} + P^{FL.max} - P^{D.min}\right)\right\}.P_k^{SSmax}\right\} \quad \forall k.t \tag{3}$$

The constraint (2) is used when the VPP wants to buy from the grid. In Eq. (2), $P^{D.max}$ is VPP's customers maximum demand (MW), $P_i^{DG.min}$ is minimum DG capacity limit for active power (MW), $P_j^{SG.min}$ is minimum SG capacity limit for active power (MW), $P^{FL.min}$ is lower limit for curtailing on flexible loads (MW), and P_k^{SSmax} is the rating of the GSP k for exchanging power with the main grid (MVA).

The constraint (3) is enabled when the VPP sells power to any of the upstream grid points. In Eq. (3), $P_i^{DG.max}$ is maximum DG capacity limit for active power (MW), $P_j^{SG.max}$ is installed capacity of stochastic DG unit j (MW), $P^{FL.max}$ is upper limit for curtailing on flexible loads (MW) and $P^{D.min}$ is minimum value of VPP's customers demand (MW).

The constraint (4) indicates that the required amount of contractual and requested power in the VPP must be met.

$$\sum_{i\epsilon DG} P_{it}^{DG} + \sum_{j\epsilon SG} P_{jt}^{SG} + P_t^{FL} - \sum_{K\epsilon GSP} P_{kt}^{Upstream} \geq P_t^D + BC_t \quad \forall t \tag{4}$$

where, P_{jt}^{SG} is generation of stochastic DG unit j and in time period t (MW).

The constraints (5) and (6) show range of variation in flexible loads at each time period which is considered as reduction in demand or load interruption.

$$P_t^{FL} \leq P_t^{FL.\max} \quad \forall t \tag{5}$$

$$P_t^{FL} \geq 0 \quad \forall t \tag{6}$$

Amount of power change in dispatchable power generation units is shown by constraints (7) and (8).

$$P_{it}^{DG} \leq P_i^{DG.max} \times v_{it}^{DG} \quad \forall i.t \tag{7}$$

$$P_{it}^{DG} \geq P_i^{DG.min} \times v_{it}^{DG} \quad \forall i.t \tag{8}$$

where v_{it}^{DG} is 0/1 variable which is equal to 1 if unit i is online in time period t.

The constraints of (9) and (10) show the amount of the SG units' capacity. $P_{jt}^{SG.max}$ is assumed as a random parameter which might be predicted by SG owners [18].

$$P_{jt}^{SG} \leq P_j^{SG.max} \times v_{jt}^{SG} \quad \forall j.t \tag{9}$$

$$P_{jt}^{SG} \geq 0 \quad \forall j.t \tag{10}$$

Constraints (11) and (12) show the ramp up/down of dispatchable unit output.

$$P_{it}^{DG} - P_{i(t-1)}^{DG} \leq r_i^{up} \quad \forall i.t \tag{11}$$

$$P_{it}^{DG} - P_{i(t-1)}^{DG} \geq -r_i^{down} \quad \forall i.t \tag{12}$$

Constraints (13) and (14) model start-up and shut-down statuses of dispatchable units and prevent being simultaneously on and off.

$$y_{it}^{DG.start} - z_{it}^{DG.shut} = v_{it}^{DG} - v_{i(t-1)}^{DG} \quad \forall i.t \tag{13}$$

$$y_{it}^{DG.start} + z_{it}^{DG.shut} \leq 1 \quad \forall i.t \tag{14}$$

where $y_{it}^{DG.start}$ is 0/1 variable which is equal to 1 if unit i is started-up at the beginning of period t and $z_{it}^{DG.shut}$ 0/1 variable which is equal to 1 if unit i is shut-down at the beginning of period t.

As said before, bad predictions of SG units can cause damage to the VPP. To cope with these problems, VPP will assign part of dispatchable units, in small scale, as a secure margin. Therefore, need for power storage will be increased relatively, due to increase in renewable units.

$$\sum_{i\epsilon DG}(P_i^{DG.max} - P_{it}^{DG} + P_t^{FL} \geq \zeta_0 \times \left(\sum_{j\epsilon SG} P_{jt}^{SG}\right) + \zeta_{total} \times \left(P_t^{FL} + \sum_{i\epsilon DG} P_{it}^{DG}\right) \quad \forall t \tag{15}$$

In Eq. (15), ζ_0 is VPP's surplus reserve (%), ζ_{total} is percentage of the total generation of dispatchable units and curtailment option of the flexible loads in the VPP coalition (%), ζ_0 is percentage of excessive storing arising from predictions of compensating damages from SG units which is equal to 5% and ζ_{total} is small percentage of total generation of dispatchable units and flexible loads which is considered equal to 2% [23].

