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Stochastic operational scheduling of distributed energy resources in a large scale virtual power plant

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ABSTRACT

Virtual Power Plant (VPP) is introduced as a tool for the integration of distributed generations, energy storages and participation of consumers in demand response programs. In this paper, a probabilistic model using a modified scenario-based decision making method for optimal day ahead scheduling of electrical and thermal energy resources in a VPP is proposed. In the proposed model, energy and reserve is simultaneously scheduled and the presence of energy storage devices and demand response resources are also investigated. Moreover, the market prices, electrical demand and intermittent renewable power generation are considered as uncertain parameters in the model. A modified scenario-based decision making method is developed in order to model the uncertainties in VPP's scheduling problem. The results demonstrated that the optimal scheduling of VPP's resources by the proposed method leads VPP to make optimal decisions in the energy/reserve market and to play a dual role as a demand/generation unit from the perspective of the upstream network in some time periods.

Introduction

The virtual power plant concept is developed in order to improve handling and visibility of Distributed Energy Resources (DERs) for system operators and other market players by making an appropriate interface among these system components. Using this concept, DERs could be considered as a substitution for Conventional Power Plants (CPPs) in both forms of production energy and capacity. So via VPP concept:

- Each DER can increase its monetization opportunities by participating in energy market.
- Operational efficiency and other system benefits are improved utilizing whole available capacity.

Introducing smart grids technology, VPPs are also able to provide the possibility for small generation unit owners to participate in both energy and ancillary services markets. The aggregation of DERs aiming at providing reserve capacity is a suitable solution for compensating the unexpected power fluctuations of intermittent renewable generations.

Many literatures have already discussed about VPPs and their challenges and opportunities in optimal scheduling issues or bidding strategies in markets. In [1], a Decision Tree based methodology that prepares for the dispatching of power equivalent to the possible loss of the highest injection of one of the sources of the VPP (according to day-ahead hourly schedule) to the rest of its sources, on an hour-ahead horizon is proposed. An open framework providing robust solution for large scale DERs integration and control is applied in [2], where an approach for solving this problem is proposed by utilizing standards-based power system communications, application modeling based on event-driven information services and algorithms for optimized VPP control. In [3], using a novel stochastic programming approach, the participation of a VPP in the day-ahead market and the balancing (real-time) market has been considered. The uncertainties involved in the electricity price, generation of renewables, consumption of loads, and the losses allocation have been taken into account in [3]. In [4], VPP is defined as a DERs aggregator whose resources are connected to various points of a medium voltage distribution network. According to Fenix project [5], VPP is a flexible representation of a portfolio of DERs including various technologies and behavior patterns which in terms of availability could be connected to different points of distribution network. In [6–8], a special price-based unit commitment method has been suggested as an appropriate solution for bidding strategies of VPPs in energy market but without considering the presence of renewable energy

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Nomenclature

Sets

s set of scenario intervals
t set of hourly intervals
z set of zones

scenario-dependent parameters

$\rho_{SR,ts}$ spinning reserve market price at hour t and scenario s
$\rho_{EM,ts}$ energy market price at hour t and scenario s
$P_{el,zts}$ total electric load power at hour t, scenario s and zone z
$P_{pv,zts}$ output power of PV modules at hour t, scenario s and zone z
$P_{wt,zts}$ output power of wind turbine at hour t, scenario s and zone z

Input parameters

$\rho^{I}_{drp,t}$, $\rho^{II}_{drp,t}$, $\rho^{III}_{drp,t}$ cost of first, second and third level of demand response program at hour t, respectively
$\rho_{ens,t}$ cost of energy not-served at hour t
$\rho_{NG,t}$ natural gas price at hour t
$\rho_{ret_{vpp},t}$ retail energy rate of VPP at hour t
$\eta_{boil,z}$ efficiency of boiler in zone z
$\eta_{chp,z}$ electric efficiency of CHP in zone z
AT_t ambient temperature at hour t
$a^{e}_{st,z}(a^{t}_{st,z})$ positive coefficient of El. (th.) storage cost function in zone z
$b^{e}_{st,z}(b^{t}_{st,z})$ positive coefficient of El. (th.) storage cost function in zone z
$E^{e}_{st,final,z}(E^{t}_{st,final,z})$ final level of energy in el. (th.) storage in zone z, respectively
$E^{e}_{st,initial,z}(E^{t}_{st,initial,z})$ initial level of energy in el. (th.) storage in zone z, respectively
$E^{e}_{st,max,z}(E^{t}_{st,max,z})$ max level of energy in el. (th.) storage in zone z, respectively
$E^{e}_{st,min,z}(E^{t}_{st,min,z})$ min level of energy in el. (th.) storage in zone z, respectively
FF fill factor of PV module
HV_{NG} heating value of natural gas
I_{MPP} current at maximum power point of PV module
I_{sc} short circuit current of PV module
$k_{chp,z}$ heat-to-electricity ratio for CHP units in zone z
K_i current temperature coefficient of PV module
K_v voltage temperature coefficient of PV module
N_{OT} nominal operating temperature of solar cell
N^{pv}_{z} number of PV modules in zone z
$P_{boil\_max,z}$ rated power of boiler in zone z
$P^{e}_{chp\_min,z}$, $P^{e}_{chp\_max,z}$ min and max operational power of CHP in zone z, respectively
$P_{r,z}$ rated power of wind turbine in zone z
$P^{e}_{st,charge,z}$, $P^{t}_{st,charge,z}$ max rechargeable power of el. and th. storage in zone z, respectively
$P^{e}_{st,discharge,z}$ $P^{t}_{st,discharge,z}$ max discharge power of el. and th. storage in zone z, respectively
$P_{line\_max,z}$ max crossed power of upstream line of zone z
$P_{thl,zt}$ thermal load power at hour t and zone z
$PMAX^{I}_{drp,zts}$ $PMAX^{II}_{drp,zts}$ $PMAX^{III}_{drp,zts}$ max amount of curtailment power in first, second and third level of demand response program at hour t, scenario s and zone z, respectively
$PMAX_{ens,zts}$ max amount of involuntary curtailment power at hour t, scenario s and zone z
$SC_{chp,z}$, $SHC_{chp,z}$ startup and shutdown costs of CHP units in zone z, respectively
$T_{C_{ts}}$ solar cell temperature at hour t and scenario s
V_{MPP} voltage at maximum power point of PV module
v^{c}_{in}, v^{c}_{out}, v_{rated} cut in, cut-off and rated speeds of wind turbine, respectively
V_{oc} open circuit voltage of PV module

Binary variables

$b_{chp,zt}$, $I_{chp,zt}$, $J_{chp,zt}$ spinning, startup and shutdown states of CHP at hour t and zone z, respectively

