Two-stage Operational Planning of a Virtual Power Plant in the Presence of a Demand Response Program

Amirali Shahkoomahalli[1], Amangaldi Koochaki[2*], Heidarali Shayanfar[3]

Abstract–The spread of the smart grid has led to the widespread penetration of small-scale distributed energy resources. Distributed generations (DGs) include conventional small-scale power plants and renewable energies with no pollutant emission. This paper presents two-stage stochastic planning for the participation of a virtual power plant (VPP) in energy and reserve markets in the presence of demand response (DR) programs. The designed VPP enables participation in these markets by aggregating DERs. Probability distribution functions are applied to generate scenarios based on the existing uncertainties in renewable energy generation, energy price, and consumer demand. The number of possible scenarios is reduced using a scenario reduction technique. Two-stage stochastic planning is proposed to manage the designed VPP. The results suggest that participation in DR programs leads to a considerable increase in optimal operational profit of the VPP.

Keywords: Demand response, Virtual power plant, Distributed generations, Renewable energies

NOMENCLATURE

Input parameters

$L_t^E,\ L_t^{TH},\ L_{t,s}^E, L_{t,s}^{TH}$	Expected and real-time electrical/thermal demand sat hour t (kW)
$P_t^{PV}, P_t^W, P_{t,s}^{PV}, P_{t,s}^W$	Expected and real-time output of PVs and wind turbines at hour t (kW)
λ_{NG}	Natural gas price ($/kWh)
$\lambda R_{t,s}^{RET}$	Hourly price of scheduled reserve provided by the grid at hour t ($/kWh)
λ_t^{RET}	Retail electricity price at hour t ($/kWh)
λ_t^{TH}	Hourly price for supplying thermal demands ($/kWh)
$L_t^{Shift,min}, L_t^{Shift,max}$	Minimum/maximum percentage of load shifting at hour t
$P_m^{MT,min}, P_m^{MT,max}, T_k^{B,min}, T_k^{B,max}$	Minimum/maximum output of MT and boiler units (kW)
$C_i^{CHP,U}, C_i^{CHP,D}, C_m^{MT,U}, C_m^{MT,D}, C_k^{B,U}, C_k^{B,D}$	Startup/shutdown cost of MT, CHP, FC and boiler units ($)
$\lambda_{sell,t}^{EV}, \lambda_{buy,t}^{EV}$	Price of selling/buying electrical power to/from the PHEVs (charging/discharging) in hour t ($/kWh)
$P_{v,ch}^{EV,max}, P_{v,dch}^{EV,max}$	Maximum charge/discharge rate of PHEV batteries(kW)
$P_{t,v}^{EV,trv}$	Electricity consumption of PHEVs(mile)

[1] Department of Electrical Engineering, Aliabad Katoul Branch, Islamic Azad University, Aliabad Katoul, Iran. Email:shahkoomahalli@gmail.com

*2 **Corresponding Author:** Department of Electrical Engineering, Aliabad katoul Branch, Islamic Azad University, Aliabad Katoul, Iran. Email: koochaki@aliabadiau.ac.ir

[3]Center of Excellence for Power Systems Automation and Operation, School of Electrical Engineering, Iran University of Science and Technology, Tehran, Iran. Email: hashayanfar@gmail.com

Received: 04.03.2022 ; Accepted:14.06.2022

1. Introduction

The electrical energy generation methods are distinguished based on various factors, including the reliability criteria, energy generation cost, and the quality of delivered energy. Distributed energy resources (DERs) is a newly emerged concept in power systems that refers to the deployment of renewable energy sources (RESs), small-scale generators, and energy storage systems. DERs offer several benefits, including energy transmission loss reduction, increased reliability of power systems, and operating cost reduction. With their high potential structure, virtual power plants (VPPs) can be proposed for maximal exploitation of distributed resources and generations to realize these benefits. VPP is an aggregator concept in the power system that integrates the distributed generations (DGs) of energy storage systems and internal consumers to form a unit profile and links the resulting coalition to the power system as an interconnected unit. Thus, it is called "VPP" because its capacity is not generated in a centralized manner. Instead, its capacity arises from the aggregation of multiple distributed resources.

Despite the benefits of renewable DGs in power systems, their excessive presence may compromise the security and stability of energy supply for consumers due to their uncertain nature. Thus, given the implication of RESs in the VPP concept, the uncertainty parameters need to be identified and accurately modeled to ensure the optimal operation of these resources [1]. Other factors contributing to uncertainty in VPP include the consumers' demand and electricity price.

Ref [4] defined VPP as a group of combined heat and power (CHP) units based on fuel cell technology for domestic consumers. Ref. [8] introduced the VPP as an aggregation of DERs that can create a single profile in which various technologies can be utilized. In Ref. [9], the VPP is regarded as a number of DERs with different technologies which can be connected to various bus bars of the distribution network to form a VPP. In Ref. [10], the DGs involved in creating a VPP are beyond the generating resources and include the controllable loads and energy storage systems as well. The technical and economic impacts of VPP on its components are evaluated in Ref [11]. Authors in Ref. [12] presented the design and operational planning of a commercial VPP consisting of DGs. The participation level of DGs is determined based on weekly contracts considering the risk of market involvement. The proposed planning framework is a two-stage optimization, where the first stage decides on the optimal coalition of DERs and bilateral contracts, and the second stage implements the optimal operational planning of the VPP to maximize its weekly profit. Ref [1] analyzed and discussed the various aspects of DER utilization in microgrids and VPPs, including modeling approaches, uncertainties, reliability issues, and participation in different energy markets such as reactive power markets and demand response (DR) programs.

Ref [13] proposed a method to cover the prediction errors associated with variations in loads and outputs of non-controllable DGs in the VPP. Ref [14] aimed to deal with the unbalanced load flow in the VPP system to minimize the energy purchase cost from the upstream market. Ref [15] developed a day-ahead scheduling scheme for a VPP consisting of conventional generation units, including wind power plants and pumped storage plants, taking into account the uncertain parameters and emissions of the conventional generation. Day-ahead scheduling of a VPP consisting of conventional DGs like wind turbines and electrical storage systems is proposed in Ref. [16]. The model considered the uncertainties in the wind speed and hourly price of electrical energy and was implemented using a robust stochastic approach. Ref [17] proposed an optimization algorithm for electrical and thermal scheduling of a VPP, including combined heat and power generation (CHP) units and electrical and thermal energy storage systems. The optimization objective in Ref. [21] was to maximize the profit from the VPP involvement in energy markets and reactive power markets. In Ref. [22], the optimal scheduling of a VPP for participation in the energy and reserve market was performed considering the uncertainty in wind speed and the electrical energy consumption. The uncertainty parameters were modeled using the fuzzy chance-constrained programming approach. Ref [23] presented two-stage stochastic programming of a VPP for participation in the energy and balancing markets, taking into account the uncertainties of energy price and renewable sources.