The constraints (16) and (17) provide the minimum up/down time limitations for dispatchable units.

$$v_{it}^{DG} - v_{i.(t-1)}^{DG} \leq v_{i.(t+TU_{iw})}^{DG}$$
$$TU_{iw} = \begin{cases} w & w < MUT_i^{DG} \\ 0 & w > MUT_i^{DG} \end{cases} \quad \forall t.\forall i \tag{16}$$

$$v_{i.(t-1)}^{DG} - v_{it}^{DG} + v_{i.(t+TD_{iw})}^{DG} \leq 1$$
$$TD_{iw} = \begin{cases} w & w < MDT_i^{DG} \\ w & w \geq MDT_i^{DG} \end{cases} \quad \forall t.\forall i \tag{17}$$

where MUT_i^{DG} is minimum up time of dispatchable unit i (h), MDT_i^{DG} is minimum down time of dispatchable unit i (h) and W is index for modeling minimum up and down time limits running from 1 to $(MUT_i^{DG} - 1)$ and $(MDT_i^{DG} - 1)$, respectively.

In constraints (18) and (19), Δ_{BC} shows permitted difference between supplied energy and a contract with an acceptable deviation. Also according to constraints (20) delivered and contractual energy in 24 hours should be equal [2].

$$BC_t \leq (1 + \Delta_{BC}) \times E_t^{contract} \tag{18}$$

$$BC_t \geq (1 - \Delta_{BC}) \times E_t^{contract} \tag{19}$$

$$\sum_{t=1}^{24} BC_t = \sum_{t=1}^{24} E_t^{contract} \tag{20}$$

where $E_t^{contract}$ is energy delivered due to bilateral contracts in time period t (MWh).

The upstream grid market is based on LMPs which is affected by line constraints and upstream grid components leading to different prices in different parts of the network. In this paper, the main goal of VPP is to maximize profit by using different LMPs of the upstream grid. In other words, buying energy from low price pool point and selling to high price points can make significant revenue.

3. Robust optimization formulation of VPP

There are several methods to cope with uncertainties which can be divided into three main groups as probabilistic methods, possibility methods or combination of them [24],[25]. All the above-mentioned methods require data and special characteristic or behavior of the system [26].

The robust optimization method investigates the effect of an uncertain parameter on optimal result, which aims to reduce the sensitivity of the optimal result to the uncertain parameter. This approach can be considered as a substitution for stochastic programming to address uncertainty in the mathematical programming model. Robust optimization approach is a risk management method that has a low computing volume in comparison with other methods [27].

When the VPP faces significant uncertainties while there is no data for unspecified parameters, abovementioned methods cannot be useful. Robust optimization method has been introduced as an interesting optimization framework to reduce sensitivity against disorder in parameter values. Random planning and robust optimization are two applicable methods which have been using for several years. Robust optimization which was introduced since the 1950s, uses worst analysis to cope with uncertainties. A few years later, random probability distribution planning was introduced as a method for uncertainties with high scenario numbers with different possibilities [28],[29].

In random probability distribution planning method, uncertainties should be recognized which probability distribution estimation uncertainties for power system problem is difficult [30]. Three main advantage of robust optimization can be listed as follows [30]:

1. Reliable results because of using worst analysis
2. No need to possibility distribution in comparison with random programming
3. Better traceability of result due to fewer calculations.

Robust optimization would be more flexible than random programming, while has very fewer calculations

[31].
A standard MIP model for the linear optimization problem is defined in Eqs. (21) -(24) which are presented as follows:

$$Min \quad \sum_{j=1}^{n} c_j \times x_j \tag{21}$$

$$s.t. \quad \sum_{j=1}^{n} a_{ij} \times x_j \; \le b_i \qquad \forall i = 1. \dots . m \tag{22}$$

$$x_j \ge 0 \qquad \forall j = 1. \dots . n \tag{23}$$

$$x_j \epsilon \, \{0.1\} \qquad for\ some\ j = 1. \dots . n \tag{24}$$

If c_j coefficients are recognized in known boundaries, a MIP formulation for robust optimization method could be formed. To do so, it is assumed that each c_j coefficient is in the interval $[c_j - d_j . c_j + d_j]$ where d_j represents the deviation from the nominal coefficient c_j. In addition, for formulation a MIP robust problem, an integer control parameter, Γ_0, is defined which is in the interval $[0. |J_0|]$.

Let $J_0 = \{j | d_j > 0\}$.

The parameter Γ_0 controls the trade-off between the probability of the violation and its effect on the objective function of the nominal problem.

If $\Gamma_0 = 0$, the robustness level in the objective function is ignored and if $\Gamma_0 = |J_0|$, maximum cost deviation is considered which leads to conservative solution.

Considering (21)– (24), this RMILP problem can be formulated as

$$minimize \sum_{j=1}^{n} c_j \times x_j + maximize \left\{ \sum_{j \in S_0} d_i |x_j| \right\} \tag{25}$$

Subject to (22) -(24) (26)

This RMILP problem can be reformulated as another RMILP. Also, the problems (25) and (26) have an equivalent RMILP formulation, as follows:

$$Min \quad \sum_{j=1}^{n} c_j \times x_j + \beta . \Gamma_0 + \sum_{j=1}^{n} \zeta_j \tag{27}$$

Subject to:

Constraints (22) -(24) (28)

$$\beta + \zeta_j \ge d_j \times \omega_j \qquad j \epsilon J_0 \tag{29}$$

$$\beta \ge 0 \tag{30}$$

$$\zeta_j \ge 0 \qquad \forall j = 1. \dots . n \tag{31}$$

$$\omega_j \ge 0 \qquad \forall j = 1. \dots . n \tag{32}$$

$$\omega_j \ge x_j \qquad \forall j = 1. \dots . n \tag{33}$$

Eqs. (27) -(33) is obtained by using duality theory [27] which a detailed description is presented [32],[33].