Continuous variables

$EP_{SR,t}$ expected value of exchanged power between VPP and spinning reserve market at hour t
$EP^{N_z}_{line,t}$ expected value of exchanged power between VPP and energy market at hour t
$P_{boil,zt}$ output power of boiler at hour t and zone z
$P^{e}_{chp,zt}$ ($P^{t}_{chp,zt}$) el. (th.) output power of CHP at hour t and zone z, respectively
$P^{I}_{drp,zts}$, $P^{II}_{drp,zts}$, $P^{III}_{drp,zts}$ electric load curtailment in first, second and third level of demand response program at hour t, scenario s and zone z, respectively
$P_{ens,zts}$ the amount of energy not served at hour t, scenario s and zone z
$P_{line,zts}$ crossed power of upstream line of zone z at hour t and scenario s
$P_{sel,zts}$ served electric load power at hour t, scenario s and zone z
$P_{sh,zt}$ surplus heat power at hour t and zone z
$P^{e}_{st,zt}$, $P^{t}_{st,zt}$ amount of charged/discharged power of el. and th. storage at hour t and zone z, respectively
$P_{SR,ts}$ exchanged power between VPP and spinning reserve market at hour t and scenario s
$SoC^{e}_{st,zt}$, $SoC^{t}_{st,zt}$ state of charge in el. and th. storages at hour t and zone z, respectively

sources and demand response programs. A new algorithm has been proposed in [9] in order to optimize thermal and electrical scheduling of a large scale VPP containing cogeneration systems and energy storages. Despite of the accurate mathematic model in [9], no specific model for renewable energy sources and their corresponding uncertainties has been investigated. In [10], a modified particle swarm optimization approach has been presented aiming at minimizing the day-ahead costs of VPP. Although the electrical storages were modeled in [10], in the case study, these resources have been ignored and therefore, the impact of storages in VPPs has not been assessed. In [11], forecast errors of wind speed and solar irradiance are modeled by related probability distribution functions and then, by using the Latin hypercube sampling (LHS), the plausible scenarios of renewable generation for day-head energy and reserve scheduling have been generated. A two-stage stochastic objective function aiming at minimizing the expected operational cost has been also implemented in [11]. Authors in [12] focus on Industrial VPP (IVPP) and its management. An IVPP can be determined as a management unit comprising generations and loads in an industrial microgrid. Since the scheduling procedure for these units is very important for their participation in a short-term electric market, a stochastic formulation is proposed for power scheduling in VPPs especially in IVPPs in [12]. An optimization methodology is proposed in [13] based on a multi-objective approach to handle with day-ahead optimal resource scheduling of a VPP in a distribution network considering different reactive power management strategies. The proposed methodology determines an optimal resource scheduling considering two competing objective functions. One objective function is expressed as the minimization of the operation cost of all distributed energy resources managed by the VPP, and the other one as the minimization of the voltage magnitude differences in all buses of the distribution network. The main goal is helping the VPP's management of a distribution network with high penetration of several distributed energy resources, such as distributed generation units, electric vehicles, and capacitor banks. Despite of the comprehensive proposed model in [13], the presence of demand response programs and cogeneration systems has not been investigated. A new method to support VPP day-ahead resource scheduling in a smart grid context considering the intensive use of V2G and other distributed energy resources is proposed in [14]. The main objective is to minimize the operation costs considering all the available resources for each operation period. With full respect to the proposed method in [14] the uncertainties modeling of renewable energy sources in operation from VPPs has not been investigated. As a proper way for modeling and implementing the demand response programs, an innovative probabilistic methodology for evaluating the impact of residential DR choices considering uncertainties related to load demand, user preferences, environmental conditions, house thermal behavior and wholesale market trends has been proposed in [15]. Moreover, a survey of DR potentials and benefits in smartgrids is presented in [16].

To the best of our knowledge, no simultaneous energy and reserve scheduling method for a VPP considering demand response resources, energy storages and uncertainties parameters has been reported in the literature. Modeling of uncertainties in operational planning problems makes the scheduled result more realistic. The innovative contributions of the proposed method are highlighted as follows:

- Simultaneous energy and reserve scheduling of a VPP.
- Aggregate electricity prices, renewable power generation and load demand uncertainties.
- Present a stepwise mathematic model to implement the scenario-based decision making method.

The rest of the paper is organized as follows: Sections 'The VPP's description', 'Scenario-based decision making methodology' and 'Mathematical model' provide the model description and formulation that completely delineates the VPP's framework and the proposed day-ahead probabilistic mixed-integer linear programming model of VPP; the simulation results of a typical case study are presented and analyzed in section 'Case study', and the paper is concluded in section 'Conclusion'.

The VPP's description

In this paper, the VPP's concept is developed for aggregating some DERs to coordinately operate for participating in both energy and reserve markets that can be just achieved within the smart grid scheme. Regarding the complete implementation of smart grid technologies, the VPP's operator is able to contact mutually with the open electricity market, demand/generation units in its territory and external entities for determining its optimal bidding strategies in the energy/reserve market and optimal scheduling of its energy resources (Fig. 1). The market framework considered in this paper is the same suggested in [6].

The local network of VPP is a typical radial network that is fed by a substation transformer as shown in Fig. 2. As thermal loads are locally fed by thermal suppliers, the overall network is split to some zones. Each zone is composed of two main parts: electrical and thermal. The resources available in electrical part consist of PhotoVoltaic (PV), wind turbine, electrical link of CHP and electrical storage (electro-chemical battery) as well as demand response resources for feeding electrical load demand or energy injecting to the upstream line. On the other hand, resources available in thermal part consist of boiler, thermal link of CHP and thermal storage for feeding thermal load demand.

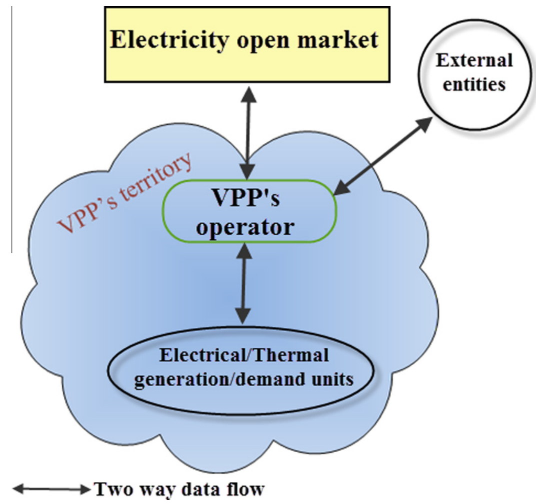

Fig. 1. The VPP's framework.

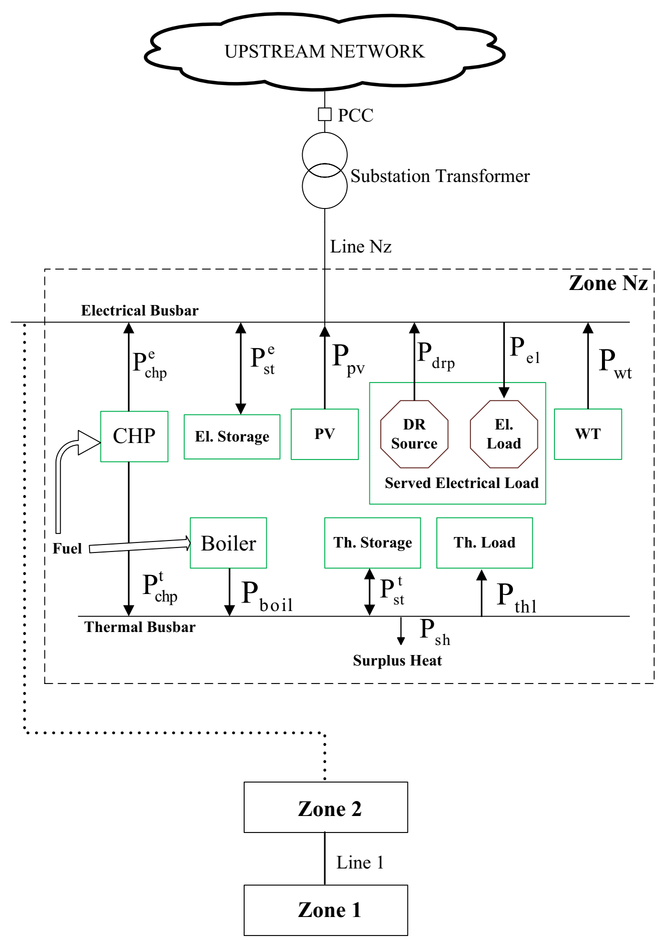

Fig. 2. Local network of VPP.