This paper presents the operational planning of a VPP containing renewable DGs and CHP units for participation in the energy and reserve market to achieve maximum profit. The uncertainties of wind speed, solar radiation, electricity market price and heat and power demand are considered in the model. The number of possible scenarios is reduced by a scenario reduction method. Electrical and thermal energy storage systems and electric and hybrid vehicles are utilized in this VPP.

2. Mathematical modeling of uncertainties in VPP

The environmental factors, including wind speed, solar radiation, and heat and power demands, are the most significant uncertain parameters in a VPP. The presence of uncertainty converts the optimization problem into a stochastic one. The wind speed and solar radiation vary at different hours of the day and on different days of the year and are not constant. Consequently, the power generation of wind turbines and PV panels will be variable and a function of these environmental factors. Consumers' energy consumption and responsiveness are also variable and cannot be predicted accurately in advance. These parameters are the model inputs, and their stochastic behavior should be captured in the modeling. A common approach to model uncertain parameters is to use their probability distribution function. The data collected from the uncertain parameters can be used to approximate their behavior closely to a probability distribution function. The Weibull probability distribution function can effectively be applied to model the wind speed uncertainty [36].

In this paper, based on the distribution function of each stochastic parameter, a limited number of possible scenarios are obtained from the scenario generation method and used for optimization and modeling problems. Solar radiation and wind speed are modeled with five scenarios, while the electrical energy consumption and electricity price are modeled with seven scenarios. The number of possible scenarios considering all the combinations of the five stochastic parameters is equal to 5*5*5*7*7. Dealing with such a large number of possible scenarios in the optimization problem appears impossible in practice and increases the computational time and load. Thus, the number of possible scenarios needs to be reduced to an acceptable level to lower the time and volume of computations while properly considering the effective scenarios in scheduling problems. The scenario reduction technique applied in this paper is based on linear optimization with an objective to minimize the number of possible states for combined scenarios without changing their probability vector. The objective function and constraints of the optimization problem are extracted from the study in Ref. [38].

2.1. Modelling the objective function and VPP equipment

The studied VPP is equipped with wind turbines and photovoltaic (PV) systems as renewable sources and microturbines and CHP units as non-renewable sources. Moreover, batteries and heat tanks are utilized as electrical and thermal energy storage systems in the VPP. The electric-hybrid vehicles are considered and modeled as both consumers and mobile storage.

2.1.1. Objective function

The considered objective function of this paper is to maximize the VPP profit in the presence of uncertainties, as shown in relation (1):

$$Max\ of = \sum_{t=1}^{24}\begin{Bmatrix} Re_t^{RET} - C_t^G \\ -C_t^{MT} - C_t^{CHP} - C_t^B \\ +PRF_t^{EV} - C_t^{BSS} - C_t^{BT}\end{Bmatrix} + \sum_{t=1}^{24}\sum_{s=1}^{Ns} p_s \times \begin{Bmatrix} ReR_{t,s}^{RET} - CR_{t,s}^G \\ -CR_{t,s}^{CHP} - CR_{t,s}^{MT} - CR_{t,s}^B\end{Bmatrix} \tag{1}$$

S.t.

$$Re_t^{RET} = (\lambda_t^{RET} \times L_t^E) + (\lambda_t^{TH} \times L_t^{TH}) \tag{2}$$

$$ReR_{t,s}^{RET} = \lambda R_t^{RET} \times \left(L_{t,s}^E - L_t^E\right) + \lambda_t^{TH} \times \left(L_{t,s}^{TH} - L_t^{TH}\right) \tag{3}$$

$$C_{g,t} = \lambda_t^{RET} \times P_t^G \tag{4}$$

$$CR_{t,s}^G = \lambda R_t^{RET} \times R_{t,s}^G \tag{5}$$

$$-0.3 \times P^{G,max} \le R_{t,s}^G \le 0.3 \times P^{G,max} \tag{6}$$

$$P_{t,s}^G - P_t^G = R_{t,s}^G \tag{7}$$

$$L_{t,s}^{E,Shifted} = L_{t,s}^E + \delta L_{t,s}^E \tag{8}$$

$$\delta L_{t,s}^E = L^{E,Shift} \times L_{t,s}^E \tag{9}$$

$$\sum_{t=1}^{24} \delta L_{t,s}^E = 0 \tag{10}$$

$$L_t^{Shift,min} \le L_{t,s}^{Shift} \le L_t^{Shift,max} \tag{11}$$

$$U_{dg,t}^{DG} - U_{dg,t-1}^{DG} \le SU_{dg,t}^{DG} \tag{12}$$

$$U_{dg,t-1}^{DG} - U_{dg,t}^{DG} \le SU_{dg,t}^{DG} \tag{13}$$

$$U_{dg,t}^{DG} - U_{dg,t-1}^{DG} = SU_{dg,t}^{DG} - SD_{dg,t}^{DG} \tag{14}$$

$$SU_{dg,t}^{DG} + SD_{dg,t}^{DG} \le 1 \tag{15}$$

$$\begin{Bmatrix} Micro\ turbines \\ CHPs \\ Boilers \end{Bmatrix} \in DGs \tag{16}$$

$$C_t^{MT} = \sum_{m=1}^{N_{MT}}\left\{(\lambda_{NG} \times \frac{P_{m,t}^{MT}}{\eta_m^{MT}} + \left(C_m^{MT,U} \times SU_{m,t}^{MT}\right) + \left(C_m^{MT,D} \times SD_{m,t}^{MT}\right)\right\} \tag{17}$$

$$CR_{t,s}^{MT} = \sum_{m=1}^{N_{MT}}\left(\lambda_{NG} \times R_{m,t,s}^{MT}\right) \tag{18}$$