Market price as an uncertain parameter in the VPP appears in the robust objective function that can be formulated in Eq. (34) as follows:

$$\begin{aligned} & Min \\ & - \left\{ \begin{aligned} & \sum_{t=1}^{T} ((P_t^D + BC_t) \times \lambda_t^{DSO.charge} + \sum_{k \epsilon GSP} P_{kt}^{Upstream} \\ & \times \lambda_{kt}^{LMP} - \sum_{i \epsilon DG} (P_{it}^{DG} \times \lambda_i^{DG.cost} + y_{it}^{DG.start} \times \lambda_i^{DG.startcost}) \\ & - \sum_{j \epsilon SG} P_{jt}^{SG} \times \lambda_j^{SG.cost} - P_t^{FL} \times \lambda_t^{FL.cost}) \end{aligned} \right\} \\ & + \beta \times \Gamma_0 + \sum_{k \in GSP} \sum_{t=1}^{T} \zeta_{kt} \end{aligned} \tag{34}$$

Subject to:

Constraints (2) -(17) (35)

Constraints (18) -(21) (if needed) (36)

$$P_t^D = a . \lambda_t^{DA.max} + b \qquad \forall t \tag{37}$$

$$\lambda_{kt}^{LMP} = \alpha_k \times \lambda_t^{DA.max} \qquad \forall k . t \tag{38}$$

$$\lambda_t^{DSO.charge} = \alpha_0 \times \lambda_t^{DA.max} \qquad \forall t \tag{39}$$

$$\beta + \zeta_{kt} \ge \left(\lambda_{kt}^{LMP.max} - \lambda_{kt}^{LMP.min} \right) \times \omega_{kt} \quad \forall t \tag{40}$$

$$P_{kt}^{Upstream} \leq \omega_{kt} \qquad \forall t \qquad (41)$$

Base equations of problem are Eqs. (34)-(41), where $P_{kt}^{Upstream}$ is related to power exchange with the upstream grid points, β and $\zeta_{k\,t}$ are dual variables of main problem for considering the $\lambda_t^{DSO.charge}$ variation range and ω_{kt} is an auxiliary expression is being used to get linear expressions. Γ_0 is in the interval [1,24] if $\{(\lambda_{kt}^{LMP.max} - \lambda_{kt}^{LMP.min}) > 0\}$ while $\Gamma_0 = 0$ if $(\lambda_{kt}^{LMP.max} - \lambda_{kt}^{LMP.min} = 0)$.

The proposed algorithm for obtaining optimal bidding and offering curves of VPP comprises the following steps:

1) Set market prices $\lambda_{kt}^{LMP} = \lambda_{kt}^{LMP.min}$ $(\forall\, k.t)$ and $\Gamma_0 = T$ to consider all possible deviations of market prices.

2) Set $d_{kt}^S = G^S(\lambda_{kt}^{LMP.max} - \lambda_{kt}^{LMP.min}); (t = 1.\ldots.24); (K = 1.11.16)$, where G^S is a coefficient that uses increasing values within [0,1] and S is the counter of iteration.

3) RMIP optimization (34)–(41) is solved to obtain the hourly scheduled power from power market at the iteration S.

4) In order to cover all ranges of coefficient G^S, the steps 2 and 3 should be repeated iteratively (categorized by S) as illustrated in Fig. 1.

5) Construct the optimal bidding and offering curves using the achieved results. The bidding and offering prices are computed in each iteration S by $\lambda_{kt}^{LMP.S} = \lambda_{kt}^{LMP.min} + d_{kt}^S$ $(\forall\, k.t)$. Also, the scheduled power for each time period and iteration S is obtained from the achieved results ($P_{K.t}^{upstream}$).

Finally, optimal bidding and offering curves of VPP are computed using the prices and the scheduled energies in all iterations results $\{\lambda_{kt}^{LMP.S} \times (P_{K.t}^{upstream.S})\}$.

It should be noted that $P_{K.t}^{upstream.S} > 0$ and $P_{K.t}^{upstream.S} < 0$ are for offering and bidding powers, respectively.

For more clarification, the flowchart of proposed algorithm is illustrated in Fig.1.

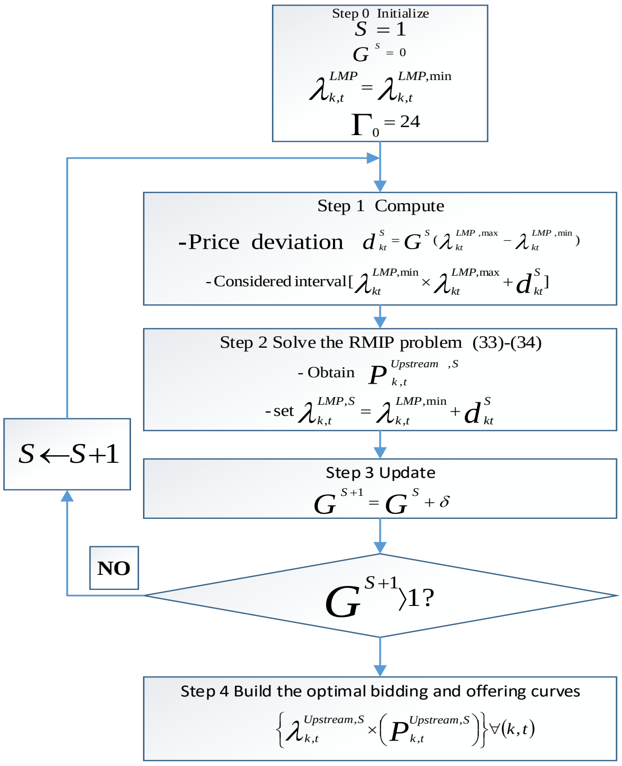

Fig. 1. Proposed algorithm structure.

