

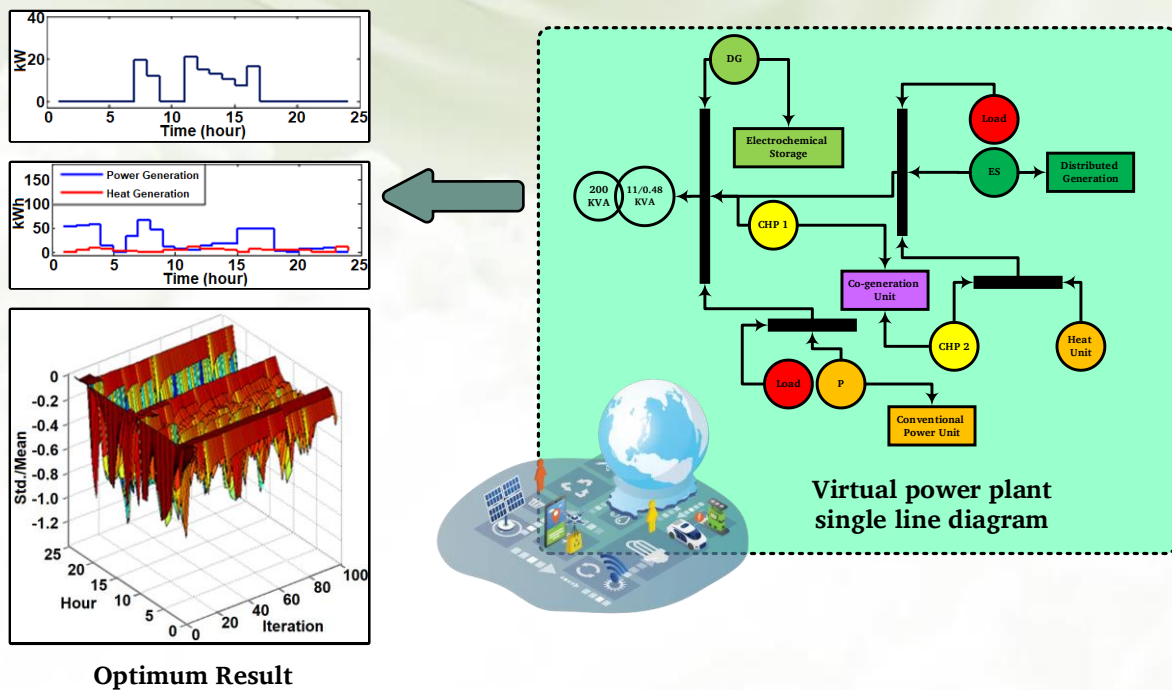
Scenario-Based Planning of Participation of Virtual Power Plants in Storage and Energy Markets in Terms of Load Response and Market Price Uncertainty

Hamidreza Hanif, Mohammad Zand, Morteza Azimi Nasab, Seyyed Mohammad Sadegh Ghiasi, Sanjeevikumar Padmanaban

Highlight

- ❖ Providing an inertial response for ESS with fast response capability
- ❖ Investigating the effect of inertial response in establishing frequency response and network behavior after sudden events
- ❖ Considering the new model of the problem and applying the novel algorithm for this problem

Graphical Abstract



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Citation

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Scenario-Based Planning of Participation of Virtual Power Plants in Storage and Energy Markets in Terms of Load Response and Market Price Uncertainty

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ABSTRACT

Environmental concerns, advancements in the new energy industry, and rising power generation and transmission costs are driving the electricity industry towards innovation. This has led to the installation of distributed energy resources (DERs) in many regions. Virtual power plants (VPPs), which manage decentralized energy systems by aggregating the capacity of various distributed generations (DGs), storage devices, and distributable loads, are used for trading energy and services. The research focuses on the planning of price-based unit commitment (PBUC) managed by VPPs over a 24-hour period. Simulation results demonstrate that the proposed framework effectively develops strategies for VPP market production and consumer interaction, especially with load-shedding capabilities. A key aspect of the study is examining the impact of uncertainties on VPP strategies. Probability density functions and the Monte Carlo method are used to model and assess these uncertainties. Simulations without energy price and demand uncertainties indicate that the model is suitable for strategizing VPP market production and consumer interaction. However, simulations that include market price uncertainties and predicted VPP loads show that VPP profits are influenced by market volatility. Increased price and demand fluctuations significantly affect VPP strategies, sometimes resulting in losses during certain periods.

1. Introduction

Due to the gradual exhaustion of fossil fuel-based energy sources and widespread concern about environmental protection, renewable energy sources (RES) and demand response (DR) technology are deployed in the power system [1-3]. However, insufficient management as well as the bottleneck of technology are the main obstacles to their further development.

1.1. Literature review

The use of distributed algorithms in the multi-player strategy optimization problem accelerates the convergence of the bidding method, which confirms the usability and effectiveness of the proposed models [4]. The problem of planning DERs has been investigated from aspects of various models including modeling techniques, solution methods, reliability, diffusion, uncertainty, stability, DR, and multi-objective perspectives in the framework of microprocessors and VPPs. This allows researchers with different perspectives to look for possible applications in microgrid planning and VPP [5]. Reference [6] outlines the unique operational requirements of DC distribution systems and highlights the challenges and opportunities they create for the market. The DC distribution systems have been introduced to the market, including tradable services, design objectives, market participants, design options, and performance metrics. A minimal cost estimation model was presented to determine the optimal DG picker portfolio. The proposed scheduling framework for the IEEE Reliability Testing System has been tested in relation to the IEEE 69-bus distribution network [7]. Literature [8] presents a new VPP model that presents all available full-scale distributed renewable technologies. The proposed VPP operates as a single plant in the wholesale electricity market to maximize profits from its performance to meet demand. In the electricity market, three common mediums to long-term electricity decomposition methods are built on average tracking times and point prices, where the latter is predicted by the ARIMA model, while the relationship between point prices and costs is also predicted. The margin of the VPP is obtained. The marginal cost can also be adjusted based on the ARIMA model. Based on the aforementioned factors concerning investment and complementary benefits, a VPP measurement model has been developed [9-10]. The proposed optimal decision model maximizes the use of clean energy to achieve higher economic benefits while reaching rational control of performance risks [11-12]. The proposed method is also easy to track for VPP operators because of less computation. Finally, power curves are obtained per hour, which the operator takes advantage of to increase or decrease the market price. Also, comparative results of deterministic and uncertainty cases are presented. The results show that the profit margin at the maximum strength is reduced by 25.91% and the VPP is resisting the uncertainty of the day's market price [13]. In Reference [14], the effect of combining distributed energy generation technologies on major electricity price changes in different EU energy markets is investigated using a maximum entropy econometric approach. Knowing how much each unit of electricity produced by each technology can change the price of electricity can be very useful for formulating optimal strategies in a decision on a portfolio of electricity technologies. In this study, the VPP model uses renewable energy sources such as wind power plants (WPP), solar power plants (SPP), biogas power plants (BPP), and pumped-hydro storage power plants (PHSP) as energy storage system (ESS). The purpose of VPP is to maximize daily net profit over 24 hours. The proposed mixed-integer linear programming (MILP) is modeled in GAMS software and solved using CPLEX [15]. This paper examines the VPP bidding strategy in