$$P_{m,t,s}^{MT} - P_{m,t}^{MT} = R_{m,t,s}^{MT} \tag{19}$$

$$-0.1 * P_m^{MT,max} \le R_{m,t,s}^{MT} \le -0.1 * P_m^{MT,max} \tag{20}$$

$$P_{min}^{MT} \times U_{m,t}^{MT} \le \begin{Bmatrix} P_{m,t}^{MT} \\ P_{m,t,s}^{MT} \\ P_{m,t}^{MT} + R_{m,t,s}^{MT} \end{Bmatrix} \le P_{max}^{MT} \times U_{m,t}^{MT} \tag{21}$$

$$P^{CHP,min}\left(T^{CHP}\right) \times U^{CHP} \le P^{CHP} \le P^{CHP,max}\left(T^{CHP}\right) \times U^{CHP} \tag{22}$$

$$T^{CHP,min}\left(P^{CHP}\right) \times U^{CHP} \le T^{CHP} \le T^{CHP,max}\left(P^{CHP}\right) \times U^{CHP} \tag{23}$$

$$C_{t,s}^{CHP} = \sum_{i=1}^{N_{CHP}}\left\{\left(\lambda^{NG} \times \frac{P_{t,i}^{CHP} + T_{t,i}^{CHP}}{\eta_i^{CHP}}\right) + \left(C_i^{CHP,U} \times SU_{t,i}^{CHP}\right) + \left(C_i^{CHP,D} \times SD_{t,i}^{CHP}\right)\right\} \tag{24}$$

$$C_{t,s}^{CHP}(t,s) = \sum_{i=1}^{N_{CHP}}\left(\lambda^{NG} \times \frac{\left(PR_{t,s,i}^{CHP}\right) + \left(TR_{t,i}^{CHP}\right)}{\eta_i^{CHP}}\right) \tag{25}$$

$$P_{i,t,s}^{CHP} - P_{i,t}^{CHP} = PR_{i,t,s}^{CHP} \tag{26}$$

$$T_{i,t,s}^{CHP} - T_{i,t}^{CHP} = TR_{i,t,s}^{CHP} \tag{27}$$

$$-0.1 * P_i^{CHP,max} \le PR_{i,t,s}^{CHP} \le -0.1 * P_i^{CHP,max} \tag{28}$$

$$-0.1 * T_i^{CHP,max} \leq TR_{i,t,s}^{CHP} \leq -0.1 * T_i^{CHP,max} \quad (29)$$

$$\begin{Bmatrix} P_{t.i}^{CHP}, T_{t.i}^{CHP} \\ P_{i,t.s}^{CHP}, T_{t.s.i}^{CHP} \\ P_{t.i}^{CHP} + PR_{i,t,s}^{CHP}, T_{t.i}^{CHP} + TR_{i,t,s}^{CHP} \end{Bmatrix} \in FOR_i \quad (30)$$

$$C_B^t = \sum_{k=1}^{N_B} \{ \left(\lambda^{NG} \times \frac{T_{t,k}^B}{\eta_k^B} \right) + \left(C_k^{B,U} \times SU_{t,k}^B \right) + \left(C_k^{B,D} \times SD_{t,k}^B \right) \} \quad (31)$$

$$C_{t,s}^B = \sum_{K=1}^{N_B} \left(\lambda^{NG} \times \frac{R_{t,s,k}^B}{\eta_k^B} \right) \quad (32)$$

$$T_{k,t,s}^B - T_{k,t}^B = R_{k,t,s}^B \quad (33)$$

$$-0.1 * T_k^{B,max} \leq R_{k,t,s}^B \leq -0.1 * T_k^{B,max} \quad (34)$$

$$T_k^{B,min} \times U_{t,k}^B \leq \begin{Bmatrix} T_{t,k}^B \\ T_{t,s,k}^B \\ T_{k,t}^B + R_{k,t,s}^B \end{Bmatrix} \leq T_k^{B,max} \times U_{t,k}^B \quad (35)$$

$$R_{t,s}^G = P_{t,s}^L - P_t^L \quad (36)$$

$$R_{m,t,s}^{MT} = P_{t,s,m}^{MT} - P_{m,t}^{MT} \quad (37)$$

$$PR_{i,t,s}^{CHP} = P_{t,s,i}^{CHP} - P_{t,i}^{CHP} \quad (38)$$

$$TR_{i,t,s}^{CHP} = T_{t,s,i}^{CHP} - T_{t,i}^{CHP} \quad (39)$$

$$R_{k,t}^B = T_{t,s,k}^B - T_{t,k}^B \quad (40)$$

$$P_t^{PV} + P_t^W + \sum_{m=1}^{N_{MT}} P_{t,m}^{MT} + \sum_{i=1}^{N_{CHP}} P_{t,i}^{CHP} + P_{dch,t}^{EV,total} - P_{ch,t}^{EV,total} + P_t^L \geq L_t^E \quad (41)$$

$$(P_{t,s}^{PV} - P_t^{PV}) + (P_{t,s}^W - P_{t,s}^W) + \sum_{m=1}^{N_{MT}} R_{m,t,s}^{MT} + \sum_{i=1}^{N_{CHP}} PR_{i,t,s}^{CHP} + R_{t,s}^G \geq L_{t,s}^E - L_t^E \quad (42)$$

The first part of the objective function includes the income from electrical and thermal energy supply to consumers, VPP's revenue and cost from energy and reserve exchange with upstream network and market, and the operating cost of controllable DGs, including CHP units, microturbines, and heat-only units, the scheduled income from electric vehicles, and operating cost of electrical and thermal energy storage systems. The second part of the cost function is related to the scenario-based income from heat and power supply to the VPP's consumers, scenario-based cost and income from exchanges with the main grid, and scenario-based cost of controllable DGs like microturbines to maintain the power balance in each scenario. The VPP operator is responsible for supplying power to the consumers based on their contracts. This energy selling is the primary source of income for the VPP. Relation (2)expresses the planned income of VPP from energy selling to end-consumers. The scenario-based income is given in relation (3) and equals the difference between scheduled and instantaneous income. Equations (4)and (5) describe the scheduled and scenario-based cost and income of VPP exchanges with energy and reserve markets. Relation (4)shows the cost and income from energy and reserve exchanges with the main grid. The income obtained from selling reserves to the market in each scenario is presented in relation (5). The spinning reserve value of each unit is confined to 30 percent of the line's transmission capacity, as shown in constraint (6). Relation (7) describes the relationship between the scheduled and scenario-based power exchange with the line and the spinning reserve of each scenario. The scenario-based load shifting is shown in relation (8). According to this relation, the consumers who participate in the DR programs shift a portion of their consumption from hours with high electricity prices to the low price hours. The amount of the consumer's load that can be increased or decreased per hour is a percentage of the consuming load, and this constraint is given by equation (9). Furthermore, relation (10) assumes that no load curtailment occurs during the day, i.e., the sum of load shifted within 24 hours is equal to zero. Likewise, the load shift is bounded within the minimum and maximum values as given by relation (11).

