Demand response strategy of a virtual power plant for internal electricity market

Ullah, Zahid; Baseer, Muhammad; Arshad

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Demand Response Strategy of a Virtual Power Plant for Internal Electricity Market

Zahid Ullah
Electrical Engineering
IGDORE
Middlesbrough, United Kingdom
Zahid.ullah@igdore.org

Muhammad Baseer
Faculty of Engineering and Informatics
University of Bradford
Bradford, United Kingdom
M.baseer@bradford.ac.uk

Arshad[2]
School of Computing, Engineering and Built
Environment, Glasgow Caledonian University
Glasgow, United Kingdom
Arshad.arshad@gcu.ac.uk

***Abstract-* Operational challenges are expected when a large amount of wind and solar energy is added to the electricity networks. It is necessary to introduce new technologies to allow more energy portfolio integration into power systems in order to compensate for the intermittent nature of renewable energy sources (RESs) such as wind and solar power due to their fluctuating nature. A potential solution to the problem of renewable energy integration in power market transactions is the virtual power plant (VPP). A VPP is a novel and smart approach of integrating distributed energy resources (DERs) such as demand response (DR) and energy storage systems (ESS). A VPP could exploit DERs and demand-side participation to mitigate peak loads and thus sustain grid stability. This paper presents a DR strategy of a VPP for simulating energy transactions within the VPP internal electricity market. The method assesses the impact of the DR program on renewable energies integration aiming to minimize VPP operating costs over the short-term planning horizon. Stochastic programming theory is used to address the optimization problem while protecting the interests of the end users. Preliminary findings show that peak load has been reduced while the overall cost of operating has decreased.**

Keywords- Distributed generator, Demand response, Distributed energy sources, Virtual power plant

I. Introduction

In recent years, the percentage of RESs has considerably increased due to growing concern about climate change worldwide. The main advantage of RESs over non-RESs is that they do not directly contribute to the carbonization of the environment or the effects of global warming brought on by carbon emissions. The steady-state transition of conventional energy markets into non-conventional energy markets is gaining a lot of attention from institutions, researchers, and scientists due to the abundance of RES, they are pollution-free, favourable to the environment, and can be managed locally. Incentives-based DR programs have been supported by different countries, including the UK, China, America, Australia, Germany, and Europe, to promote investment in renewable power generations, allowing these power generators to trade electricity or provide power networks with reserve capacity services and relieve peak hours' pressure on the grid [1][2].

However, it is quite difficult to integrate RESs into the power markets. Climate change has a significant impact on how well RESs perform, mainly wind turbines (WTs) and photovoltaics (PVs). Their output is inconsistent, variable, and location constrained. Hence, the power system's operating performance will be impacted, resulting in grid instability [3][4]. Additionally, the production of RESs is typically limited, particularly when considering PVs, which can have a 10-kW maximum output. Consequently, it is therefore challenging to forecast whether RESs will be able to meet the power market's claimed schedule.

To address these problems, the idea of a VPP is put forward, designed, and implemented. A VPP is a modularly designed entity that economically integrates the capacities of distributed energy resources such as DR programs and energy storage systems (ESS) using information and communication technologies (ICTs), optimizing internal generation and consumption. Where a DR is a term that refers to the process of managing dispatchable load demand for economic or technical purposes. It is a useful approach used to minimize peak load. There are several studies in the literature reviewed encouraging the strategy of a DR program's optimization for VPPs, demonstrating that using it within the VPPs environment offers both technical and economic benefits.

A VPP is described as a form of an innovative and unified platform capable of bringing together a variety of energy resources. They more effectively take into account possible variations from forecasted internal generation and demand. DERs could participate in the power market. Their visibility in the power market will be increased while its access and operation costs will also be reduced under the VPP setting. In addition, the DR strategy of the VPP permits internal energy consumers to participate in reducing the load demand during peak hours and in return get remuneration which helps to maximize the reliability of the grid [5].

II. Literature review

The authors of [6] demonstrated how load curtailment can be implemented to keep the VPP's frequency within its working range. Load levelling could also be achieved with a DR program. The authors of [7] simulated a DR program in conjunction with distributed generation scheduling, reducing the operational cost of the VPP. A VPP is a viable platform to communicate with demand-side resources, allowing them to actively partake in power trading activity. Participating in the DR program under the VPP setting could provide additional benefits to decentralized generation and small-scale residential consumers as stated by [8]. The DR program is used to complement the power demand side of the VPP. According to the literature [9], a DR optimization model is developed based on incentive and price-based DR to maximize the social welfare of the electricity market.