the energy services and regulatory market. The performance of distributed energy sources (DER) and battery energy storage within a VPP is analyzed. The VPP bidding strategy includes the spin reserve contract and the bid/bid contract of the day. A robust two-step optimization model is proposed to determine the VPP buying/selling power of each contract to maximize the profit of VPP [16]. With the rapid development of renewable energy, VPP technology has gradually become a key technology for solving large-scale renewable energy development. The optimization of gas-VPP's stochastic dispatching is discussed [17]. The effects of resource utilization techniques, for example, processing time (PT), response time (RT), computational cost, and energy consumed by resources have also been analyzed [18]. The authors in [19] examine two different sources of uncertainty: the stochastic, applied approach to market price uncertainty, and the information gap decision theory (IGDT), incorporated in the model of counting for uncertainty in wind power generation. Uncertainty is involved in the problem through random electricity prices as well as uncertain wind power generation. The bidding problem for a working day is set as a Markov Decision Process (MDP) that is solved using a kind of stochastic dual programming algorithm [20-21]. The Stack Berg two-stage game model is linearized and solved with the Column Generation and Constraint (CC&G) algorithm. In addition, the thermal unit operating in automatic generation control (AGC) mode guarantees optimal real-time scheduling of total actuators for the entire dispatch cycle [22]. Experimental results show that the proposed DRL-based algorithm can successfully learn the characteristics of DGs and industrial user demands. It can be learning to choose measures to minimize the cost of VPPs [23-24]. Reference [25] investigates the real-time multi-stage random power management strategy of a VPP using a three-tiered language protocol based on the computer programmer's compiler, which utilizes the possibility of storing the battery in a VPP.

The problem addressed [26] is the participation planning of price-based unit commitment (PBUC) that is resolved by the VPP over a fixed period (24 hours). Price and demand have uncertainty in this problem and normal logarithmic and normal probability functions have been used to model these uncertainties. The Monte Carlo method is used to investigate the impact of the possible variables mentioned on how the VPP strategy is implemented. The study network consists of 2 samples. In the first case, the presence of CHP units in the network is neglected. The objective function is to maximize the profit of VPPs for the market taking into account its constraints. In reference [27], a model for developing a strategy for proposing VPP production to the electricity wholesale market is presented, in which the desired optimization problem is a Price-based Unit Commitment (PBUC) participation planning problem, while Supply and demand balance constraints and VPP security constraints are also considered in the problem. It is worth mentioning that in the mentioned model, the market prices in the studied period are available as input Information without error in forecasting. In other words, VPP strategies are formulated in the absence of uncertainty in price and predicted demand. Also, in reference [28], it was mentioned how to set the price of the power plant taking into account the uncertainty of the price. To model the uncertainty, the probability density function has been used. In this

method, it is necessary to examine the pricing in such a way that the market is considered daily and the producers and consumers present their offer curves hourly, in blocks of energy and price.

1.2. Main contributions

The hypotheses made in the article are:

The target problem in this research is the participation planning of PBUC, which is solved by VPP in a certain period (24 hours).

- I. Probability density functions are used to model uncertainty.
- II. The Monte Carlo method is used for the effect of these uncertainties on the indicators of the problem.
- III. Among the highlights of this research is the investigation of the effects of uncertainty on the strategy of the virtual power plant.

1.3. Structure of the paper

In the following, the structure of the article is described. In the second part, we examine the objective function and constraints of the problem (taking into account CHP units). In the third section, the network under study and assumptions together with simulation scenarios are introduced. In the fourth part, the review, simulation, and analysis of results for VPP 1 considering the energy market are discussed, and finally, in the fifth part, conclusions and suggestions are provided.

2. Objective function and constraints of the problem (taking into account CHP units)

One of the most important issues addressed in research today is the replacement of traditional generation units with other units. Alternative power plants, renewable energy sources, and CHP units are among the problems faced by dispersed power plants, which are defective in their control. The VPP needs to be adjustable at any time. One of the reasons for accepting the replacement of traditional units with VPPs is the production of electricity at a price close to the traditional ones. It is important to note that cogeneration units typically require more investment than conventional energy conversion systems. However, their energy consumption is much lower; in other words, the average cost of converting one unit of energy into CHP units is lower than other methods [28].

The objective function of the problem of economic distribution of cogeneration is given in Equation (1) [26]:

$$\min f_{cost} = \sum_{i=1}^{N_p} C_i(P_i) + \sum_{j=1}^{N_c} C_j(O_j, H_j) + \sum_{k=1}^{N_h} C_k(T_k) \quad (1)$$

Equality constraints include Equations (2)-(3):

$$\sum_{i=1}^{N_p} P_i + \sum_{j=1}^{N_c} O_j = P_d \quad (2)$$

$$\sum_{j=1}^{N_c} H_j + \sum_{k=1}^{N_h} T_k = H_d \quad (3)$$

Inequality constraints are provided in Equations (4)-(10):

$$P_i^{min_i} \leq P_i \leq P_i^{max_p} \tag{4}$$

$$O_i^{min_j} \leq O_i \leq O_i^{max_c} \tag{5}$$

$$H_j^{min_j} \leq H_j \leq H_j^{max_c} \tag{6}$$

$$T_k^{min_k} \leq T_k \leq T_k^{max_h} \tag{7}$$

$$C_i(P_i) = a_i + b_i P_i + C_i P_i^2 \tag{8}$$

$$C_j(O_j, H_j) = a_j + b_j O_j + c_j O_j^2 + d_j H_j + e_j H_j^2 + f_j O_j H_j \tag{9}$$