The DGs considered in this paper include microturbines, CHP units, and heat boilers. Microturbines are low-capacity gas power plants, with their output power ranging from several kW to several hundred kW. CHP units are heat and power cogeneration plants participating in electrical and thermal load supply. The boilers also provide a portion of the heat load to the VPP's consumers. Relations (12)-(15) demonstrate the operating conditions of these units and are nearly the same for all DG units. The generation variables of these units are not scenario-dependent and are related to the first programming stage. Relation (16) gives the operating cost of these units, including the fuel cost and startup and shut down cost. Moreover, the hourly reserve cost of these units is presented in relation (17). The constraint on the reserve delivered by microturbines is considered in equation (19). Relation (20) displays the constraints on the generated electrical power and the scheduled and instantaneous reserve of microturbines. CHP units are capable of concurrent electrical and thermal energy generation. The electrical and thermal outputs of these units form a closed curve known as FOR curve in the power-heat plane (Figure 1). Therefore, the heat and power generation of these units are interdependent. The operating constraints of CHP units and the equations describing the FOR curve are provided as follows. Equation (23)shows the operating cost of CHP units in scheduled mode, and relation (24) gives the reserve generation cost of these units. Additionally, equations (25)to (29) formulate the boundary lines forming the FOR of cogeneration units along with their electrical and thermal constraints. The scheduled operating cost of heat-only units is obtained from relation (30), which contains the fuel cost and startup and shut down costs of the boiler. The reserve cost of the boiler is also shown in relation (31). The relation (34)is also added to the boiler’s operating constraints to ensure the sum of the boiler's heat generation and the reserve does not exceed its nominal capacity. The RESs utilized in the VPP configuration include PV systems and wind turbines. The power generation from renewable sources is a function of environmental conditions and varies during different hours and days of the year. The energy storage systems, to some extent, can compensate for these power fluctuations at various hours. The mathematical models of PV systems and wind turbines are formulated following the equations presented in Ref. [39]. The surge in fuel consumption for transportation is a major factor contributing to increased air pollution, which poses significant challenges to humans in today's society. Electric vehicles can offer an effective solution to this growing problem. However, the utilization of electric vehicles in developed countries has led to a remarkable increase in the electrical energy demand of power systems. VPP aggregates various DG sources to satisfy the power demands of these vehicles and mitigate the impact of their presence in the distribution network. Due to their electrical energy storage capability, electric vehicles can increase the storage capacity of the distribution system. Thus, the VPP operator can use bilateral contracting to encourage electric vehicle owners to participate in VPP planning. The mathematical model of electric vehicles is taken from the study in Ref. [39].

The energy storage system can help establish the instantaneous power balance in VPP and enhance the power system's flexibility. This equipment can further be beneficial to renewable distributed generation resources in that it can partly reduce the increase or decrease in renewable resource generation based on their storage capacity. The pumped storage systems have the highest electrical energy storage capacity. The mathematical modeling of electrical and thermal energy storage systems is derived from Ref. [39]. Microturbines, CHP units, and the exchanged power with the main grid are the sources that can resolve the unbalanced production and consumption arising from the uncertainty in VPP. Similarly, the heat generation by CHP and boiler units can have a major role in thermal energy imbalance. The reserve capacity of each source covers the maximum difference between the pre-assumed and instantaneous values. Under these circumstances, even with the worst-case scenario, the system reliability improves, and the appropriate performance is guaranteed. Relations (34)-(38)demonstrate the reserve value supplied by the mentioned sources. Another important equation that should be considered in the VPP operation is the instantaneous power balance as described in relations (41) and (42).

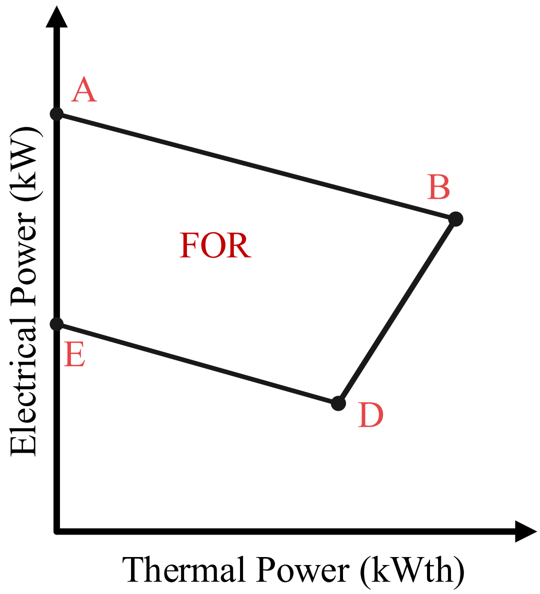

Figure 1. Feasible operation region of the CHP unit

3. Simulation

This section evaluates and discusses the effectiveness and performance of the proposed model in terms of two case studies under different conditions. The proposed mixed-integer programming (MIP) model is solved in the GAMS software environment using the CPLEX solver.

3.1. Input data

The hourly price of electrical and thermal energies, heat and power demand, wind speed, solar radiation, and natural gas price during the day are extracted from Ref. [41]. The daily price of electrical energy is taken from the data provided in Ref. [40] for August 2016. The electrical energy price is assumed fixed and equal to 100 dollars/MWh. The reserve energy price is also considered equal to 30 percent of the hourly energy price. Data related to wind turbines, PVs, and electric vehicles are extracted from Ref. [44]. Moreover, scenario generation and scenario reduction methods are also adopted from Ref. [44]. The highest power exchange between the main grid and VPP is taken as 900 kW.