However, the preceding literature did not systematically evaluate the impact of demand response resources on VPP's internal electricity market once they were aggregated under the VPPs setting and subsequent impact on grid reliability.

This work presents an incentive-based DR program of a VPP in a VPP internal energy market environment, aiming to minimize running costs while accounting for DGs and electrical load demand uncertainties subject to equality and inequality constraints. A Scenarios-tree approach is used to model the uncertainties associated with wind speed, solar irradiation, and dispatchable load demand. Where a scenario is defined as a possible realization of an uncertain parameter. The probability density function (PDF) is used for each wind speed, solar irradiation, and dispatchable load demand to generate 31 scenarios. The method analyses the impact of an incentive-based DR program on a VPP operational cost over the planning horizon. The method will be used to simulate WT, PV, and dispatchable load demand in a test case study system.

In this study, we designed and developed a mathematical model for the trading of electricity between the VPP and its internal participating members. This motivates internal electrical consumers to minimize their load demand during peak hours while this mechanism also helps maximizes the utilization of DERs, which supports stabilizing the system's aggregated net load.

III. Description of the proposed VPP internal market

Fig 1 shows the structural design of the proposed internal electricity market of a VPP, in which the VPP operators aggregate the capacities of WTs, and PVs, to supply power to the consumer's demands. The VPP can act as both a consumer and a supplier: buying electricity during periods when the DGs system is not operational or when electricity rates are low. Selling surplus capacity to the day ahead market If the DGs system has any surplus left. To relieve load demand strain, the VPP permits internal consumers to engage in the DR program and compensates those consumers in return. In this study, we suppose the VPP acts as a price taker given its low capacity makes it hard for it to impact market pricing. The VPP participates in the markets with non-priced reserve offers and energy bids, that are supposed to be cleared in the day-ahead market.

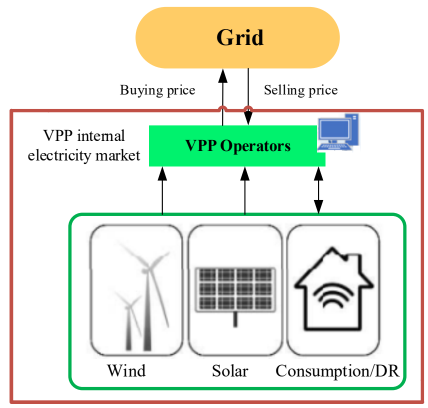

Fig. 1. Structure of the proposed VPP internal electricity market

A. Uncertainty modeling

A scenario-tree approach is used to model the uncertainties related to wind speed, solar irradiation, and load demand. Where a scenario is defined as a possible realization of an uncertain parameter. The probability density function (PDF) is used for each wind speed, solar irradiation, and load demand to generate 31 scenarios.

1) Wind Speed Modeling

The wind speed variation in a specific area is modeled using the Weibull PDF. The PDF function that correlates the wind speed and the WTs module output power is expressed by (1).

$$PDF(v)=\left(\frac{k}{c}\right)\left(\frac{v}{c}\right)^{k-1}\exp\left[-\left(\frac{v}{c}\right)^{k}\right] \quad (1)$$

Where *v, c,* and *k* represent the wind speed, Weibull *PDF* scale index, and the shape index. Therefore, the WT module output power can be examined by employing its power curve.

$$P_{wt}(v)=\begin{cases}0, & 0\le v\le v_{ci}\\ P_{rated,}\times\dfrac{v-v_{ci}}{v_r-v_{ci}}, & v_{ci}\le v\le v_r\\ P_{rated,} & v_r\le v\le v_{co}\\ 0, & v_{co}\le v\end{cases} \quad (2)$$

Where Pw and Prated represent the WT output power and the rated power. *vci* and vco represent the cut-in and the cut-out speed. The rated speed of WT is represented by $\boldsymbol{v_r}$ [10] and [11]. Fig 2 shows the wind speed power curve of WT.