$$C_k(T_k) = a_k + b_k T_k + c_k T_k^2 \tag{10}$$

here, the minimum fuel cost is f_{cost} , and production costs of traditional power plants, cogeneration, and thermal units are $c_i, c_j, c_k, a_i, b_i, c_i$. Also, $a_j, b_j, c_j, d_j, e_j, f_j$ are the fuel cost coefficients of cogeneration unit j , a_k, b_k, c_k are the fuel cost coefficients of the thermal unit k . The output power of the traditional and cogeneration units is given by P_i and O_j . The heat generated in the cogeneration unit and heat in the thermal unit are shown as H_j and T_k . Heat demand and power demand are denoted by H_d and P_d . Also, $N_p, N_c,$ and N_h indicate the number of traditional power units, cogeneration, and heat. P_i^{min} and P_i^{max} are the minimum and maximum power output of traditional units, O_j^{min} and O_j^{max} express the minimum and maximum power output of cogeneration units, H_j^{min} and H_j^{max} are the minimum and maximum heat production of cogeneration units, and minimum and maximum heat production of thermal units are denoted by T_k^{min} and T_k^{max} . Also, in this study, binary coding methods, sequential selection, and two-point combinations are used. The coded variables include U_t with string length 1, $P_{dg}, P_{capacity},$ and P_{curt} with string length 8. The initial population size is 200, the probability of a cut is 0.95, and the probability of a mutation is 0.05. The number of iterations for the Monte Carlo simulation is 100 iterations. The single-line diagram of the first virtual power plant is shown in Figure 1. To ensure the accuracy of the results of the algorithm implementation, the simulation results are compared with the results of [27].

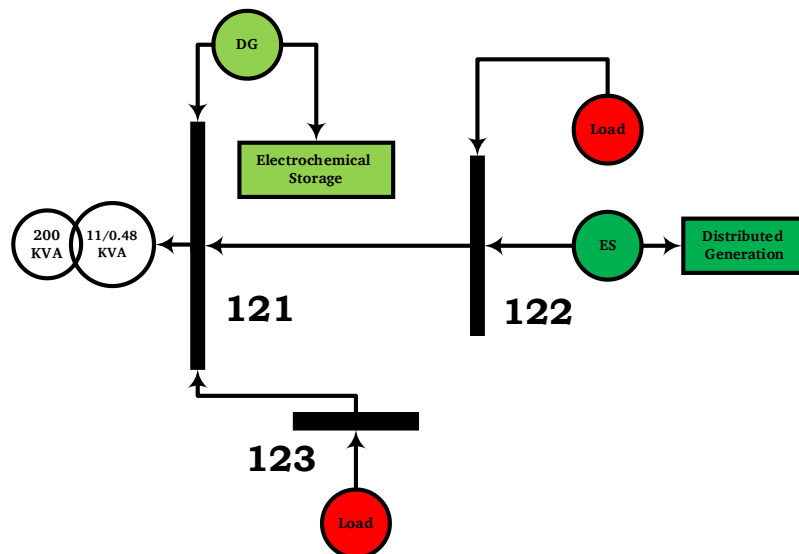


Figure 1. Single-line diagram of VPP 1.

2.1. Simulation and Analysis of Results for VPP 1 Considering Energy Market

Due to the disconnected loads in the system, it is possible to disconnect up to a maximum of 25 kW at 7-8 and 11-18 hours. Also, the cost of the load interruption to pay the consumer is obtained by the relationship $C(P) = 0.01P^2 + P$, where P is the power not supplied. The binary variable U_{DG} was used to indicate the switched on/off status of the DG. The DG production cost function is calculated according to $C(dg) = 0.01P_{dg}^2 + 8.5P_{dg}$. The maximum profit is 29227\$. Table 1 provides the hourly input data including the amount of load, energy price, hourly retail, wholesale, and reservation amounts. Figure 2 provides the hourly deterministic baseline simulation considering the energy market. As mentioned earlier, the minimum battery life is 5 kWh.

Table 1. Hourly input data [27].

Hour	Load (kW)	Energy price (\$/MWh)			Hour	Load (kW)	Energy price (\$/MWh)		
		retail	Wholesale	Reservation			retail	Wholesale	Reservation
1	97	9	11.5	12.5	13	135	11	14.5	15
2	92	9	11.5	12.5	14	128	11	14.5	15
3	90	9	11.5	12.5	15	115	11	14.5	15
4	88	9	11.5	12.5	16	105	11	6.5	7
5	90	9	11.5	12.5	17	104	9	6.5	7
6	92	9	11.5	12.5	18	105	9	6.5	7
7	95	9	11.5	12.5	19	108	9	6.5	7
8	100	9	11.5	12.5	20	108	9	6.5	7
9	105	9	11.5	12.5	21	106	9	6.5	7
10	110	11	11.5	12.5	22	104	9	14	14.5
11	120	11	14.5	15	23	102	9	14	14.5
12	135	11	14.5	15	24	98	9	14	14.5

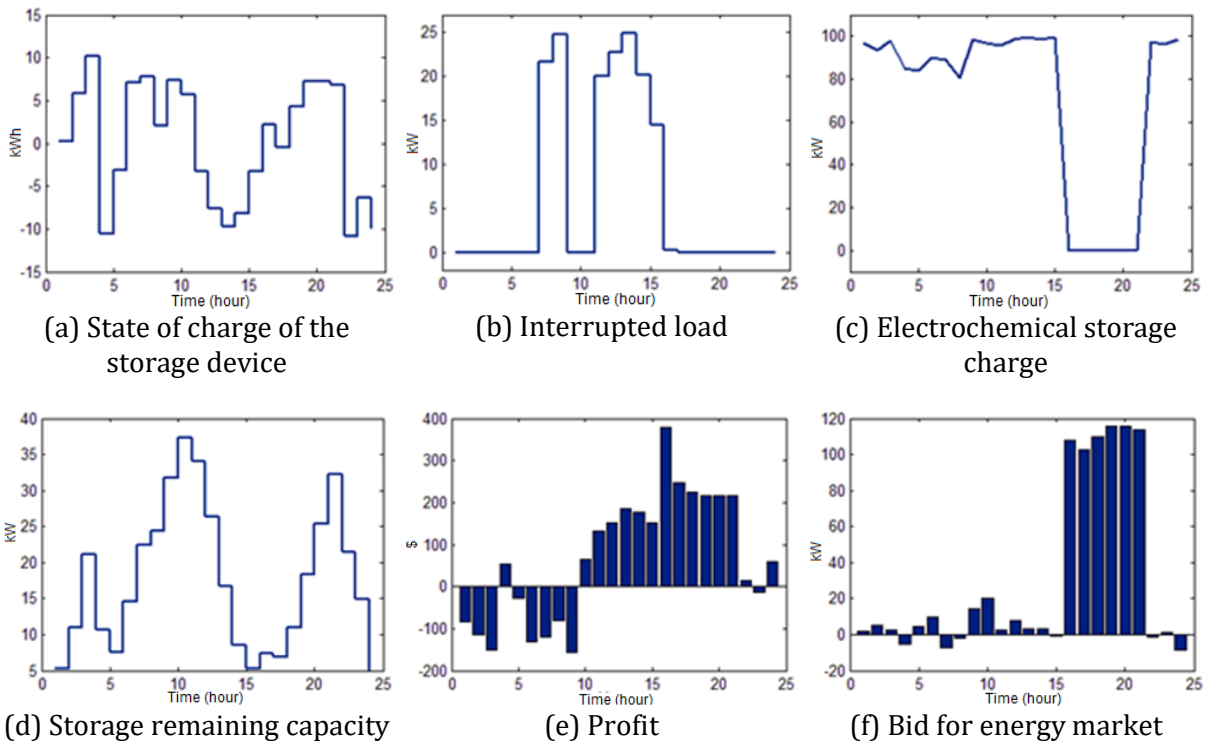


Figure 2. Hourly Deterministic Baseline simulation considering the energy market.