3.2. Case studies

Two case studies are analyzed in this paper:

- **Case study 1:** operational planning of a VPP without DR program
- **Case study 2:** operational planning of a VPP with DR program

3.2.1. Case study 1

In this case study, the DR program effect is not considered in VPP operation. The optimal operational profit obtained in this case is $1235.4992. Figure 3 illustrates the power generation of each unit, the power exchange with the grid, the charge and discharge of storage systems, and electric vehicles' connection to the network. According to the hourly electrical demand table and overall power generation and consumption in this figure, the power balance is entirely satisfied. Figure 4 depicts the thermal power supply in the VPP. Due to the low energy price at 1-6 a.m., the operator buys the required energy for its consumers from the main grid. Given the high wind speed and renewable generation, microturbines are off during these hours, whereas CHPs and boilers are operating to meet the heat demand. Thus, a portion of electrical energy is supplied by CHPs according to their operating point. With a rise in energy prices between 7-17 o'clock, the microturbines start operating. The resulting increased generation allows for selling a portion of produced power to the grid to achieve higher profit. As the electrical demand increases at 6-10 p.m., the power generation of VPP units alone is not sufficient to supply the electrical demand. Thus, the operator purchases the power from the main grid to compensate for this deficiency. With load drop at 22-24 o'clock, VPP lowers the power generation of microturbines and provides the required load from the main grid.

Storage systems are charged at hours with low energy prices and deliver the stored energy to the grid at high energy price hours. Electric vehicle owners charge their batteries at low price hours to minimize their costs and sell their surplus energy to the grid at high price hours. Given that these vehicles travel their predicted distance during the day, their energy charge level is higher than their discharged level. Thus, they cannot optimally charge and discharge like a storage system. The 3D plot of reserve vs. time and scenario is drawn to analyze the reserve exchange between the power plant components. For simplicity, the plot is divided into two positive and negative segments. As shown in Figure 5, the reserve of components is zero or very small for scenario 4 because the uncertainty values are close to their predicted values. As electrical load increases in scenarios 5 to 7, the combination of the purchased reserve from the main grid and units' power with a 10 percent increase is utilized to supply the added load. Likewise, the load reduction in scenarios 1-3 is compensated for by reducing the power generation of units and selling reserves to the main grid to maintain the power balance.

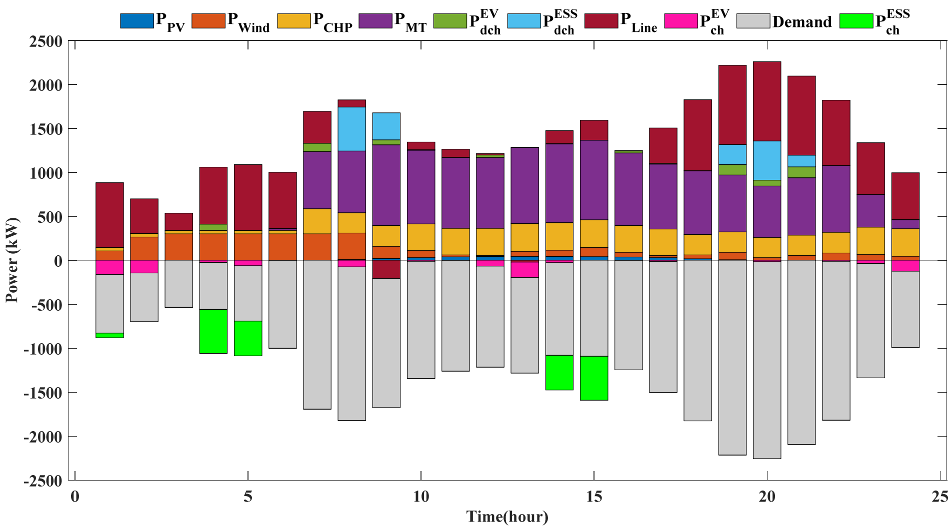

Figure 3. Electrical power balance.

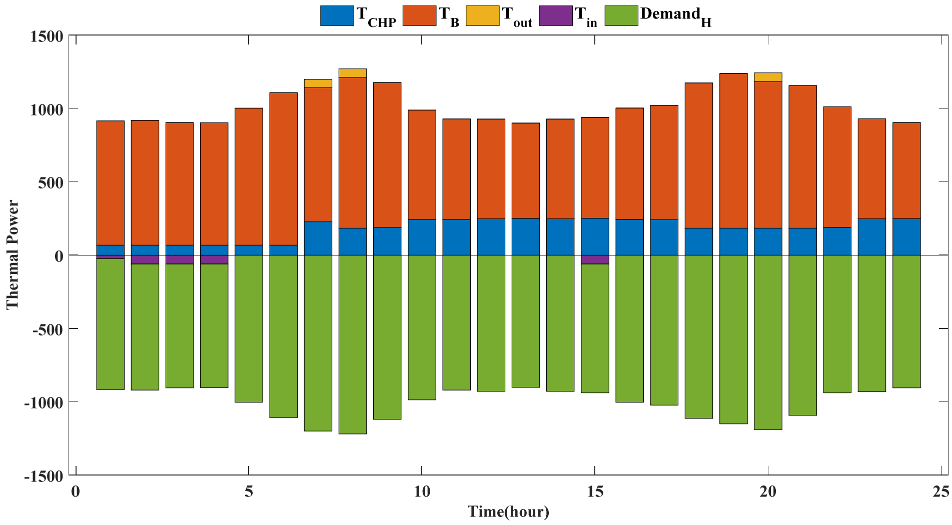

Figure 4. Thermal power balance.

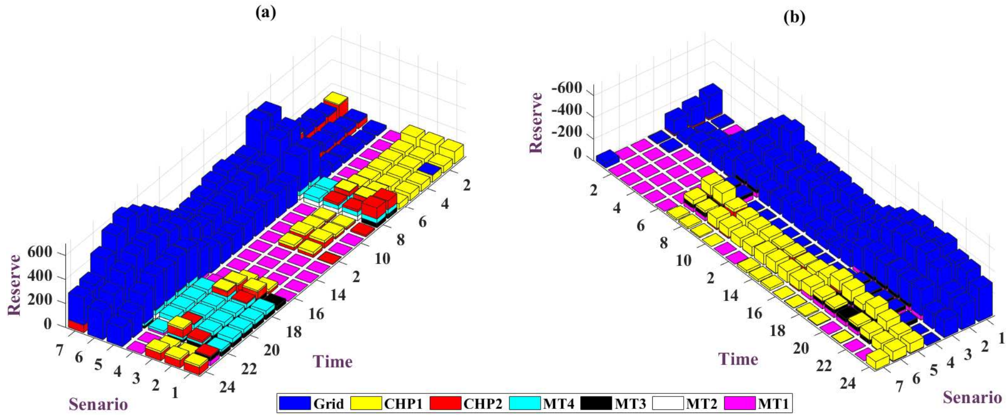

Figure 5. A) The positive segment of reserves. B) The negative segment of reserves.