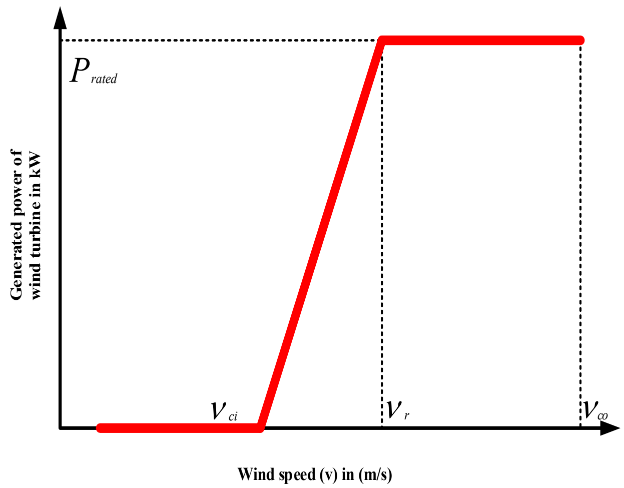

Fig. 2. WTs speed power curve

Therefore, the output power of the WT module at bus *i* and scenario *w* can be expressed as follows:

$$0 \le P_{i,w}^{wt} \le \gamma_{i,w}^{wt} \times P_{i.rated}^{wt} \quad (3)$$

Where $\gamma_{i,w}^{wt}$ is the WT power generation percentage.

2) Modeling of Solar Irradiance

Beta PDF is employed to model solar irradiance as presented by (3) [1].

$$PDF(S) = \begin{cases} \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)+\Gamma(\beta)} \times s^{\alpha-1} \times (1-s)^{\beta-1}, & 0 \le s \le 1, 0 \le \alpha, \beta \\ 0 & else \end{cases} \quad (4)$$

The solar irradiance in (kilowatt per meter square) is represented by *S.* The Beta PDF parameters (i.e. α and β) can be determined as follows:

$$\beta = (1-\mu) \times \left(\frac{\mu \times (1-\mu)}{\sigma^2} - 1 \right) \quad (5)$$

$$\alpha = \frac{\mu \times \beta}{1-\mu} \quad (6)$$

Where μ and σ denote the mean value and the standard deviation. Solar irradiation and ambient temperature are the key parameters in determining the PV module output power, expressed by using Eqs. (6) and (7)

$$P_{PV} = P_{STC} \left\{ \frac{G}{100} \left[1 + \delta \left(T_{cell} - 25 \right) \right] \right\} \quad (7)$$

$$T_{cell} = T_{amb} + \left(\frac{NOCT - 20}{800} \right) G \quad (8)$$

Where P_{STC} and P_{PV} denote the power in (MW) under standard test conditions and the PV module output power in kilowatts, respectively. The power-temperature coefficient in (%/°C) is denoted by δ. T_{amb}, T_{cell}, and NOCT represent the ambient temperature in °C, the cell temperature in °C, and the nominal operating cell temperature conditions in °C. G represents solar irradiance in (watt per meter square) [12] [13].

3) Load Demand Uncertainty Modeling

The normal PDF function is used to model each bus's load demand. For uncertain load *l,* the normal distribution PDF is provided by (8).

$$PDF(l) = \frac{1}{\sigma_l \sqrt{2\pi}} \times \exp\left[-\left(\frac{\left(l - \mu_l \right)^2}{2\sigma_l^2} \right) \right] \quad (9)$$

Where μ_l and σl denote the mean value and the standard deviation [14][15].

B. Objective Function

The optimal strategy of the VPP objective function is to participate in the electricity market and minimize its operating cost-effectively over the planning horizon, as stated in (10)

$$Min\,Cost = \sum_{t=1}^{T} \left[\begin{array}{l} \sum_{i=1}^{NB} \sum_{w=1}^{NW} LR_{(i,w)}^{VPP} \cdot C_{(i,w)}^{VPP} + \sum_{i=1}^{NB} \sum_{w=1}^{NW} P_{(i,w)}^{Wind} \cdot C_{(i,w)}^{Wind} \\ + \sum_{i=1}^{NB} \sum_{w=1}^{NW} P_{(i,w)}^{Solar} \cdot C_{(i,w)}^{Solar} + \sum_{i=1}^{NB} \sum_{w=1}^{NW} DR_{(i,w)}^{Cons} \cdot C_{(i,w)}^{Cons} \end{array} \right] \quad (10)$$