Scenario-based decision making methodology

Optimal operation of power systems have always been faced with some uncertainties. That is due to some uncertain input parameters that extremely effect on performance of power systems. So far, many efforts have been made to identify and model these uncertainties. According to the obtained results of these efforts, several useful approaches are introduced and developed to simulate existing uncertainties of power systems (e.g. probabilistic models, robust optimization, interval arithmetic, etc.). Among these methods, the probabilistic techniques are more appropriate for impact assessment of renewable generation, electricity prices and load demand variations. The main reason for this fact is that the output of renewable energy resources basically depends on the characteristics of their primary energy resources such as solar radiation, wind speed, and environmental temperature. The historic data of these parameters is usually available and they can be modeled using a probability density function (PDF) [17]. The main probabilistic models include Monte Carlo simulations, Point Estimate Method and scenario-based decision making. In [18], Different scenarios for uncertain PV and wind units and day-ahead energy prices are generated based on the Monte Carlo simulations for optimal daily operation of a VPP. Two probabilistic optimal operation management schemes of microgrid and Decision making of a VPP under uncertainties are proposed using Point Estimate Method (PEM) in [19–21], respectively.

Scenario-based decision making, as a subcategory of probabilistic models, is a suitable tool for modeling of power system uncertainties. As the uncertain parameters have infinite uncountable ranges, the entire defined space of each uncertain parameter is divided into countable finite sections (scenarios) with a specific weight (probability). Via employing this method, a list of scenarios is generated using the PDF of each uncertain parameter. It could just be implemented by applying following steps:

Step 1. Computing the hourly average and standard deviation values of historical data for each uncertain parameter to form its PDF. The type of PDF of each uncertain parameter, in a special site, usually specifies by comparing the actual observed values of the uncertain parameter with the estimated one by its PDF. To this end, the Weibull and beta PDFs are respectively selected for wind speed and solar radiation uncertain parameters [22]. The normal PDF is considered for uncertain parameters of energy/spinning reserve market price and electric load demand [23,24].

The weibull PDF ($\mathrm{PDF}(\upsilon)$) for wind speed is given as follows:

$$\mathrm{PDF}(\upsilon) = \frac{k}{c}\left(\frac{\upsilon}{c}\right)^{k-1} \exp\left(-\left(\frac{\upsilon}{c}\right)^{k}\right)\Bigg| k = \left(\frac{\sigma}{\mu}\right)^{-1.086} \text{ and } c = \frac{\mu}{\Gamma(1+\frac{1}{k})} \tag{1}$$

where k is called the shape index, and c is called the scale index. With knowing the average and standard deviation of wind speed for each time segment, k and c can be attained by the relations shown in (1) [25]. The beta PDF ($\mathrm{PDF}(sor)$) utilized for solar radiation modeling is shown in (2).

$$\mathrm{PDF}(sor) = \begin{cases} \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} * sor^{\alpha-1}(1-sor)^{(\beta-1)}, & \\ \quad \text{for } 0 \leqslant sor \leqslant 1, \alpha \geqslant 0, \beta \geqslant 0 & \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

That in which:

$$\beta = (1-\mu) * \left(\frac{\mu * (1+\mu)}{\sigma^2} - 1\right) \quad \text{and} \quad \alpha = \frac{\mu * \beta}{1-\mu}$$

where (α, β) are beta parameters. The normal PDF ($\mathrm{PDF}(x)$) shown in (3) is selected for modeling of energy/spinning reserve market price and electric load power uncertain parameters.

$$\mathrm{PDF}(x) = \frac{1}{\sigma\sqrt{2\pi}} exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right) \quad \text{for } x = \{\rho_{EM} \text{ or } \rho_{SR}, P_{el}\} \tag{3}$$

where constant coefficients μ and σ are equal to average and standard deviation of corresponding uncertain parameters, respectively.

Step 2. Determining the start and end points of each scenario for each uncertain parameter based on its average values and operating parameters of renewable units to calculate the probability of each scenario. The occurrence probability of each scenario is determined by (4). Assuming occurrence independency of stochastic parameters, the probability of each scenario (π_s) is determined by multiplying the occurrence probabilities of related uncertain parameters. The uncertain parameter x can adopt each ones of considered uncertain parameters in this paper such as solar radiation (sor), wind speed (υ), market price (ρ_{EM} & ρ_{SR}) and load demand (P_{el}).

$$\begin{aligned} &\rho_{x,s} = \int_{x_{start,s}}^{x_{end,s}} PDF(x)dx \\ &\pi_s = \prod_x \rho_{x,s} \end{aligned} \qquad \text{for } s = 1:N_s \tag{4}$$

where $x_{start,s}$, $x_{end,s}$ and $\rho_{x,s}$ are, respectively, the start point, end point and occurrence probability of scenarios for uncertain parameter x and $\mathrm{PDF}(x)$ is the probability density function of x at each time segment.

For accurate modeling, a set of scenarios is defined for each uncertain parameter that is named S_x. in fact, S_x is a set of the intervals (scenarios) that in which each interval contains the range of each scenario for each uncertain parameter x; the number of intervals (N_x) in S_x shows the number of scenarios considered for uncertain parameter x; the combined scenarios set, named CS (Combined Set), is made by Cartesian product of S_x sets. The number of intervals (N_s) in CS shows the number of scenarios considered in this paper. s and n_x are, respectively, the counter of scenarios (intervals) in set CS and set S_x. to clarify this issue, suppose that $n_x = 1$ and $s = 1$, the first one refers to the interval $[x_{start,1}, x_{end,1}]$ and the second one refers to set of all first intervals of uncertain parameters ($[x_{start,1}, x_{end,1}]$ for all considered uncertain parameters). Note that after formation of set CS, the subscript n_x expands to s for each interval. After this, "scenario" refers to set CS and all relationships in the mathematical model point to this set with scenario's counter s. The related mathematic expression is shown in (5).

$$\begin{aligned} &\{CS\} = \prod_x \{S_x\} \Bigg| S_x = \{[x_{start,1}, x_{end,1}], \ldots, [x_{start,n_x}, x_{end,n_x}], \ldots, [x_{start,N_x}, x_{end,N_x}]\} \\ &CS = \left\{\{[x_{start,1}, x_{end,1}]\}_{for\ all\ x}, \ldots, \{[x_{start,s}, x_{end,s}]\}_{for\ all\ x}, \ldots, \{[x_{start,N_s}, x_{end,N_s}]\}_{for\ all\ x}\right\} \\ &N_s = \prod_x N_x \end{aligned} \tag{5}$$

Step 3. Calculating the amount of each uncertain parameter at each hour according to hourly behavior of average values curve that would be obtained by the proposed relation as shown below:

$$x_{ts} = x_{start,s} + \left(\frac{x_{ave,t} - x_{min\_ave}}{x_{max\_ave} - x_{min\_ave}}\right) * range_{x,s} \quad \text{for } s = 1:N_s, \; t = 1:24 \tag{6}$$

where x_{ts} is the value of uncertain parameter x at hour t and scenario s; $x_{ave,t}$, x_{max_ave} and x_{min_ave} are, respectively, the hourly, maximum and minimum average values of x extracted from average values curve of x; $range_{x,s}$ is the created interval length of x at scenario s that can be set manually or by applying any other approaches.