4. Numerical studies

Clear In this section, a study on comparison of robust optimization with deterministic optimization method is presented. These comparisons are considered to show the ability of proposed algorithm in decision making of uncertainties.

In this paper, 18 buses distribution system which is part of known IEEE 30 buses with 33 KV is used [6],[34]. This system has four DG at buses 2, 7, 8 and 14 as shown in Fig. 2. Two DG units located at buses 15 and 18 which VPP is expected to control sum of distributed DGs. Also buying and selling energy from market is done by three stations with different LMPs which are located at buses 1, 11 and 16 as shown in Fig. 2.

According to the market price at GSPs 1, 11, and, 16 day-ahead prices are predicted as 95, 105, and 100, respectively with assumption $\lambda_t^{DA.forecast} = \lambda_t^{DA.max}$. As result, the value of the parameter $\alpha_0$is considered to be one. The capacity of each transformer is shown at each substation [35],[36]. Also predicted price information is given in Table 1 and price and amount of flexible loads are presented in Table 2 for 24 hours. It should be denoted that price deviation from the forecasted value is assumed 10 percent. Amount of power demand for supplying costumers load and power values of bilateral contracts are given in Table 3.

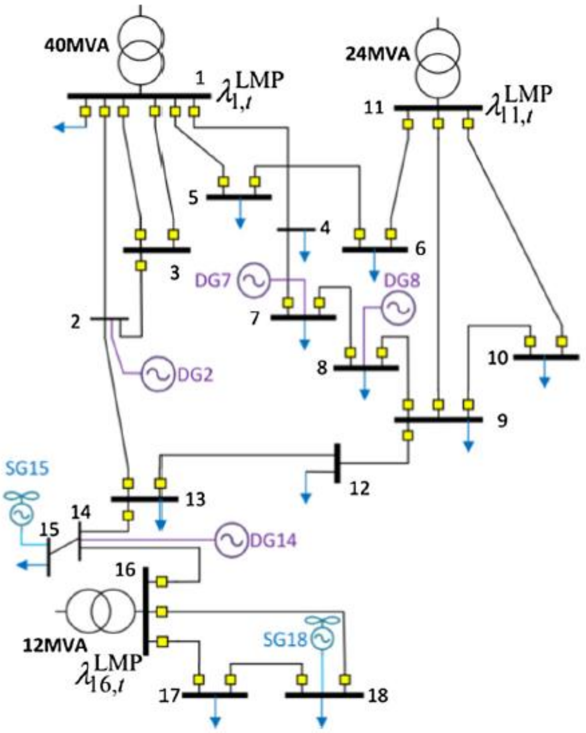

Fig. 2. Schematic diagram of the 18-bus distribution system.

Table 1. Market price forecasts for one day.

t(h)	λ_{kt}^{LMP}($/MWH)	t(h)	λ_{kt}^{LMP}($/MWH)	t(h)	λ_{kt}^{LMP}($/MWH)
1	46.03	9	76.95	17	108.31
2	45.14	10	69.09	18	89.54
3	45.50	11	65.84	19	76.83
4	45.70	12	59.47	20	73.60
5	55.80	13	56.47	21	59.59
6	82.28	14	53.77	22	52.47
7	84.80	15	52.90	23	47.77
8	83.44	16	71.44	24	39.17

Table 2. Characteristics of the flexible loads for one day.

t(h)	$\lambda_t^{FL.cost}$ ($/MWH)	$P_t^{FL.max}$ (MW)
1	37.30	0.591
2	40.96	0.585
3	51.52	0.426
4	53.83	0.589
5	57.80	0.610
6	74.83	1.132
7	99.91	0.852
8	89.50	1.217
9	61.96	1.021
10	66.88	0.871
11	63.87	0.601
12	50.12	0.643
13	46.93	0.660
14	51.04	0.689
15	58.35	0.700
16	85.61	0.799
17	105.10	1.017
18	84.44	0.859
19	81.78	1.067
20	75.91	0.696
21	68.03	0.557
22	44.10	0.474
23	41.69	0.656
24	43.90	0.533

Table 3. Bilateral contract and demand powers.