To study the effect of uncertainty on energy price forecasting and demand on the VPP strategy, various scenarios are defined as tabulated in Table 2. In these scenarios, the standard deviation rate has different values, indicating market price volatility [6].

In the first scenario, the results are similar to the base case and are only averaged over the results after 100 iterations. As a result, they do not differ significantly from the base case, so the results of this section are ignored. In the sixth scenario, by applying standard deviation $S = 0.$, the product has high fluctuations (relative to standard deviation 0.02). As has been stated, production has changed to the standard deviation. Expected VPP profits in the energy market under price uncertainty are provided in Table 3, and bid for the energy market in different iterations is given in Figure 3.

Table 2. Scenarios.

Scenario number	Standard deviation	Price uncertainty	Demand Uncertainty
1	0.00	×	×
2	0.02	✓	×
3	0.05	✓	×
4	0.10	✓	×
5	0.15	✓	×
6	0.02	✓	✓
7	0.05	✓	✓
8	0.10	✓	✓
9	0.15	✓	✓

Table 3. Expected VPP profits in the energy market under price uncertainty.

Scenario number	1	2	3	4	5
Profit (\$)	30012	28534	19856	5610.7	463.9693

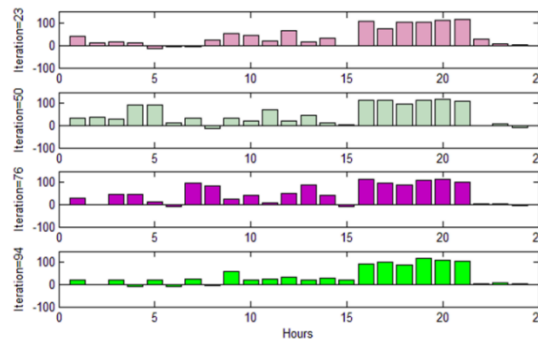


Figure 3. Bid for the energy market in different iterations ($S = 0.05$).

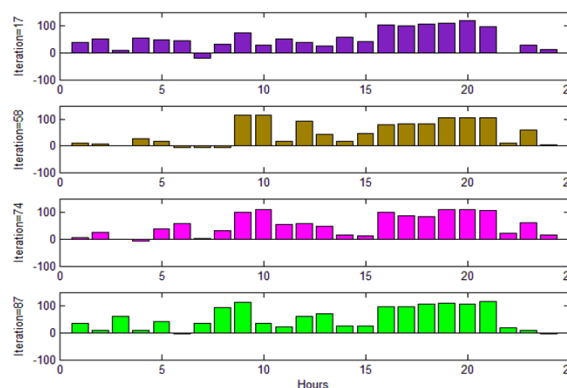


Figure 4. Bid for the energy market in different iterations ($s = 0.10$).

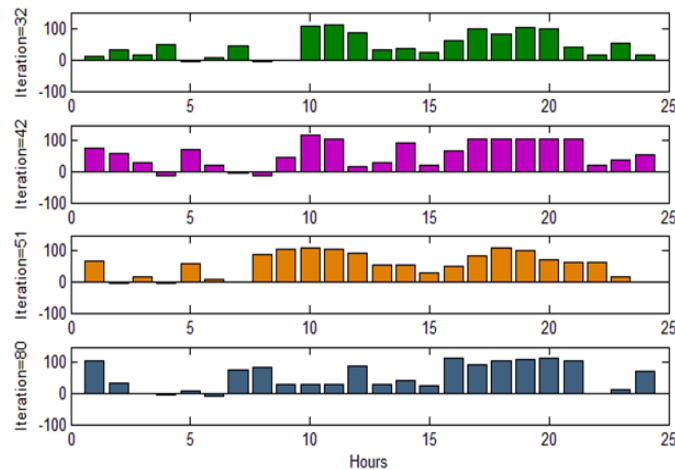


Figure 5. Bid for the energy market in different iterations ($s = 0.15$).

2.2. Sixth to Ninth Scenarios (In the Presence of Price and Demand Uncertainty)

In this case, in addition to the energy price, the load is also uncertain and the normal density function is used for modeling. It is seen from Figures 4-10 that despite the uncertainty of the load along with the uncertainty of the price, changing the production of DG, electrochemical storage device, bid and sell strategy, and profit of the plant is affected.

2.3. Simulation and Analysis of Results for VPP 1 in the Reserve Market

In this case, the problem is solved by considering the possibility of involving the VPP in the spinning reserve market. It is worth noting that DG and disconnected loads are spin reserve resources. The maximum capacity of the DG to supply the reservation is 30 kW as we can see in Figure 6(a).

Figure 6(b) shows the charge and discharge of the electrochemical device. During 1-8 hours, the amount of VPP load is low. Therefore, the device is charged. The device is then discharged at high load times. At hours 7-8 and 15-11, the retail price is lower than the energy price. So, in this case, the maximum profit will be generated by cutting off, as we can see in Figure 6(c).

In Figures 6(d)-(g), respectively, the amount of VPP bid for rotational energy and reserve and profit and the remaining storage capacity are shown. The VPP bid rate for and spinning reservation is zero when DG is not switched off. In Figure 6(d), the positive values represent the VPP purchase from the market and the negative values represent the VPP energy sold to the market. In this case, the maximum profit is 106×2.8651 . Table 4 provides the VPP expected profit in the energy market under uncertainty of demand for scenarios 6-9. Table 5 presents the expected VPP profit in the reserve market under price uncertainty for scenarios 1-9.

Table 4. VPP expected profit in the energy market under uncertainty of demand.