It should be mentioned that excluding electric load demand, the other uncertain parameters are assumed to be independent from zones. The below equations are employed to model the value of electric load demand for each zone:

$$P_{tel\_ave,t} = \sum_{z=1}^{N_z} P_{el\_ave,zt} \quad \text{for } t = 1:24 \tag{7}$$

$$k_{el,zt} = \frac{P_{el\_ave,zt}}{P_{tel\_ave,t}} \quad \text{for } z = 1:N_z, t = 1:24 \tag{8}$$

where $P_{el\_ave,zt}$ and $k_{el,zt}$ are, respectively, the average value and the participation factor of electric load demand in zone z and time segment t and $P_{tel\_ave,t}$ is the VPP's average electric load demand at time segment t. After determination of $k_{el,zt}$, the Eqs. (4) and (6) are executed by replacement of x with P_{tel} (total VPP's electric load demand). Now, the occurrence probability ($\rho_{x,s}$) and scenarios arrangement (x_{ts}) of total VPP's electric load demand are formed at each time segment. The last step is making the arrangement of electric demand at each zone, time segment and scenario that is provided by (9):

$$P_{el,zts} = k_{el,zt} * P_{tel,ts} \quad \text{for } s = 1:N_s, t = 1:24 \quad \text{and} \quad z = 1:N_z \tag{9}$$

By applying the aforementioned procedure, all infinite uncountable uncertain parameters are split to finite countable scenarios with a specific probability.

Mathematical model

Objective function

The objective function of the proposed energy and reserve scheduling method is the expected day-ahead profit of VPP as given in (10). It should be noted that this objective function includes two main stages. The upper and lower stages are, respectively, scenario-dependent and scenario-independent expressions. Because of considering the startup and shutdown states of CHP units and state of charge in storages, the output power of CHP units and the charged or discharged power of storages at each hour depend on the corresponding values at previous period. Hence, due to the occurrence of different scenarios at different periods, these decision variables and the thermal part of the presented method are considered to be scenario-independent. Accordingly, the exchanged power between VPP and energy or spinning reserve markets in addition to electrical load demand among all other decision variables (at each period and each zone) are just intended to be scenario-dependent.

Each stage of the objective function is composed of three main parts that is described as follows:

- The exchanged cash flow between VPP and the electricity market shown in the first line of the objective function. As line N_z is connected to Point of Common Coupling (PCC) of VPP with upstream network, the crossed power through this line ($P^{N_z}_{line,ts}$) is the same offered to the energy market; positive and negative values of $P^{N_z}_{line,ts}$ indicate selling power to and purchasing power from energy market, respectively. It is assumed that the spinning reserve hourly price is directly related to electricity price by coefficient λ.
- The costs corresponding to running the three-level demand response programs and the considered penalty for not served electrical loads shown in second and third lines of the objective function. Each unit of not served electrical load is penalized by a high value that is known as VOLL (Value of Lost Load). The VOLL is an important measure in electricity markets. It represents customer's willingness to pay for electricity service (or avoid curtailment). In electricity markets, VOLL is usually measured in dollars per MWh. VOLL depends on multiple factors such as the type of customer affected, regional economic conditions and demographics, time and duration of outage, and other specific traits of an outage [26].
- The obtained revenue from end-consumers according to the hourly retail rates of VPP shown in 4th line of the objective function.
- The cost of fuel that is injected to boilers and CHP units shown in 5th line of the objective function. There are some mechanisms for estimating the fuel cost of CHP units. Based on an Italian pricing framework, a gas volume (m^3) numerically correspondent to one fourth of produced electricity (kW h) is out of fiscal ruling, i.e., conventionally associated to electricity production; the remaining part is considered for heat generation purposes by assigning two rates to fuel dependent on the type of application (e.g. heat or electricity generation purposes) [9]. In this paper, the consumption fuel cost of CHP units ignoring the application type has been considered. Otherwise, some other mechanisms could be embedded in the model. Both CHPs and boiler are gas-fired. According to (10), 860 is kW h-to-kcal ratio and by using this coefficient and heating value of natural gas (HV_{NG}), the unit of $\rho_{NG,t}$ converts from dollars per cubic meter to dollars per kW h.
- The startup and shutdown costs of CHP units shown in 6th line of the objective function.
- The operational cost of electrical and thermal storages is generally concerned with maintenance costs, it is assumed to be a linear function of the absolute of its charged or discharged capacity at each hour [7], as shown in the last line of the objective function.

$$\text{profit} = \max \sum_{t=1}^{24}\sum_{s=1}^{N_s} \pi_s * \left\{ \begin{array}{l} \rho_{EM,ts} * P^{N_z}_{line,ts} + \rho_{SR,ts} * P_{SR,ts} \\ + \sum_{z=1}^{N_z} \left\{ \begin{array}{l} -(\rho^{I}_{drp,t} * P^{I}_{drp,zts} + \rho^{II}_{drp,t} * P^{II}_{drp,zts} \\ +\rho^{III}_{drp,t} * P^{III}_{drp,zts} + \rho_{ens,t} * P_{ens,zts}) \\ +p_{sel,zts} * \rho_{ret_{vpp},t} \end{array} \right\} \end{array} \right\}$$
$$+ \sum_{t=1}^{24}\sum_{z=1}^{N_z} \left\{ \begin{array}{l} \frac{-860*\rho_{NG,t}}{HV_{NG}} * \left(\frac{P^{e}_{chp,zt}}{\eta_{chp,z}} + \frac{P_{boil,zt}}{\eta_{boil,z}}\right) \\ -(SC_{chp,z} * I_{chp,zt} + SHC_{chp,z} * J_{chp,zt}) \\ -(a^{e}_{st,z}|P^{e}_{st,zt}| + b^{e}_{st,z} + a^{t}_{st,z}|P^{t}_{st,zt}| + b^{t}_{st,z}) \end{array} \right\} \tag{10}$$

where $\rho_{SR,ts} = \lambda * \rho_{EM,ts}$.

Cogeneration systems (CHP)

The thermal output power of cogeneration systems is related with the electric one by multiplying the heat-to-electric power ratio (k) [27]. The output power of CHP units could be zero or between the technical minimum and maximum rates. The set of constraints shown in (12)–(14) ensure that the inter-relationships of the three binary decision variables of CHP units, $b_{chp,zt}$, I_{zt}, and J_{zt}, are in sequential logical order and there are no conflicting situations.

$$\begin{array}{l} P^{t}_{chp,zt} = k_{chp,z} * P^{e}_{chp,zt} \\ b_{chp,zt} * P^{e}_{chp\_min,z} \leqslant P^{e}_{chp,zt} \leqslant b_{chp,zt} * P^{e}_{chp\_max,z} \end{array} \quad \text{for } z = 1:N_z, t = 1:24 \tag{11}$$

$$b_{chp,zt} - b_{chp,z(t-1)} \leqslant I_{chp,zt} \quad \text{for } z = 1:N_z, t = 1:24 \tag{12}$$

$$b_{chp,z(t-1)} - b_{chp,zt} \leqslant J_{chp,zt} \quad \text{for } z = 1:N_z, t = 1:24 \tag{13}$$

$$b_{chp,zt} - b_{chp,z(t-1)} = I_{chp,zt} - J_{chp,zt} \quad \text{for } z = 1:N_z, t = 1:24 \tag{14}$$

Boiler

A boiler could be applied if the CHP unit and thermal storage are not able to cover thermal load, entirely, or when using them is not economical. The output power of each boiler is bounded by its operational constraint.

$$0 \leqslant P_{boil,zt} \leqslant P_{boil\_max,z} \quad \text{for } z = 1:N_z, t = 1:24 \tag{15}$$