t(h)	λ_{kt}^{LMP}($/MWH)	$BC_t\ (MW)$	P_t^{Demand}(MW)
1	46.03	2.5	11.222
2	45.14	2.5	11.160
3	45.50	2.5	11.185
4	45.70	2.5	11.199
5	55.80	2.5	11.906
6	82.28	2.5	13.760
7	84.80	2.5	13.936
8	83.44	2.5	13.841
9	76.95	2.5	13.387
10	69.09	4	12.836
11	65.84	4	12.609
12	59.47	4	12.163
13	56.47	4	11.953
14	53.77	7.5	11.764
15	52.90	7.5	11.703
16	71.44	7.5	13.001
17	108.31	4	15.582
18	89.54	4	14.268
19	76.83	4	13.378
20	73.60	4	13.152
21	59.59	4	12.171
22	52.47	4	11.673
23	47.77	4	11.344
24	39.17	2.5	10.742

Prediction of day-ahead prices and technical and economical specification of DGs are shown in Tables 4 and 5, respectively. This data is evaluated based on set-up cost, maintenance cost, operation time, DGs lifetime, and most importantly market price from DG owners to VPP. In addition, control and coordination of EMS with DGs have some costs which should be added to levelized cost of electricity (LCOE) [12].

Table 4. Characteristics of dispatchable units included in VPP portfolio.

DER	DG2	DG7	DG8	DG14
$P_i^{DG.min}$	0	0	0	0
$P_i^{DG.max}$	4	5	5.5	7
$\lambda_i^{DG.cost}$	37	40	35	45
r_i^{up}	1	1.25	1.375	1.75
r_i^{down}	1	1.25	1.375	1.75
$\lambda_i^{DG.startcost}$	20	20	50	50
$\lambda_i^{DG.shutcost}$	25	25	25	25

Table 5. Characteristics of stochastic unit units included in VPP portfolio.

DER	$P_j^{SG.min}$	$P_j^{SG.max}$	$\lambda_j^{SG.cost}$
SG15	0	9	55
SG18	0	7	65

5. Results comparison and discussion

In this section, the results comparison of deterministic and RO models is provided. The obtained profit for one day by using MIP model under GAMS software is \$17,776.296 in deterministic approach. The results obtained for the deterministic case are presented in Table 6.

Table 7. The profit of VPP in the robust optimization approach.

Γ_0	Profit (\$)	Reduced Profit (%)
1	17317.241	2.582
2	16919.139	4.82
3	16545.397	6.92
4	16194.691	8.897
5	15883.975	10.645
6	15601.320	12.235
7	15344.706	13.678
8	15114.516	14.974
9	14907.688	16.137
10	14717.433	17.207
11	14539.550	18.208
12	14382.046	19.094
13	14262.011	19.769
14	14154.146	20.376
15	14047.602	20.975
16	13943.822	21.559
17	13841.726	22.134
18	13739.871	22.706
19	13640.914	22.263
20	13544.553	23.805
21	13449.058	24.342
22	13354.111	24.877
23	13260.683	25.402
24	13170.528	25.910

Γ_0 is robustness level in RO approach which its upper amount increases the resistance level against uncertainties. $\Gamma_0 = 0$ means robustness is zero and it is equal to deterministic approach which revenue is obtained as \$17,776.296.

According to its policy, VPP can change Γ_0 value. Maximum robustness is attained when $\Gamma_0 = 24$ and the minimum profit is as result which is equal to \$13,170.528 \$. In Table 7, profits and its difference with deterministic method for 24 cases are presented in percent. According to calculations, it can be seen that the maximum profit in the maximum robustness value is 25.910% less than deterministic case. Fig. 3 shows the profit amount for the different robustness values.

For analyzing three upstream grid connection points, the exchanged power between upstream grid and connection points 1, 11 and 16 are shown in Figs. 4, 5 and 6, respectively. It is noteworthy that, positive sign shows the sold power and negative sign shows the procured power from the upstream grid. For each hour, it can be seen that taken power from buses 1 and 16 is more than costumers demand. In fact, buying from inexpensive bus and selling to expensive one shows the arbitrager of VPP. Furthermore, according to Fig. 4, it is seen that procured power from connection point 1 is reduced in robust optimization approach in comparison with deterministic case in order to get more robust scheduling of VPP. Also, according to Fig. 5, it is seen that sold power from connection point 11 is reduced in robust optimization approach in comparison with deterministic case. Finally, according to Fig. 6, procured power from connection point 16 is reduced and sold power in robust optimization in comparison with deterministic approach.

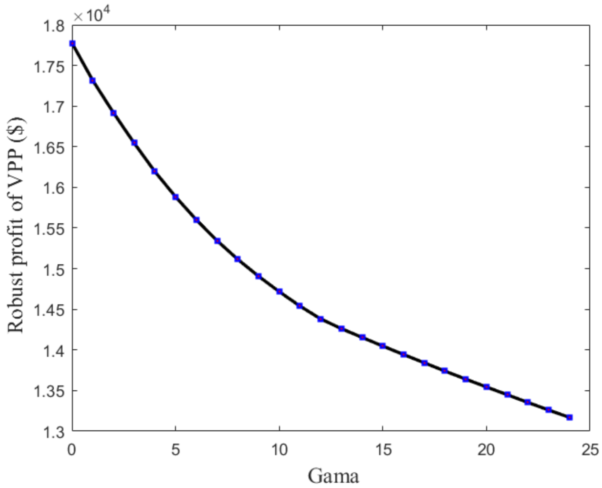

Fig. 3. Profit values for the different robustness values.