Scenario number	6	7	8	9
Profit (\$)	12625	6432.6	210.53	-12.8107

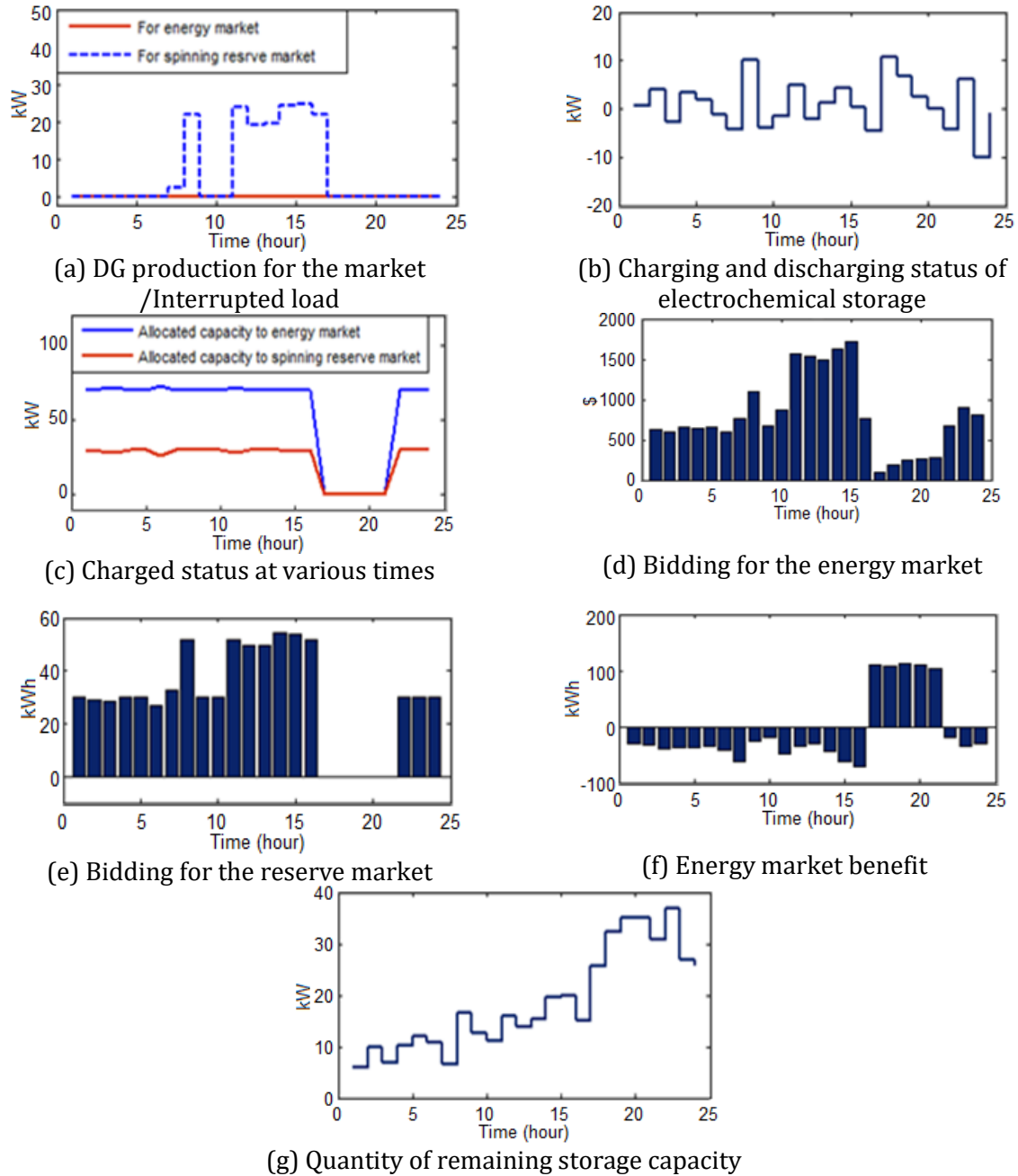


Figure 6. Baseline simulation results with reservation market in mind.

Table 5. Expected VPP profit in the reserve market under price uncertainty.

Scenario number	1	2	3	4	5	6	7	8	9
Profit (1000\$)	2993	1984.8	751.18	87.094	1.6253	1980.8	300.76	56.643	1.0093

2.4. Case Study II (VPP 2)

In this section, a new network is considered. This network is based on the previous network with the addition of 4 new units. These 4 units comprise one traditional power generation unit (P1), one heat generator unit (T1), and two CHP units (O1, H1, O2, H2) as shown in Figure 7.

assumptions, a definitive load is allowed between hours 7-8 and 18-11. However, since the DG is off at hours 16-18 and the retail price is high, there is no need for a definitive load. Figure 8(c) illustrates the amount of charge and discharge of the electrochemical storage device. Similar to the previous simulation, the positive values indicate the storage device charge and the power transfer to the grid (power injection to the grid) and the negative values denote the storage device discharge and power absorption from the grid.

Figure 8(g) shows the production rate (power and heat) for cogeneration unit 1. The power generating unit is switched off during the hours 4-8, 13-12, and 17-24, and power generation is done through other sources. Given the constraints in the problem, the second cogeneration unit and the first power-generating unit must produce a total of 150 kW. Referring to Figures 8(h) and (i), this is well evident. And, the total power of these three producers will be 150. It is also switched off during hours 6-8, 12-31 and 20-22. As explained above, the cogeneration unit and the first heat-generating unit compensate for this shortfall in aggregate and produce 15 kW of heat in total.

Units are switched on and off due to the use of a genetic algorithm, coding and applying binary variables (U1, U2, U3, U4), and applying the bit transfer method. The power plant biddings to the market are visible in Figure 8(d). It is observed that it always has negative values, which means selling energy to the market. The reason for this and the difference with the base grid is the application of the new power generation capacity to the equilibrium of energy production and consumption. Figures 8(d) and (e), respectively, show the results of the bid for the energy market and the amount of VPP profit during the study period. The maximum profit is 8.0864×10^3 . With the increase in production units, there will be opportunities for more production and more profit for the plant.