Storages

Energy storage devices can usually be modeled by their minimum and maximum allowable level of energy. The minimum allowable level of energy is detected by the Depth of Discharge (DoD) of storages that has a significant effect on their life cycle. To this end, the State of Charge (SoC) of each storage device must be bounded to the mentioned ranges as shown in (16)–(19) for electrical storages and (20)–(23) for thermal storages. $P^e_{st,zt}$ is assumed to be positive and negative if storage is in discharging and charging modes,respectively. It should be mentioned that $P^e_{st,zt}$ is assumed to remain constant during each time segment (one hour in here); so, power and energy values of storages could be combined for each time segment (as shown in (16) and (20)).

$$\mathrm{SoC}^e_{st,zt} = \mathrm{SoC}^e_{st,z(t-1)} - P^e_{st,zt} \quad \text{for } z = 1:N_z, t = 1:24 \tag{16}$$

$$\mathrm{SoC}^e_{st,zt} = E^e_{st,initial,z} \quad \text{for } z = 1:N_z, t = 0 \tag{17}$$

$$\mathrm{SoC}^e_{st,zt} = E^e_{st,final,z} \quad \text{for } z = 1:N_z, t = 24 \tag{18}$$

$$E^e_{st,min,z} \leqslant \mathrm{SoC}^e_{st,zt} \leqslant E^e_{st,max,z} \quad \text{for } z = 1:N_z,\ t = 1:24 \tag{19}$$

$$\mathrm{SoC}^t_{st,zt} = \mathrm{SoC}^t_{st,z(t-1)} - P^t_{st,zt} \quad \text{for } z = 1:N_z,\ t = 1:24 \tag{20}$$

$$\mathrm{SoC}^t_{st,zt} = E^t_{st,initial,z} \quad \text{for } z = 1:N_z, t = 0 \tag{21}$$

$$\mathrm{SoC}^t_{st,zt} = E^t_{st,final,z} \quad \text{for } z = 1:N_z, t = 24 \tag{22}$$

$$E^t_{st,min,z} \leqslant \mathrm{SoC}^t_{st,zt} \leqslant E^t_{st,max,z} \quad \text{for } z = 1:N_z, t = 1:24 \tag{23}$$

Another important characteristic of storages is the rate of charge and discharge at each time segment. The input power to or output power from storage must be between the maximum charge and discharge power at each hour given as follows:

$$-P^e_{st,charge,z} \leqslant P^e_{st,zt} \leqslant P^e_{st,discharge,z} \quad \text{for } z = 1:N_z, t = 1:24 \tag{24}$$

$$-P^t_{st,charge,z} \leqslant P^t_{st,zt} \leqslant P^t_{st,discharge,z} \quad \text{for } z = 1:N_z, t = 1:24 \tag{25}$$

Electrical load curtailment

To implement demand response programs in the proposed method, an incentive-based three-level demand response program is modeled. The demand response resources are divided to three capacity programs, first, second and third level. A specified capacity with corresponding incentive payment is considered for each level of demand response program. The allowable electric load curtailment at each level of demand response program is modeled by (26)–(28).

If it is not possible to meet the entire electricity demand, due to network constraints or inadequacy of the local production, a load curtailment, that is known as Energy Not Served (ENS), is scheduled, considering a share of the electric demand, up to a maximum value, $PMAX_{ens,zts}$, as given by (29):

$$0 \leqslant P^{I}_{drp,zts} \leqslant PMAX^{I}_{drp,zts} \quad \text{for } z = 1:N_z, t = 1:24, s = 1:N_s \tag{26}$$

$$0 \leqslant P^{II}_{drp,zts} \leqslant PMAX^{II}_{drp,zts} \quad \text{for } z = 1:N_z, t = 1:24, s = 1:N_s \tag{27}$$

$$0 \leqslant P^{III}_{drp,zts} \leqslant PMAX^{III}_{drp,zts} \quad \text{for } z = 1:N_z, t = 1:24, s = 1:N_s \tag{28}$$

$$0 \leqslant P_{ens,zts} \leqslant PMAX_{ens,zts} \quad \text{for } z = 1:N_z, t = 1:24, s = 1:N_s \tag{29}$$

The output power of PV modules

The Eqs. (30)–(34) are used to calculate the output power of the PV module. This parameter is dependent on the solar irradiance and ambient temperature of the site as well as the characteristics of the module itself that is well addressed in [22].

$$T_{C_{ts}} = AT_t + sor_{ts} * \left(\frac{N_{OT} - 20}{0.8}\right) \quad \text{for } s = 1:N_s, t = 1:24 \tag{30}$$

$$I_{ts} = sor_{ts} * [I_{sc} + K_i * (T_{C_{ts}} - 25)] \quad \text{for } s = 1:N_s, t = 1:24 \tag{31}$$

$$V_{ts} = V_{oc} - K_v * T_{C_{ts}} \quad \text{for } s = 1:N_s, t = 1:24 \tag{32}$$

$$P_{pv,zts}(sor_{ts}) = N^{pv}_z * FF * V_{ts} * I_{ts} \quad \text{for } s = 1:N_s, t = 1:24 \text{ and } z = 1:N_z \tag{33}$$

$$FF = \frac{V_{MPP} * I_{MPP}}{V_{oc} * I_{sc}} \tag{34}$$

The output power of wind turbines

There are some known approaches to determine the output power of wind turbines according to wind speed of the site. In this paper, a linear relation for modeling the performance of wind turbines has been used [22,28].

$$P_{wt,zts}(v_{ts}) = \begin{cases} 0 & v_{ts} \leqslant v^c_{in} \text{ or } v_{ts} \geqslant v^c_{out} \\ \frac{v_{ts} - v^c_{in}}{v_{rated} - v^c_{in}} P_{r,z} & v^c_{in} \leqslant v_{ts} \leqslant v_{rated} \\ P_{r,z} & v_{rated} \leqslant v_{ts} \leqslant v^c_{out} \end{cases} \quad \text{for } s = 1:N_s, t = 1:24 \text{ and } z = 1:N_z \tag{35}$$

The exchanged power with spinning reserve market

The reserve concept is commonly defined as a power balancing source to improve the reliability margin of power system. In the proposed model, the reserve requirement of VPP is just provided by the reserve market. As given in (36), the difference between the expected value of exchanged power and the values of exchanged power in scenarios is defined as reserve requirement in each period. The maximum difference is considered in order to cover the reserve requirement in all scenarios. The negative sign in (36) is considered to properly model the purchasing and selling modes from reserve market.

$$EP_{SR,t} = -max_s\{EP^{N_z}_{line,t} - P^{N_z}_{line,ts}\} \quad \text{for } t = 1:24 \tag{36}$$

It is assumed that the substation transformer capacity is restricted by the thermal limit of line N_z (P_{line_max,N_z}). The value of the exchanged power with spinning reserve market in each scenario should meet the constraints expressed in (37) and (38).

$$P_{SR,ts} \leqslant P_{line\_max,N_z} - P^{N_z}_{line,ts} \quad \text{for } t = 1:24, s = 1:N_s \tag{37}$$

$$-P_{line\_max,N_z} - P^{N_z}_{line,ts} \leqslant P_{SR,ts} \quad \text{for } t = 1:24, s = 1:N_s \tag{38}$$

Thermal limit of power lines

The power flow through each line should be bounded by thermal limit of the line. Because of radial topology of the network, this constraint is the only one that is considered to involve grid constraints. It is assumed that system power factor is set to unit and therefore the reactive power flow relationships are ignored in this paper.

$$|P_{line,zts}| \leqslant P_{line\_max,z} \quad \text{for } z = 1:N_z, t = 1:24,\ s = 1:N_s \tag{39}$$