Where $LR_{i,w}^{VPP}$ is the load reduction at bus *i* and scenario *w,* and $C_{i,w}^{VPP}$ is the VPP's corresponding incentive price for each consumer at bus *i* and scenario *w.* $P_{i,w}^{Wind} / P_{i,w}^{Solar}$ represent the generated power of WT and PV units at bus *i* and scenario *w,* while $C_{i,w}^{Wind} / C_{i,w}^{Solar}$ is the corresponding cost of WT and PV power generation at bus *i* and scenario *w.* $DR_{i,w}^{Cons}$ represents bid of consumers at bus *i* and scenario *w,* while $C_{i,w}^{Cons}$ is the bid cost of consumers at bus *i* and scenario *w.*

C. Constraints

$$0 \le P_{(i,w,t)}^{Wind} \le P_{(i,w,t)}^{Wind.\max} \tag{11}$$

$$0 \le P_{(i,w,t)}^{Solar} \le P_{(i,w,t)}^{Solar.\max} \tag{12}$$

$$0 \le \sum_t LR_{(i,w,t)}^{VPP} \le LR_{(i,w,t)}^{Cap} \tag{13}$$

$$0 \le DR_{(i,w,t)}^{Cons} \le DR_{(i,w,t)}^{Cons.\max} \tag{14}$$

$$P_{(i,w,t)}^{Wind} + P_{(i,w,t)}^{Solar} + DR_{(i,w,t)}^{Cons} \ge LR_{(i,w,t)}^{VPP} \tag{15}$$

Constraints (11) and (12) represent the minimum and maximum power generation range of wind turbine and photovoltaic units. The constraint (13) limits the overall load reductions to safeguard both consumers and VPP operator's interests. The constraint (14) represents the minimum and maximum demand response range of consumers. The constraint (15) represents the power balance that has to be met at each bus and scenario.

VI. Case study and simulation results

In this work, we concentrate on the internal consumer load reduction strategy during peak hours. Fig 3 shows the load profile of the consumers over the planning horizon. Fig 4 shows the predicted power generation of both solar and wind turbines. The Incentive price scheme of the VPP to its internal consumers in regards to the load reduction is shown in Fig 5. GAMS, an optimization software is used to formulate the optimization problem and the CPLEX solver returned optimal results.

Fig 6 shows the load minimization in each scenario over the planning horizon. In scenario 12, the load reduction has the highest value, which is around (7kW). This is due to the fact that this scenario has the highest incentive price offered to the VPP internal consumers. While scenario 6 has the lowest value, which is around 0.1kW. It is due to the fact that this scenario has the lowest incentive price offered to the VPP internal consumers.

The VPP is ready to offer each consumer comparatively high incentive prices, as shown in Figs. 5, resulting in load demand reduction during hours of high price (e.g., hour 19). This helps in mitigating load demand at peak hours. This is specifically true, during scenario 12, in Fig 6 which is a time when the VPP internal market is experiencing considerably high load demand. The VPP offered reasonably high incentive prices to each consumer, motivating them to reduce their energy consumption and, as a result, reducing load demand pressure on the VPP internal electricity market.

We undertake a benchmark case and compare the results to validate the efficacy of the proposed incentive-based DR program. In the baseline case, the VPP offers identical incentive prices to all consumers regardless of their individual attributes. According to Table 1, the proposed approach surpasses the benchmark case. The proposed approach leads to a higher overall decrease, a bigger incentive payment, and a lower overall operating cost for the VPP.

TABLE I. Results comparison

Cases	**Load reduction (kW)**	**Incentive payment ($)**	**VPP operation cost ($)**
Benchmark	767.48	2389.34.4	15265.78
This paper	805.03	3267.09	14856.03