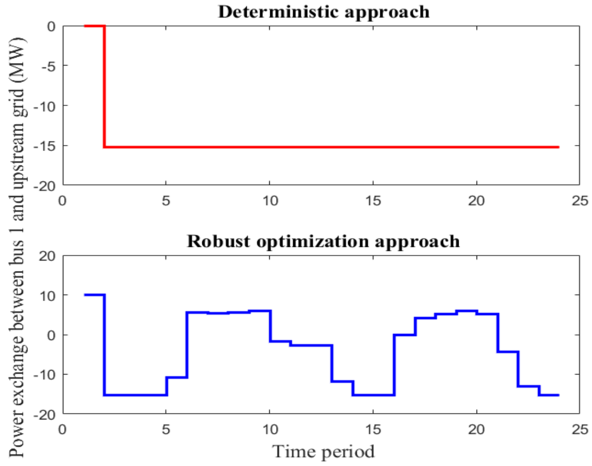

Fig. 4. Power exchange between bus 1 and the upstream grid

Table 6: Results of VPP short-term trading in deterministic approach (MW)

t(h)	$\lambda_t^{DA.forechastic}$($/MWH)	$\sum_{i\epsilon DG} P_{iT}^{DG}$(MW)	$\sum_{j\epsilon SG} P_{jT}^{SG}$(MW)	P_t^{FL}(MW)	BC_t (MW)	$\sum_K P_{kt}^{Upstream}$(MW)	$\sum_{j\epsilon SG} P_{jT}^{SG}$(MW)
1	46.03	16.483	0	0.591	2.250	3.102	0
2	45.14	18.307	0	0.585	2.250	5.482	0
3	45.50	17.917	0	0	2.250	4.482	0
4	45.70	17.917	0	0	2.250	4.468	0
5	55.80	17.948	9.0	0.610	2.250	13.402	9.0
6	82.28	18.005	16.0	1.132	2.750	18.627	16.0
7	84.80	17.818	16.0	0.852	2.750	17.984	16.0
8	83.44	18.061	16.0	1.217	2.750	18.688	16.0
9	76.95	17.931	16.0	1.021	2.750	18.815	16.0
10	69.09	17.831	16.0	0.871	4.400	17.465	16.0
11	65.84	17.942	9.0	0.601	3.600	11.335	9.0
12	59.47	17.970	9.0	0.643	3.600	11.850	9.0
13	56.47	17.982	9.0	0.660	3.600	12.089	9.0
14	53.77	18.376	0	0.689	8.250	0.551	0
15	52.90	17.917	0	0	8.250	-2.036	0
16	71.44	17.783	16.0	0.799	8.250	13.331	16.0
17	108.31	17.928	16.0	1.017	3.600	15.763	16.0
18	89.54	17.823	16.0	0.859	4.400	16.364	16.0
19	76.83	17.961	16.0	1.067	3.600	17.250	16.0
20	73.60	17.714	16.0	0.696	3.600	17.658	16.0
21	59.59	17.913	9.0	0.557	3.600	11.699	9.0
22	52.47	18.233	0	0.474	4.400	2.634	0
23	47.77	16.483	0	0.656	3.600	1.395	0
24	39.17	13.483	0	0	2.250	0.491	0

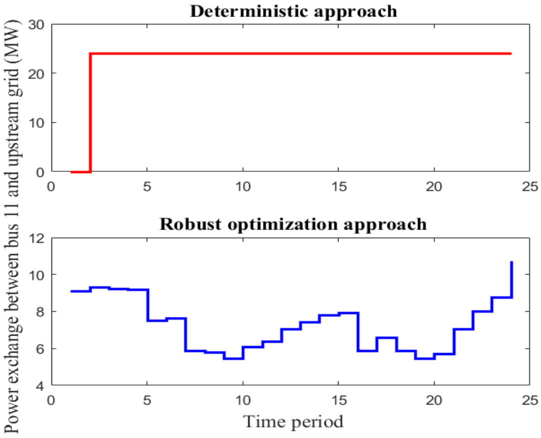

Fig. 5. Power exchange between bus 11 and the upstream grid.

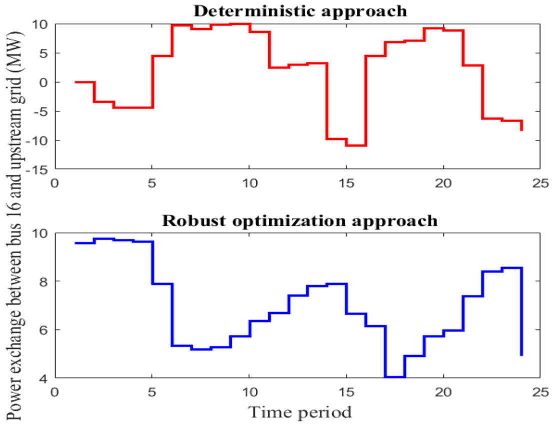

Fig. 6. Power exchange between bus 16 and the upstream grid.

Generally, it can be considered that if internal generation cannot supply internal demand, VPP can benefit from the upstream grid. Total exchanged power between the VPP and the upstream grid in deterministic and robust optimization approaches is shown in Fig. 7. It can be seen that procured power in robust optimization approach is reduced in comparison with deterministic approach because VPP wants to be more robust against day-ahead market price uncertainty. Therefore, less power is procured from upstream grids while more power is used to supply consumers' demand.