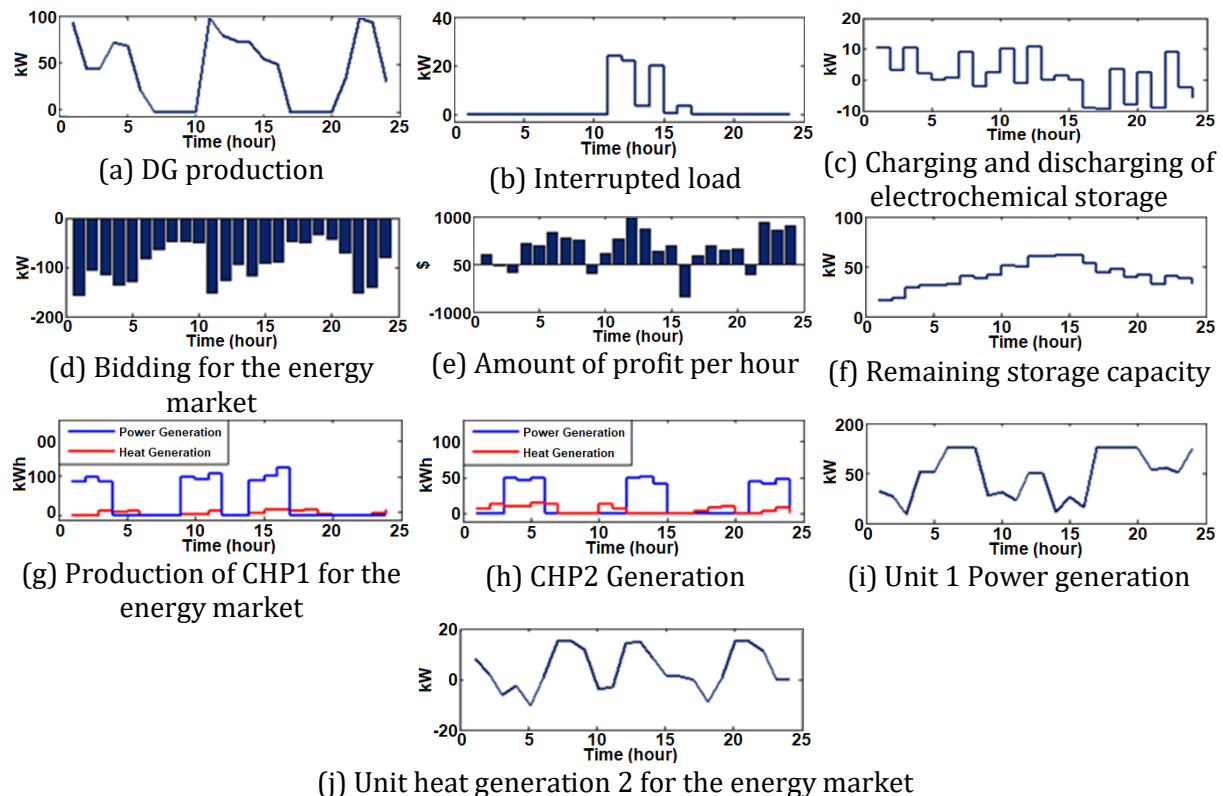


Figure 8. Simulation results of the new grid considering the energy market.

Figure 8(f) shows the amount of remaining battery capacity per hour. As mentioned earlier, the minimum battery life is 5 kWh.

2.6. Second to fifth scenarios (in the presence of energy price uncertainty)

Similar to the first network simulation (VPP1), in this section, the results are simulated for uncertainty in the energy price, and the normal logarithmic function is used for modeling. Table 6 provides the expected VPP profit (including CHP units) in the energy market under price uncertainty for scenarios 1-5.

The results are compiled for different scenarios and are ignored because of their similarity to the first network. In Figures 9(g) and (h), the amount of output is reduced relative to the base case. This is in line with the description of the preceding sections.

2.7. Sixth-ninth scenarios (in the presence of uncertainty in price and demand)

In this section, the results are simulated for uncertainty in demand, and the normal function is used to model. Given the uncertainty of demand along with price uncertainty, the dispersion rate increases, and the results change (predominantly, decrease). Table 7 tabulates the expected VPP profit (including CHP units) in the energy market under price uncertainty for scenarios 6-9.

Table 6. Expected VPP profit (including CHP units) in the energy market under price uncertainty.

Scenario number	1	2	3	4	5
Profit (\$)	7448.3	6957.7	947.48	613.69	987.834

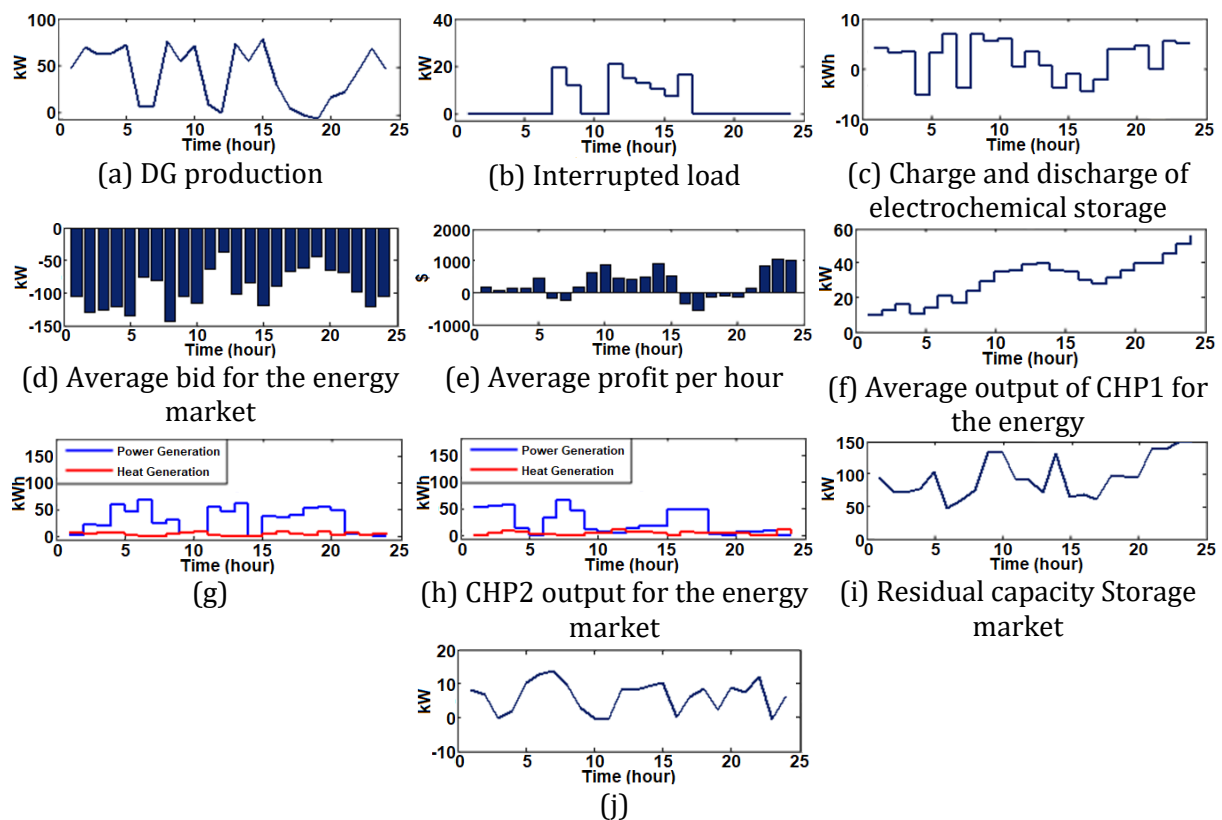


Figure 9. Simulation results of the new grid (in the presence of price uncertainty and $S = 0.02$) considering the energy market.