3.2.2. Case study 2

A 20 percent DR program is added to the model in this case study. Given that a portion of the load is shifted from high price to low price hours, the optimal operational profit of the VPP increases to $1292.1719. Figure 6 plots the variations in electrical demand by applying the 20 percent DR program for scenario 4. Figure 7 displays the amount of shifted load per hour. As shown, the electrical demand has increased at low price hours and decreased at high price hours. Figure 8 illustrates the reserve amount of each component after implementing the 20 percent DR program. As can be observed, the required reserve level has decreased in the worst-case scenario, and the reserve curve has become smoother.

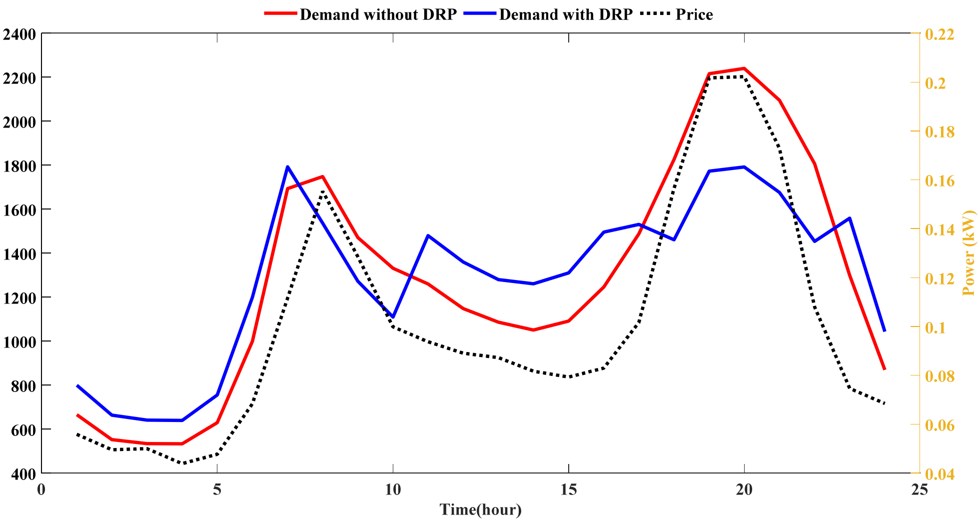

Figure 6. The effect of DR program on electrical load curve.

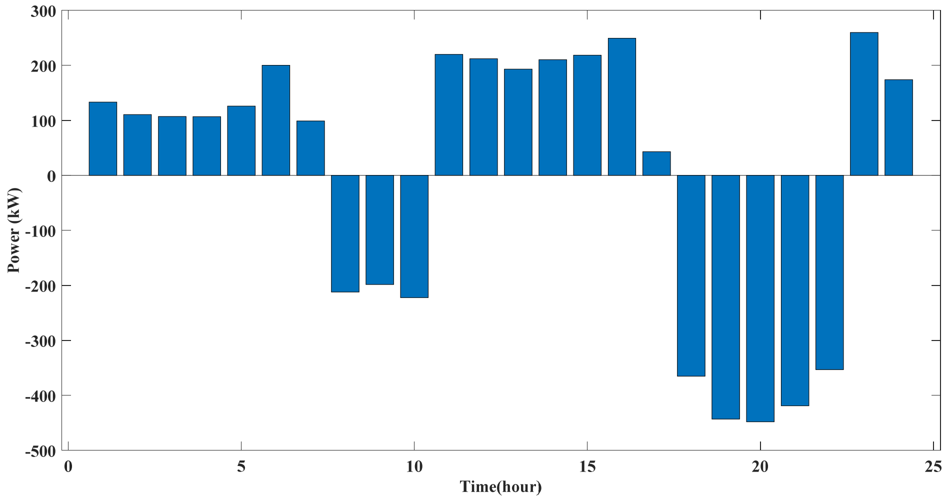

Figure 7. The shifted load per hour.

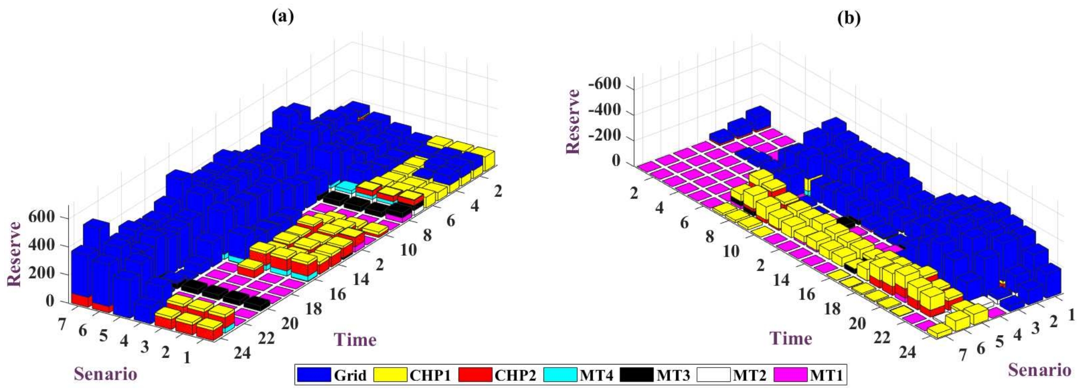

Figure 8. A) The positive segment of reserves. B) The negative segment of reserves.