Power balance

As the presented model is composed from two sections, the electrical and thermal parts, two power balance equations must be included for each zone as expressed by (40)–(43). In (40), $P_{sel,zts}$ is the served electrical load demand used in objective function and is interpreted in (41). $P_{eq,zts}$, is an auxiliary variable that reflects the equivalent electric output power of each zone.

$$P_{eq,zts} = P^{e}_{chp,zt} + P_{pv,zts} + P^{e}_{st,zt} - P_{sel,zts} + P_{wt,zts}$$
$$\text{for } z = 1:N_z, t = 1:24 \text{ and } s = 1:N_s \tag{40}$$

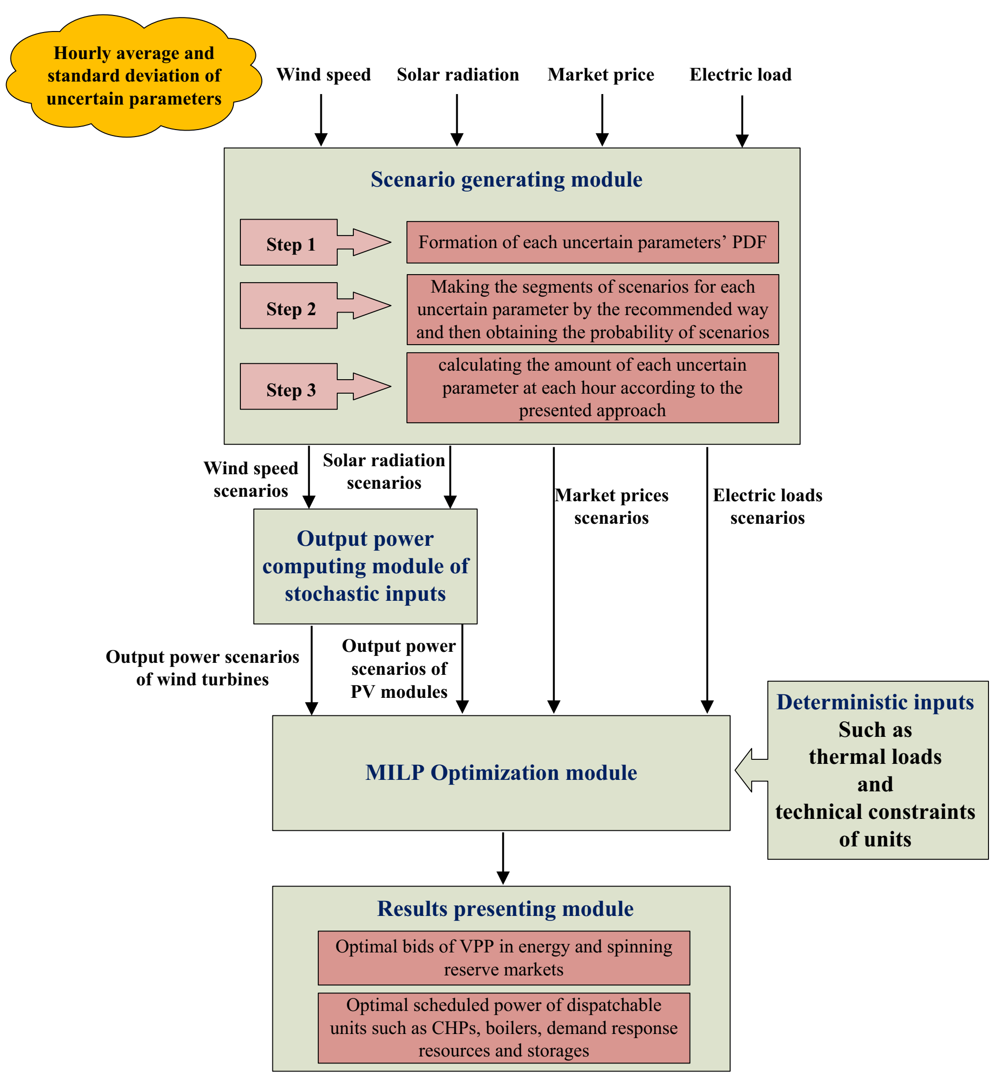

Fig. 3. The complete procedure of the proposed Probabilistic Mixed-Integer Linear Programming (PMILP) model.

$$P_{sel,zts} = P_{el,zts} - (P^{I}_{drp,zts} + P^{II}_{drp,zts} + P^{III}_{drp,zts} + P_{ens,zts})$$
$$\text{for } z = 1 : N_z, t = 1 : 24 \text{ and } s = 1 : N_s \tag{41}$$

$$P_{line,zts} = P_{eq,zts} + \sum_{i=1}^{z-1} P_{eq,its} \quad \text{for } z = 1 : N_z, t = 1 : 24, s = 1 : N_s \tag{42}$$

$$P_{thl,zt} = k_{chp,z} * P^{e}_{chp,zt} + P_{boil,zt} + P^{t}_{st,zt} - P_{sh,zt}$$
$$\text{for } z = 1 : N_z, t = 1 : 24 \text{ and } s = 1 : N_s \tag{43}$$

The complete procedure of the proposed day-ahead Probabilistic Mixed-Integer Linear Programming (PMILP) model of VPP is shown in Fig. 3. The proposed model is solved using Mixed Integer Linear Programming (MILP) solver XPRESS under GAMS software.

Case study

The proposed method is tested on a typical radial network shown in Fig. 2 that is fed by a substation transformer. As the renewable energy plants are fed by free sources (solar and wind) and in support of clean energies, no charge is considered for these resources [29,30]. Otherwise, any other tariffs can be embedded in the presented model.

The considered VOLL in this paper, that is called as the cost of energy not served in here ($\rho_{ens,t}$), is supposed equal to 4000 ($/MW h) for all hours [26].

Table 1
Input data for units.

Parameter	Zone 1	Zone 2	Zone 3	Zone 4
Input data for CHPs, boilers, storages and thermal limits of power lines				
$P^{e}_{chp\_max,z}$ (kW)	50	80	100	90
$P^{e}_{chp\_min,z}$ (kW)	5	10	20	55
$k_{chp,z}$	1.5	0.7	1.1	0.9
$\eta_{chp,z}$	0.3	0.25	0.25	0.33
$SC_{chp,z}$ ($)	0.24	0.22	0.29	0.22
$SHC_{chp,z}$ ($)	0.104	0.094	0.125	0.94
$\eta_{boil,z}$	0.85	0.95	0.9	0.85
$a^{e}_{st,z}$ ($/kW h)	0.0008	0.0008	0.001	0.0008
$a^{t}_{st,z}$ ($/kW h)	0.001	0.0008	0.001	0.001
$b^{e}_{st,z}$ ($/h)	0.015	0.015	0.02	0.015
$b^{t}_{st,z}$ ($/h)	0.015	0.015	0.02	0.015
$E^{e}_{st,initial,z}$ (kW h)	18	60	0	20
$E^{t}_{st,initial,z}$ (kW h)	20	50	10	40
$E^{e}_{st,final,z}$ (kW h)	18	60	0	20
$E^{t}_{st,final,z}$ (kW h)	20	50	10	40
$E^{e}_{st,max,z}$ (kW h)	30	60	10	20
$E^{t}_{st,max,z}$ (kW h)	50	70	20	40
$E^{e}_{st,min,z}$ (kW h)	10	20	0	0
$E^{t}_{st,min,z}$ (kW h)	10	10	5	0
$P^{e}_{st,charge,z}$ (kW)	7	5	1	10
$P^{t}_{st,charge,z}$ (kW)	7	5	1	10
$P^{e}_{st,discharge,z}$ (kW)	5	10	5	5
$P^{t}_{st,discharge,z}$ (kW)	5	10	5	5
$P_{line\_max,z}$ (kW)	200	250	275	300