2.8. Second to fifth scenarios (in the presence of energy price uncertainty)

This section provides the results for scenarios 1 to 5, where the focus is on the Virtual Power Plant (VPP) profit in the reserve market under energy price uncertainty. Table 8 highlights the expected VPP profit (with CHP units) for each scenario, showing a range from \$419.77 in scenario 5 to \$24,565 in scenario 1.

2.9. Sixth-ninth scenarios (in the presence of uncertainty in price and demand)

In this section, the results are simulated for uncertainty in demand, and the normal function is used to model. Given the uncertainty of demand along with price uncertainty, the dispersion rate increases, and the results change (predominantly, decrease) as shown in Table 9. Simulation results of the new network (in the presence of price and demand uncertainty and $S = 0.02$) with respect to the reserve market are provided in Figure 10.

Table 7. VPP expected profit (including CHP units) in the energy market under uncertainty of demand.

Scenario number	6	7	8	9
Profit (\$)	6577.8	712.02	489.76	643.780

Table 8. Expected VPP profit (with CHP units) in the reserve market under price uncertainty.

Scenario number	1	2	3	4	5
Profit (\$)	24565	17680	8367.5	2230.3	419.77

Table 9. VPP expected profit (including CHP units) in the energy market under uncertainty of demand.

Scenario number	6	7	8	9
Profit (\$)	6577.8	712.02	489.76	643.780

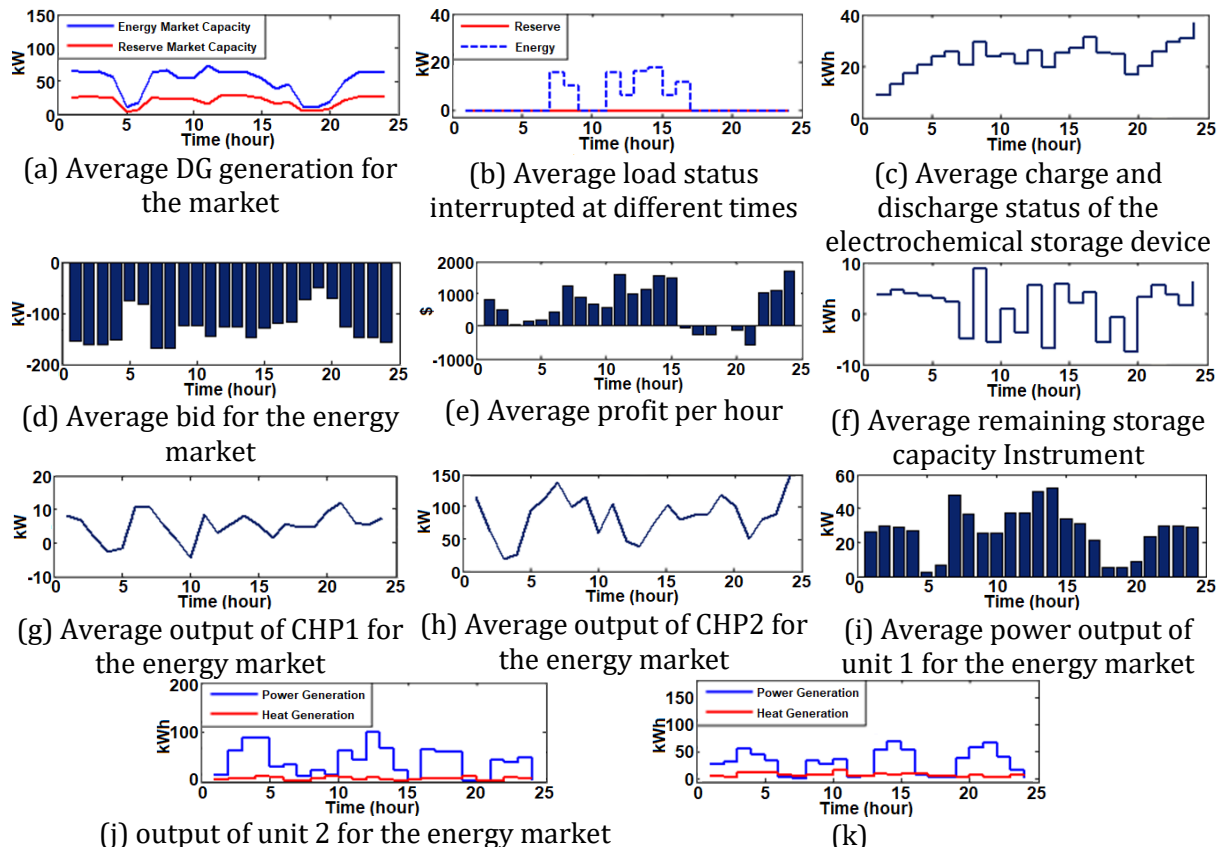


Figure 10. Simulation results of the new network with respect to the reserve market.

3. Simulation results of standard deviation to mean Monte Carlo stop

Standard deviation to average ratio (in the presence of price uncertainty and $s = 0.02$) given the reserve market is illustrated in [Figure 11](#).

[Figure 11\(a\)](#) provides the standard deviation to average profit ratio at hour 17 taking into account price uncertainty per standard deviation 0.02, while [Figure 11\(b\)](#) depicts the standard deviation to average energy purchase and sale by applying price uncertainty per standard deviation 0.02, 24-hour time.