4. Conclusion

The power systems are evolving toward the growing utilization of distributed energy resources as one of the main components of the smart grid. Due to the small scale of DGs, these sources emit less pollution and provide more flexibility. DGs include small-scale conventional power plants and renewable energies with zero-emission. In this paper, two-stage stochastic planning for the participation of VPP in energy and reserve markets in the presence of the DR program was presented. The designed VPP enabled participation in these markets by aggregating the DERs. The generated reserve of each power production source that was considered to compensate for the existing imbalances in different scenarios was also analyzed and discussed. Two case studies were developed to verify the effect of the DR program on optimal operational profit and reserve exchange of VPP. The results suggested that the DR program can result in a 4.58 percent increase in the optimal operational profit. Further suggestions for future studies are presented as follows:

1. Operational planning of a virtual power plant considering to a peer-to-peer energy trading
2. Two-stage operational planning of a virtual power plant considering to a peer-to-peer energy trading
3. Robust optimization based Operational planning of a virtual power plant with/without considering to a peer-to-peer energy trading

References

[1] S. M. Nosratabadi, R. A. Hooshmand, and E. Gholipour, "A comprehensive review on microgrid and virtual power plant concepts employed for distributed energy resources scheduling in power systems," *Renew. Sustain. Energy Rev.*, vol. 67, pp. 341–363, 2017, doi: 10.1016/j.rser.2016.09.025.

[2] X. Wang, Z. Liu, H. Zhang, Y. Zhao, J. Shi, and H. Ding, "A Review on Virtual Power Plant Concept, Application and Challenges," in *2019 IEEE PES Innovative Smart Grid Technologies Asia, ISGT 2019*, 2019, pp. 4328–4333, doi: 10.1109/ISGT-Asia.2019.8881433.

[3] F. W. Bliek *et al.*, "The role of natural gas in smart grids," *J. Nat. Gas Sci. Eng.*, vol. 3, no. 5, pp. 608–616, 2011, doi: 10.1016/j.jngse.2011.07.008.

[4] E. A. Setiawan, *Concept and controllability of Virtual Power Plant*. Ph.D. dissertation; Dept. Electrical Engineering/Computer; Science. EngUniv. Kassel, 2007.

[5] S. Awerbuch and A. Preston, *The Virtual Utility: Accounting, Technology & Competitive Aspects of the Emerging Industry*, vol. 26. Kluwer Academic Pub, 1997.

[6] N. Naval and J. M. Yusta, "Virtual power plant models and electricity markets-A review," *Renew. Sustain. Energy Rev.*, vol. 149, p. 111393, 2021.

[7] H. M. Rouzbahani, H. Karimipour, and L. Lei, "A review on virtual power plant for energy management," *Sustain. energy Technol. assessments*, vol. 47, p. 101370, 2021.

[8] C. Kieny, B. Berseneff, N. Hadjsaid, Y. Besanger, and J. Maire, "On the concept and the interest of Virtual Power plant: Some results from the European project FENIX," 2009, doi: 10.1109/PES.2009.5275526.

[9] D. Pudjianto, C. Ramsay, and G. Strbac, "Virtual power plant and system integration of distributed energy resources," *IET Renew. Power Gener.*, vol. 1, no. 1, p. 10, 2007, doi: 10.1049/iet-rpg:20060023.

[10] O. Sadeghian, A. Oshnoei, R. Khezri, and S. M. Muyeen, "Risk-constrained stochastic optimal allocation of energy storage system in virtual power plants," *J. Energy Storage*, vol. 31, p. 101732, 2020.

[11] K. Dietrich, J. M. Latorre, L. Olmos, and A. Ramos, "Modelling and assessing the impacts of self supply and market-revenue driven Virtual Power Plants," *Electr. Power Syst. Res.*, vol. 119, pp. 462–470, 2015, doi: 10.1016/j.epsr.2014.10.015.

[12] M. Shabanzadeh, M. K. Sheikh-El-Eslami, and M. R. Haghifam, "A medium-term coalition-forming model of heterogeneous DERs for a commercial virtual power plant," *Appl. Energy*, vol. 169, pp. 663–681, May 2016, doi: 10.1016/j.apenergy.2016.02.058.

[13] Y. Yuan, Z. Wei, G. Sun, Y. Sun, and D. Wang, "A real-time optimal generation cost control method for virtual power plant," *Neurocomputing*, vol. 143, pp. 322–330, Nov. 2014, doi: 10.1016/j.neucom.2014.05.060.

[14] M. M. Othman, Y. G. Hegazy, and A. Y. Abdelaziz, "Electrical energy management in unbalanced distribution networks using virtual power plant concept," *Electr. Power Syst. Res.*, vol. 145, pp. 157–165, Apr. 2017, doi: 10.1016/j.epsr.2017.01.004.

[15] A. Shayegan-Rad, A. Badri, and A. Zangeneh, "Day-ahead scheduling of virtual power plant in joint energy and regulation reserve markets under uncertainties," *Energy*, vol. 121, pp. 114–125, 2017, doi: 10.1016/j.energy.2017.01.006.

[16] A. Baringo, L. B.-I. T. on P. Systems, and undefined 2016, "A stochastic adaptive robust optimization approach for the offering strategy of a virtual power plant," *ieeexplore.ieee.org*.

[17] M. Giuntoli and D. Poli, "Optimized thermal and electrical scheduling of a large scale virtual power plant in the presence of energy storages," *IEEE Trans. Smart Grid*, vol. 4, no. 2, pp. 942–955, 2013, doi: 10.1109/TSG.2012.2227513.

[18] A. G. Zamani, A. Zakariazadeh, S. Jadid, and A. Kazemi, "Stochastic operational scheduling of distributed energy resources in a large scale virtual power plant," *Int. J. Electr. Power Energy Syst.*, vol. 82, pp. 608–620, Nov. 2016, doi: 10.1016/j.ijepes.2016.04.024.

[19] A. G. Zamani, A. Zakariazadeh, and S. Jadid, "Day-ahead resource scheduling of a renewable energy based virtual power plant," *Appl. Energy*, vol. 169, pp. 324–340, May 2016, doi: 10.1016/j.apenergy.2016.02.011.

[20] T. Sousa, H. Morais, Z. Vale, and R. Castro, "A multi-objective optimization of the active and reactive resource scheduling at a distribution level in a smart grid context," *Energy*, vol. 85, pp. 236–250, Jun. 2015, doi: 10.1016/j.energy.2015.03.077.

[21] H. Nezamabadi and M. Setayesh Nazar, "Arbitrage strategy of virtual power plants in energy, spinning reserve and reactive power markets," *IET Gener. Transm. Distrib.*, vol. 10, no. 3, pp. 750–763, Feb. 2016, doi: 10.1049/iet-gtd.2015.0402.