N_{OT} (°C)	I_{MPP} (A)	V_{MPP} (V)	N^{pv}_{z}	K_i (A/°C)	K_v (V/°C)	I_{sc} (A)	V_{oc} (V)
Input data for PV modules (per zone)							
43	4.76	17.32	320	0.00122	0.0144	5.32	21.98

v_{rated} (m/s)	v^{c}_{out} (m/s)	v^{c}_{in} (m/s)	$P_{r,z}$ (kW)
Input data for wind turbine (per zone)			
6.704	20.11	2.235	18

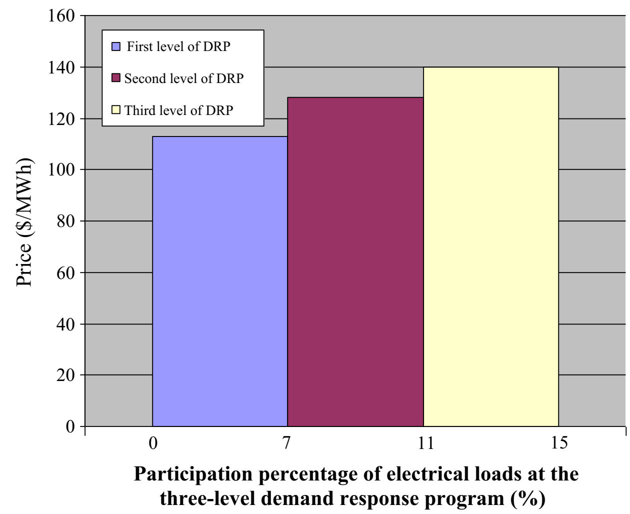

Fig. 4. The values pertaining to prices and allowable curtailed load of the three-level demand response program.

The required technical input data for the generating units are provided in Table 1. The operational parameters of PV modules, wind turbines and CHP units are taken from [22,31,9], respectively. Electrical and thermal storages data are adapted by combining available data in [9,7]. For gas-fired resources (boilers and CHPs), According to (10), $\rho_{NG,t}$ is selected equal to 0.2623 dollars per cubic meter, based on the same that is reported in Ontario Energy Board (OEB) for winter 2014 [32]. Besides, the heating value of natural gas (HV_{NG}) equals 10,852 kcal/m^3 [33]. The values pertaining to prices and allowable curtailed load of the three-level demand response program are shown in Fig. 4, as well.

The data used for wind speed and solar radiation are gathered from data archives of waterloo university for one month (November 2014) to provide average and standard deviation of these two parameters at each hour [34]. The applied average data for uncertainty modeling of energy market price are derived from OEB, equal to 90% of the TOU prices announced for residential applications [35]. The hourly average values and generated scenarios are shown in Fig. 5.

The proposed method has been evaluated in three different cases as follows:

Case 1. Deterministic state

In this case, the determined values are taken into account as input data. The hourly profit of VPP is shown in Fig. 6. As can be seen in this figure, the VPP's profit is low in the beginning and end times of the entire time axis where the level of solar energy is zero and the wind power is in the lowest level. However, at hours 8:00–12:00 and 16:00–19:00, because of increasing the renewable power generation and selling more power to the energy market, the VPP's profit is in the highest levels. Moreover, the VPP's profit is in lower levels in periods 12:00–16:00 comparing to the other middle hours why that the energy market price and VPP's retail rate are reducing in these periods. Fig. 7 shows the thermal output power of CHP systems and thermal load demand to make a possible for assessing the thermal part of the proposed model. According to the results, CHPs in zones 1 and 4 are fully committed at all hours because the efficiencies of CHPs are at a high level. However, CHP in zone 1 can't meet the entire thermal demand (also in zone 2). Because of economic benefits in electrical part, the thermal output power of CHP exceeds from thermal demand

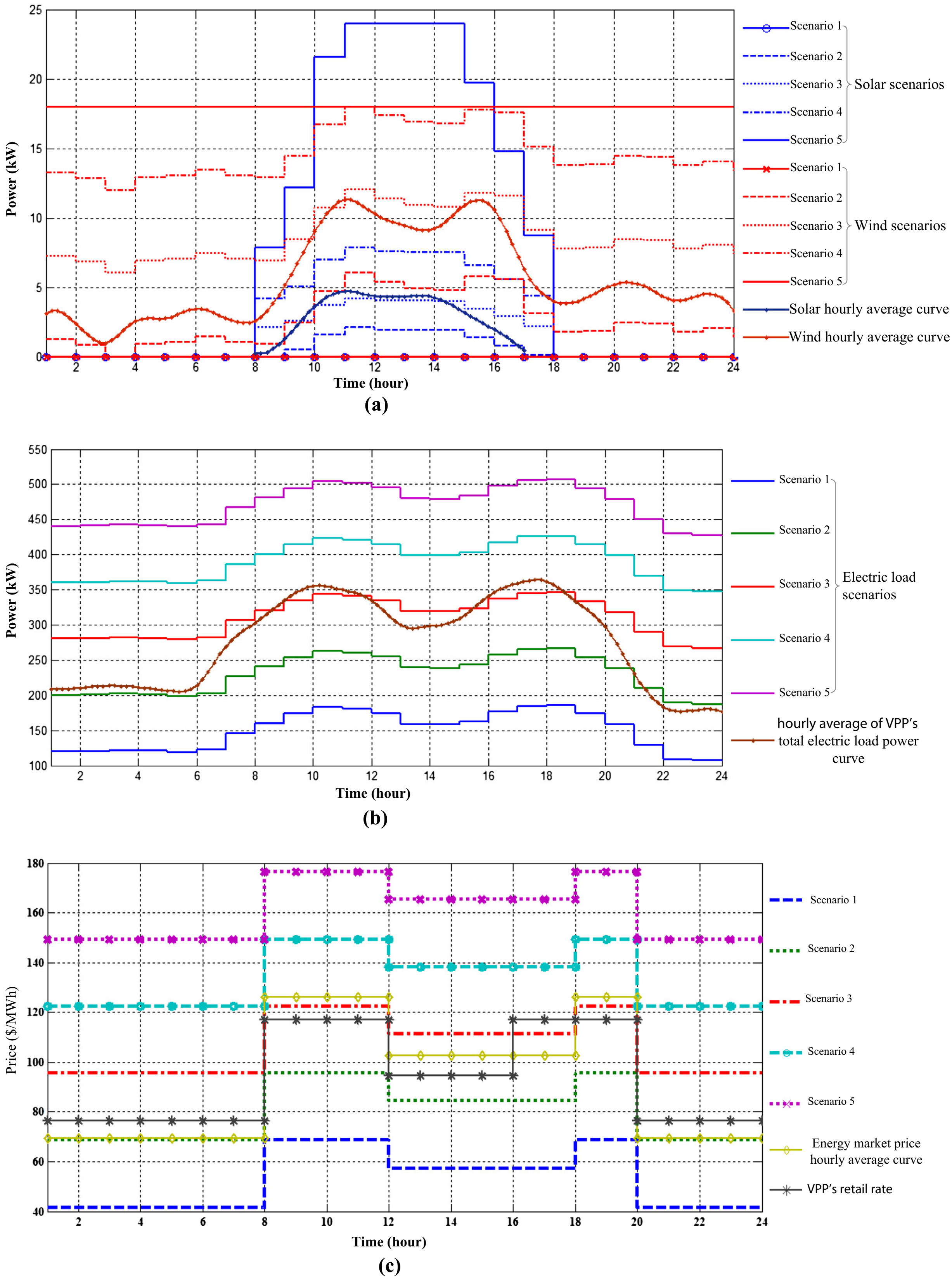

Fig. 5. Hourly average amounts and generated scenarios for (a) output power of PVs and wind turbines, (b) electrical load power and (c) energy market price in addition to contracted prices between VPP and end-consumers.