4. Conclusions

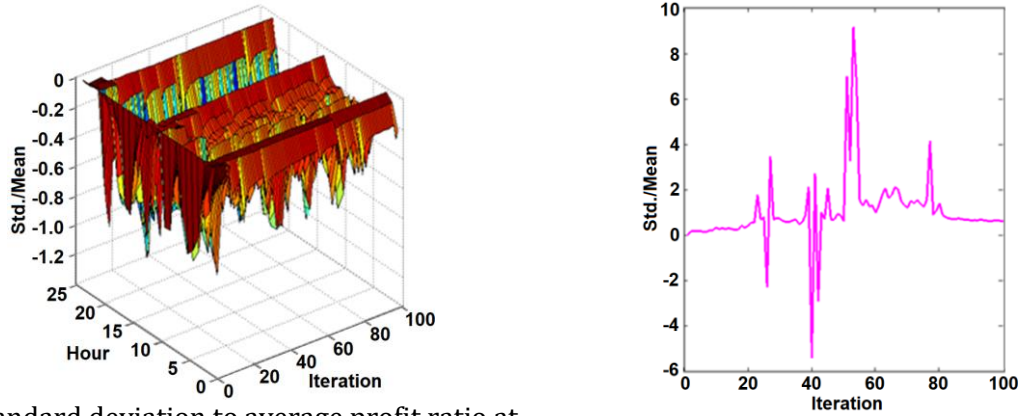
In this research, the introduction of two networks and the simulation and analysis of the results related to each of them were discussed. The reason for choosing CHP units as distributed generation units in this research is the energy production of these units with a cost close to the cost of traditional power plants.

Also, the uncertainty of price and demand was applied to affect different parameters of the problem along with different scenarios. To model these uncertainties, logarithmic and normal functions were used. Also, in this research, the binary coding method, sequential selection, and two-point combination were used. The coded variables include U_t with a string length of 1, P_{dg} , $P_{capacity}$, and P_{cut} with a string length of 8.

The size of the initial population is 200, the cut-off probability is 0.95 and the mutation probability is 0.05. The number of iterations in the Monte Carlo simulation is 100. From the results of the simulation, it can be pointed out the effect of different amounts of standard deviation on the production units in such a way that with increased standard deviation, the dispersion has increased and the nature of those products has undergone decreasing changes.

It can also be stated that the profit of the power plant increases due to different reasons such as the connection of the virtual power plant into the reservation market because of the high reservation price compared to other energy market rates and the addition of CHP units due to the increase in production opportunities. Also, the profit increase is 8.0864×10^3 compared to the base scenario.

Due to the addition of production units, the opportunity for production will increase and the power plant will earn more profit. From the study of different scenarios, it can be concluded that the use of the Monte Carlo method is a suitable tool to stop the simulation process because by increasing the number of iterations in this method, convergence is achieved and ideal results appear.



(a) Standard deviation to average profit ratio at hour 17 taking into account price uncertainty per standard deviation 0.02

(b) Standard deviation to average energy purchase and sale by applying price uncertainty per standard deviation 0.02, 24-hour time

Figure 11. Standard deviation to average ratio (in the presence of price uncertainty and $s = 0.02$) given the reserve market.

Nomenclature

i, j	Bus indices
t	Time index
S_b	Setting of VPP branches
S_{dg}	Setting of DGs
$S_{hour,i}$	Settings of the allowed clock (time) that may be interrupted if load interruption is necessary.
S_{int}	Setting of interrupted loads
S_{str}	Setting of electrochemical storage
S_n	Setting of the VPP curve (node)
E_t	VPP's bid for the energy market (positive and negative values indicate the amount of buying from the energy market and selling to the energy market, respectively)
$I_{i,t}$	Binary values showing the state of participation of a DG
$J_{i,t}$	Binary values indicating the DG startup
$K_{i,t}$	Binary values indicating the DG shutdown
$Load_{E,t}$	VPP-supplied load if the bid for spinning reserve and market for generation is not called.
$Load_{ER,t}$	VPP-supplied load if the bid for spinning reserve and market for generation is called.
$Loos_{E,t}$	VPP's power loss if the spinning reserve for generation is not called.
$LOSS_{ER,t}$	VPP's power loss if the spinning reserve for generation is called.
$P_{curt,i,t}$	Load not-supplied for trading in the electricity market
$P_{dg,i,t}$	DG generation for the electricity market
$P_{g,i,t}$	Total real power generation at the node (pathway)
$P_{i,t}$	Real power injection to node i
$P_{str,i,t}$	The charge/discharge amount of the electrochemical storage in kWh (negative and positive values indicate the discharge and charge states, respectively)
$Q_{g,i,t}$	Reactive power generated at node i
$Q_{i,t}$	Total reactive power injected to node i
$R_{curt,i,t}$	Load not-supplied to provide spinning reserve service
$R_{dg,i,t}$	DG generation for market spinning reserve
R_t	VPP bid for market spinning reserve
S_{ij}	Apparent power flow from node i to node j
$V_t(V_{1,t}, V_{2,t}, \dots, V_{N_n,t})$	Voltage amplitude vector
$V_{i,t}$	Voltage magnitude at node i

$\theta_t(\theta_{1,t}, \theta_{2,t}, \dots, \theta_{N_n,t})$	Voltage angle vector
$\theta_{i,t}$	Voltage angle at node i
AR_k	Establishment of a proper reserve by VPP
E_{exch}^{max}	Refers to the heating rate of transformer capacity connection or contractual capacity for power exchange between VPP and the upstream network
$LOAD_t$	The total expected load of VPP.
MSR_i	Ability to increase DG reservation kW/min
MUT_i, MDT_i	Limitation on the minimum time of operation and DG shutdown per hour
N_n	Number of VPP nodes.
$P_{curt,i}^{max}$	Upper limit for breaking on interruptible load
$P_{d,i,t}$	Real power demand at node i
$P_{dg,i}^{min}, P_{dg,i}^{max}$	Upper and lower limits on DG generation
$P_{str,i}^{max}$	The installed capacity of the electrochemical storage in kWh
$Q_{d,i,t}$	Reactive power demand at node i.
$R_{dgu,i}, R_{dgd,i}$	Limits of increasing and decreasing DG in kWh
$R_{str-ch,i}, R_{str-dch,i}$	Maximum rate of charge and discharge of electrochemical storage in kW
S_{ij}^{max}	Capacity of the line between node i and node j
$T_{i,t}^{on}, T_{i,t}^{off}$	The number of hours DG units were on/off in t hours
V_i^{max}, V_i^{min}	Maximum and minimum voltage magnitude at node i
$\rho_{E,t}$	Price at energy market
$\rho_{R,t}$	Price at spinning reserve market
$\rho_{L,t}$	Retail energy rate of the VPP
$C_{dg,i,t}(P_{dg,i,t})$	The cost function of DG generation
$C_{int,i,t}(P_{curt,i,t})$	The consumer's fixed cost curve for interrupting its load
$C_{str}(P_{srt,i,t})$	Operating cost of electrochemical storage
$SC_{dg,i,t}, SHC_{dg,i,t}$	DG startup and shutdown costs

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, redundancy, have been completely observed by the authors.

Credit Authorship Contribution Statement

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