[22] S. Fan, Q. Ai, and L. Piao, "Fuzzy day-ahead scheduling of virtual power plant with optimal confidence level," *IET Gener. Transm. Distrib.*, vol. 10, no. 1, pp. 205–212, Jan. 2016, doi: 10.1049/iet-gtd.2015.0651.

[23] M. A. Tajeddini, A. Rahimi-Kian, and A. Soroudi, "Risk averse optimal operation of a virtual power plant using two stage stochastic programming," *Energy*, vol. 73, pp. 958–967, Aug. 2014, doi: 10.1016/j.energy.2014.06.110.

[24] M. Shabanzadeh, M. K. Sheikh-El-Eslami, and M. R. Haghifam, "Risk-based medium-term trading strategy for a virtual power plant with first-order stochastic dominance constraints," *IET Gener. Transm. Distrib.*, vol. 11, no. 2, pp. 520–529, Jan. 2017, doi: 10.1049/iet-gtd.2016.1072.

[25] S. R. Dabbagh and M. K. Sheikh-El-Eslami, "Risk Assessment of Virtual Power Plants Offering in Energy and Reserve Markets," *IEEE Trans. Power Syst.*, vol. 31, no. 5, pp. 3572–3582, Sep. 2016, doi: 10.1109/TPWRS.2015.2493182.

[26] S. Hadayeghparast, A. SoltaniNejad Farsangi, and H. Shayanfar, "Day-ahead stochastic multi-objective economic/emission operational scheduling of a large scale virtual power plant," *Energy*, vol. 172, pp. 630–646, Apr. 2019, doi: 10.1016/j.energy.2019.01.143.

[27] Z. Luo, S. H. Hong, and Y. M. Ding, "A data mining-driven incentive-based demand response scheme for a virtual power plant," *Appl. Energy*, vol. 239, pp. 549–559, Apr. 2019, doi: 10.1016/j.apenergy.2019.01.142.

[28] N. Naval, R. Sánchez, and J. M. Yusta, "A virtual power plant optimal dispatch model with large and small-scale distributed renewable generation," *Renew. Energy*, vol. 151, pp. 57–69, 2020, doi: 10.1016/j.renene.2019.10.144.

[29] S. Yin, Q. Ai, Z. Li, Y. Zhang, and T. Lu, "Energy management for aggregate prosumers in a virtual power plant: A robust Stackelberg game approach," *Int. J. Electr. Power Energy Syst.*, vol. 117, May 2020, doi: 10.1016/j.ijepes.2019.105605.

[30] A. Alahyari, M. Ehsan, and M. S. Mousavizadeh, "A hybrid storage-wind virtual power plant (VPP) participation in the electricity markets: A self-scheduling optimization considering price, renewable generation, and electric vehicles uncertainties," *J. Energy Storage*, vol. 25, Oct. 2019, doi: 10.1016/j.est.2019.100812.

[31] C. Xiao, D. Sutanto, K. M. Muttaqi, and M. Zhang, "Multi-period data driven control strategy for real-time management of energy storages in virtual power plants integrated with power grid," *Int. J. Electr. Power Energy Syst.*, vol. 118, Jun. 2020, doi: 10.1016/j.ijepes.2019.105747.

[32] A. Hany Elgamal, G. Kocher-Oberlehner, V. Robu, and M. Andoni, "Optimization of a multiple-scale renewable energy-based virtual power plant in the UK," *Appl. Energy*, vol. 256, Dec. 2019, doi: 10.1016/j.apenergy.2019.113973.

[33] A. Kulmukhanova, A. T. Al-Awami, I. M. El-Amin, and J. S. Shamma, "Mechanism Design for Virtual Power Plant with Independent Distributed Generators," *IFAC-PapersOnLine*, vol. 52, no. 4, pp. 419–424, 2019, doi: 10.1016/j.ifacol.2019.08.246.

[34] M. H. Abbasi, M. Taki, A. Rajabi, L. Li, and J. Zhang, "Coordinated operation of electric vehicle charging and wind power generation as a virtual power plant: A multi-stage risk constrained approach," *Appl. Energy*, vol. 239, pp. 1294–1307, Apr. 2019, doi: 10.1016/j.apenergy.2019.01.238.

[35] M. Shafiekhani, A. Badri, M. Shafie-khah, and J. P. S. Catalão, "Strategic bidding of virtual power plant in energy markets: A bi-level multi-objective approach," *Int. J. Electr. Power Energy Syst.*, vol. 113, pp. 208–219, Dec. 2019, doi: 10.1016/j.ijepes.2019.05.023.

[36] H. Wang, Y. Jia, C. S. Lai, and K. Li, "Optimal Virtual Power Plant Operational Regime under Reserve Uncertainty," *IEEE Trans. Smart Grid*, 2022.

[37] A. Jani, H. Karimi, and S. Jadid, "Multi-time scale energy management of multi-microgrid systems considering energy storage systems: A multi-objective two-stage optimization framework," *J. Energy Storage*, vol. 51, p. 104554, 2022.

[38] H. Karimi and S. Jadid, "A strategy-based coalition formation model for hybrid wind/PV/FC/MT/DG/battery multi-microgrid systems considering demand response programs," *Int. J. Electr. Power Energy Syst.*, vol. 136, p. 107642, 2022.

[39] W. Hu, Q. Guo, E. Valipour, and S. Nojavan, "Risk-averse trading strategy for a hybrid power plant in energy and carbon markets to maximize overall revenue," *J. Energy Storage*, vol. 51, p. 104586, 2022.

[40] "Hourly Ontario Energy Price (HOEP)." .

[41] S. Heunis and M. Dekenah, "A load profile prediction model for residential consumers in South Africa," 2014, doi: 10.1109/DUE.2014.6827763.

[42] "Data archives for University of Waterloo weather station." .

[43] S. Nojavan and H. A. Aalami, "Stochastic energy procurement of large electricity consumer considering photovoltaic, wind-turbine, micro-turbines, energy storage system in the presence of demand response program," *Energy Convers. Manag.*, vol. 103, pp. 1008–1018, Jul. 2015, doi: 10.1016/j.enconman.2015.07.018.

[44] A. SoltaniNejad Farsangi, S. Hadayeghparast, M. Mehdinejad, and H. Shayanfar, "A novel stochastic energy management of a microgrid with various types of distributed energy resources in presence of demand response programs," *Energy*, vol. 160, pp. 257–274, 2018, doi: 10.1016/j.energy.2018.06.136.