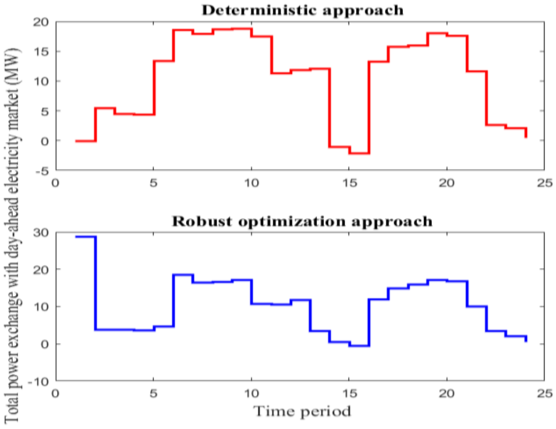

Fig. 7. Total exchanged power with day-ahead market.

Fig. 8 shows the load interruption in two cases. In robust optimization case, load interruption is less than deterministic one. With the precision of the Fig. 8, it can be concluded that when the curtailed load price is higher than the market price, the amount of curtailed load will be lower, but in other hours, by comparing market price to flexible load price, the amount of load curtailment increases. In RO approach, it can be concluded from Fig. 8 that due to the conservatism, the amount of curtailed load has been reduced, which is one of the reasons why the profit in RO approach will be less than deterministic approach.

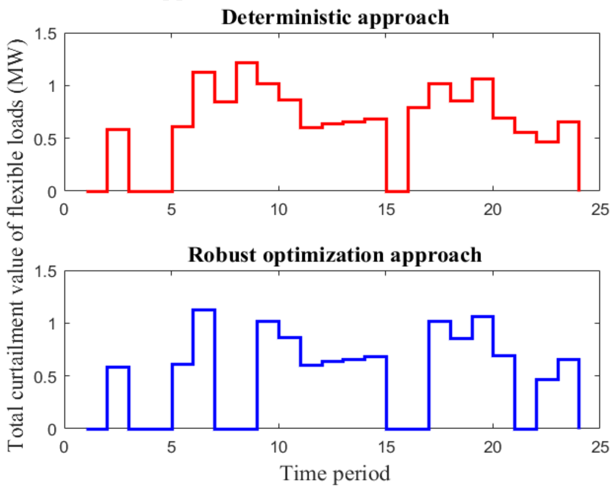

Fig. 8. Total curtailment value of flexible loads.

According to the constraint (20), VPP is responsible to supply power demand of contracts with an error equal to $\Delta_{BC} = 10\%$. For bilateral contracts in deterministic case, when energy price is low, VPP uses 10% of error as opportunity and sells less power. On the other hand, when market price is increased, more power will be delivered. Total energy delivery of bilateral contract is depicted in Fig. 9. According to Fig. 9, delivered power is almost same for both cases.

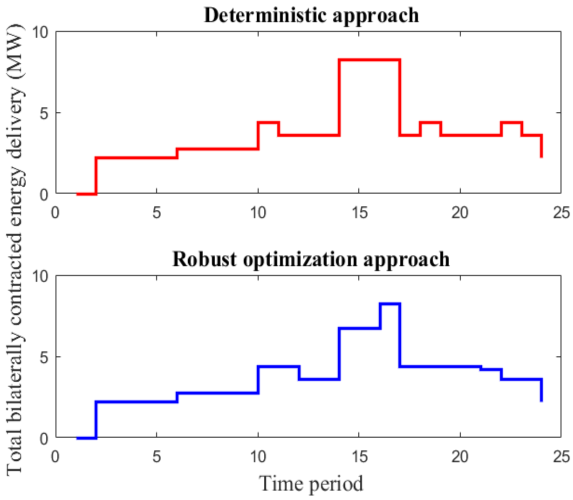

Fig. 9. Total bilateral contract energy delivery.

By comparing Table 5 and Table 3, it can be seen that average market price at hours 3, 4 and 24 is cheaper than DG units' power price. In this case, DGs are reluctant to produce power and need to load interruption is decreased at this hour which in this case VPP buys powers from upstream grid.

In this paper, VPP obtains optimal bidding and offering curves based on proposed robust optimization approach to offer and bid to the day-ahead market. Bidding curves indicate that increase in the market price will reduce purchasing power from the power market which in this situation internal generation will be used to supply power. Offering curves indicate that by increasing market price, sold power to the grid will be increased and vice versa. The optimal bidding/offering curve of VPP should be proposed to the market operator for buying/selling power from/to the upstream grid. In this case, to propose price and power to day-ahead market for each day, VPP presents bidding step curve instead of proposing deterministic amount [37]. Figures 10 and 11 show the optimal bidding curves for 11th and 16th hours in connection point 1 which are obtained based robust optimization approach.