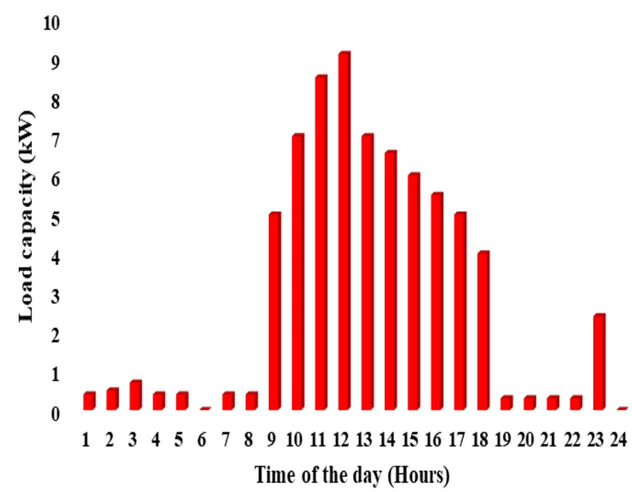

Fig. 3. Consumer's load profile

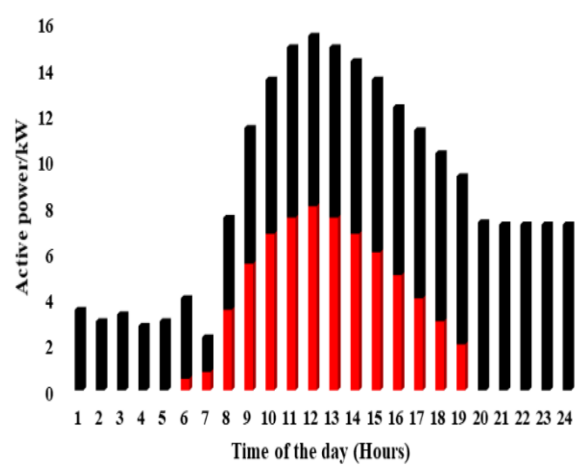

Fig. 4. The predicted outputs of solar and wind power

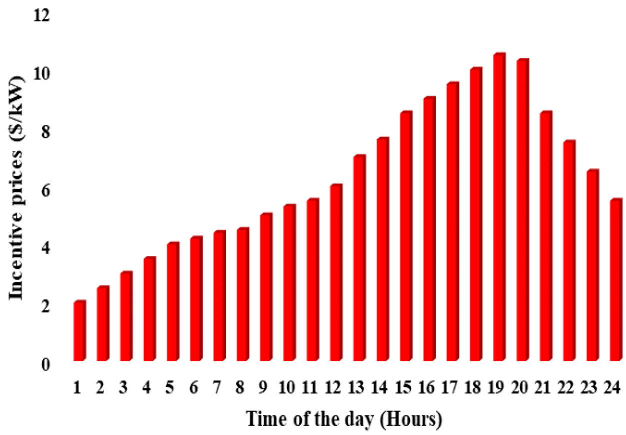

Fig. 5. Incentive scheme of the VPP

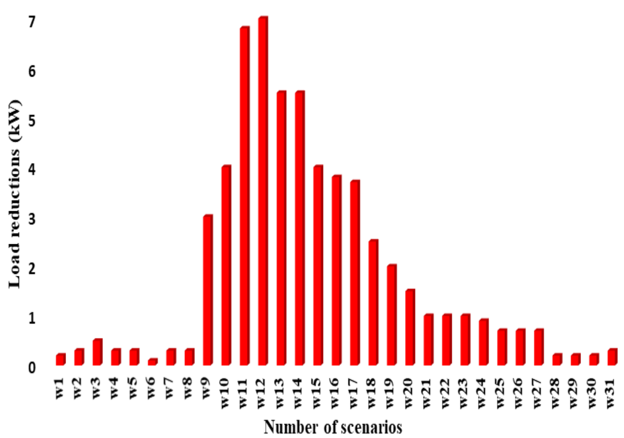

Fig 6. Scenario-wise load reductions of consumers over the planning horizon

V. Conclusions and Future Research

In this study, we proposed an incentive-based DR program for the internal electricity market of a VPP. This approach enables the VPP to calculate and offer appropriate incentive prices for the end-users (consumers) in response to peak load reduction aiming to minimize the overall operating cost of a VPP such as electricity market costs. Moreover, this scheme helps in alleviating peak load demand therefore, contributing to the reliability of the power system. Finally, this adaptable approach encourages more internal consumer load reductions, which further lowers VPP running costs and optimizes consumer utility usage which mitigates pressure on the electrical grid during peak periods. In the future, the VPP's incentive-based demand response program will be expanded to include penalty considerations and the addition of an energy storage system.

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