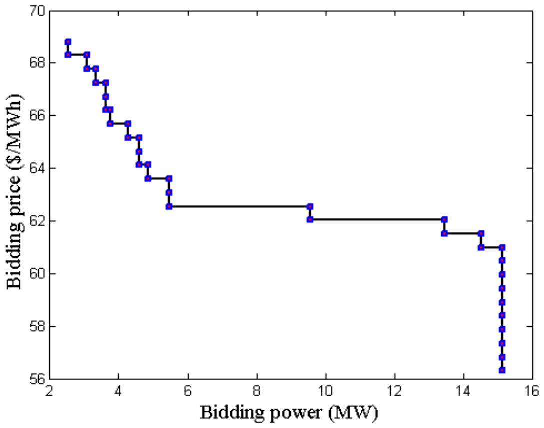

Fig. 10. Proposed bidding step curve for 11th hour in connection point 1 by the VPP.

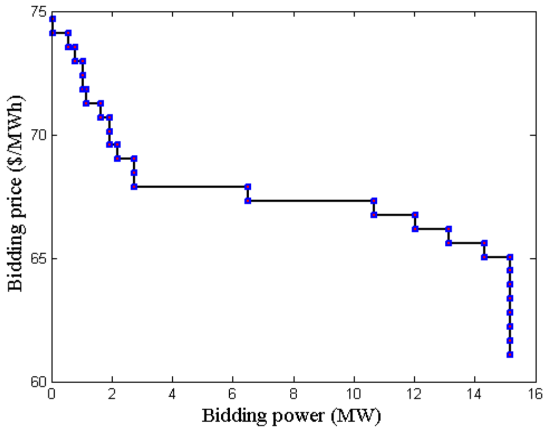

Fig. 11. Proposed bidding step curve for 16th hour in connection point 1 by the VPP.

When price increases in the grid, VPP puts internal generation into priority to supply costumers and sells power to the market. In this case, offering curve for day-ahead market for each hour will be proposed [38]. Figures 12 and 13 show the optimal offering curve for 2th and 20th hours in connection point 11 which are obtained based on robust optimization approach.

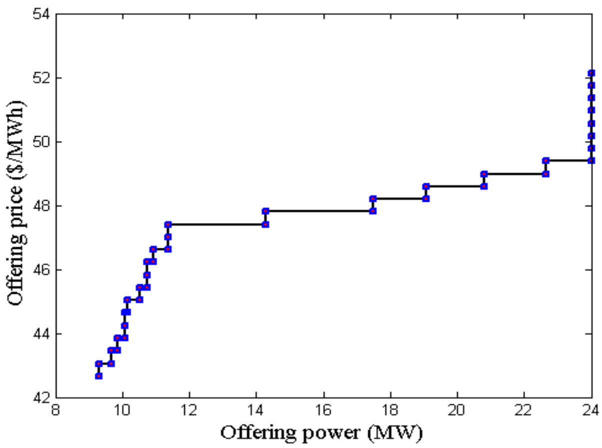

Fig. 12. Proposed offering step curve for 2th hour in connection point 11 by the VPP.

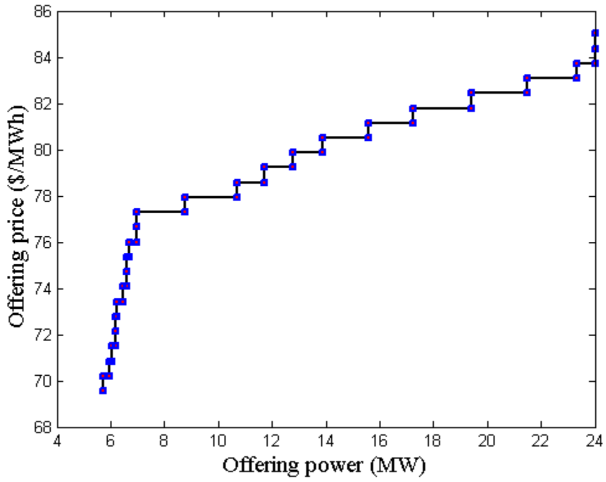

Fig. 13. Proposed offering step curve for 20th hour in connection point 11 by the VPP.

In order to face uncertainties increasing Γ_0 value will significantly decrease the VPP's profit in which robustness increment is not appreciated by the VPP. So, the VPP operators can get better Γ_0 over time by experience [39].

6. CONCLUSIONS

In this paper, robust optimization method due to less calculation and better accuracy is proposed by the VPP operators to maximize revenue with better tractability. VPP has contracts with costumers with predetermined prices while market prices have significant uncertainties. By considering these matters, risk management tool is proposed to ensure getting the least profit. Due to VPP's internal generation and using different LMPs for selling energy to buses with expensive prices, VPP proposes the offering curve of each hour to market operators in order to sell energy. Also, by considering market price at low load hours which is more cost-effective than using the internal generation, the VPP proposes bidding curve to market. If the internal resources link is totally disconnected from the VPP, it can be said with certainty that VPP can benefit from differences in upstream grid prices. The amount of choice value that has a great impact on profits can be selected over time by the policies of each particular VPP. In the maximum robustness case, profit amount is reduced 25.910%, which shows VPP has resisted against pool market uncertainty. The proposed method can be useful for VPP management because of its utility and simplicity to maximize VPP profits with regard to the risk-taking strategy. Also, according to RO strategy, bidding and offering curves for each hour is obtained which is proposed to market with considering VPPs goals and policies and setting of robustness value.

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