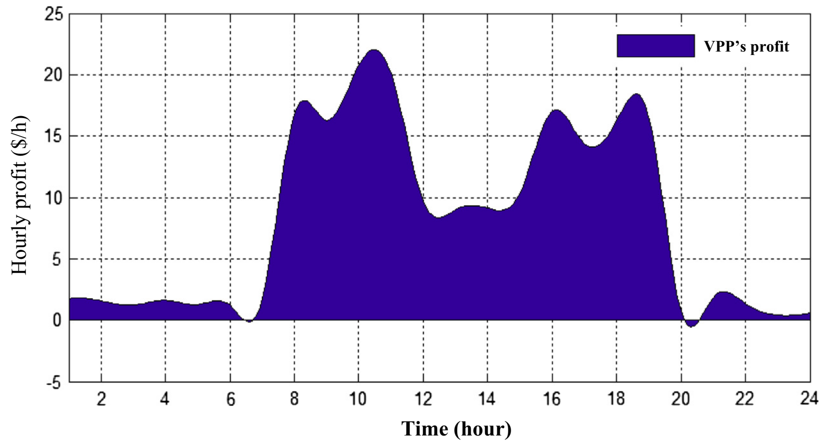

Fig. 6. Hourly profit of VPP for case 1.

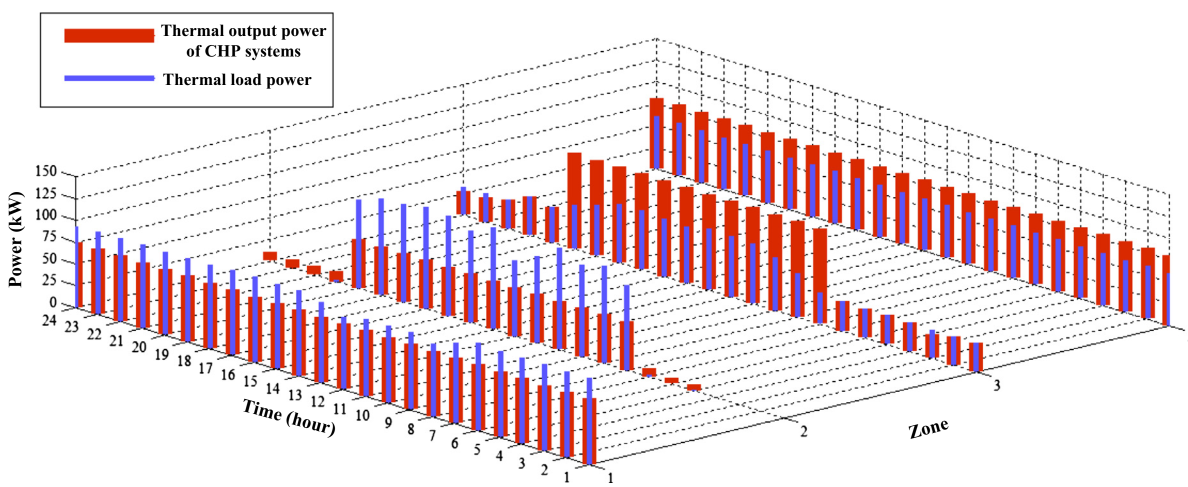

Fig. 7. Thermal output power of CHP systems and thermal load power in each zone and hour for case1.

in zone 3 and the surplus heat is used for recharging thermal storages.

Case 2. Probabilistic state

In this case, the proposed model is implemented where several scenarios are generated based on the scenario-based method described in section 'Scenario-based decision making methodology' for each uncertain parameter. It should be mentioned that all presented results for each decision variable in this case equal to its expected value. Fig. 8 shows the expected value of VPP's hourly profit and the exchanged power between VPP and energy market is shown in Fig. 9. According to these figures, during hours 1:00–7:00 and 20:00–24:00, VPP is purchasing from energy market and its hourly profit is at lowest levels, Because, the level of solar energy equals zero (night hours) and the energy and retail prices are in lowest levels (lower than marginal costs of CHPs in zones 2 and 3). For the other hours (8:00–19:00), VPP acts similar to a real power plant and sells specific amounts of energy to energy market. The state of charge in electrical storages is shown in Fig. 10. As can be seen in this figure, in periods 8:00–11:00 and 18:00–19:00, where the electricity price is the most expensive if compared to the other periods, electrical storages are consequently in discharging mode. On the other hand, when the electricity price is low (in periods 1:00–7:00 and 20:00–24:00), electrical storages are consequently in charging mode.

Case 3. Special state

In this case, a special state for performance assessment of the proposed model in the VPP's resources management encountering the network limitations is investigated. To this end, it is supposed that the power flow through the upstream line of zone 2 is bounded up to 120 kW. This case is implemented for two conditions, whether the presence of the proposed demand response program (DRP) is taken into account or not. The VPP's hourly profits, curtailed power due to running the demand response program and the energy not-served are shown in Figs. 11–13, respectively. The results demonstrate that when the demand response resources are scheduled, the VPP's hourly profit and energy not-served value are significantly improved. Taking a look at these figures it can be found that the curtailed load power from executing DRP is replaced with the energy not-served value at hour 18:00 in which a sharp drop is occurred in the VPP's profit; so, the cost due to an incentive-based payment is substituted with VOLL that consequently imposes much more cost to VPP.

In order to compare the three investigated cases, the obtained results for VPP's daily profit at each case are reported in Table 2.

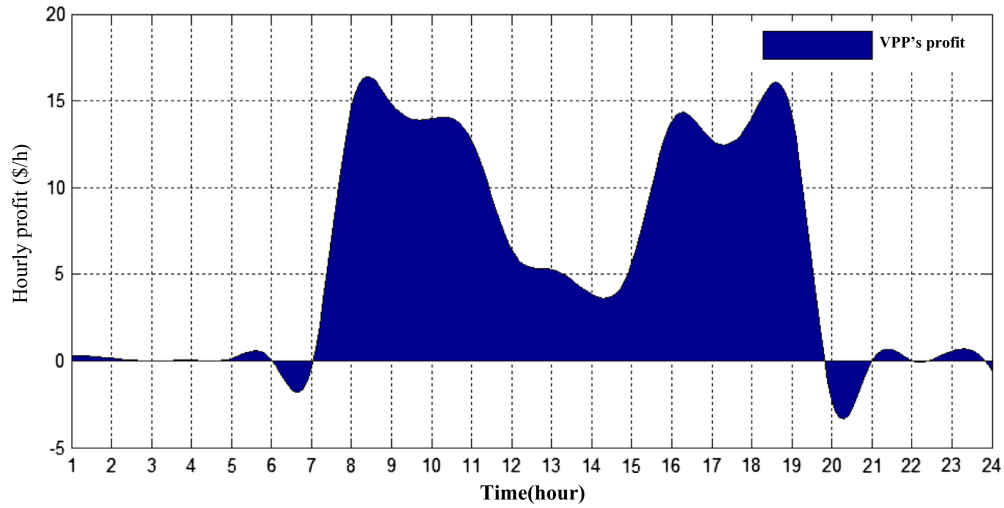

Fig. 8. The expected value of VPP's Hourly profit for case 2.

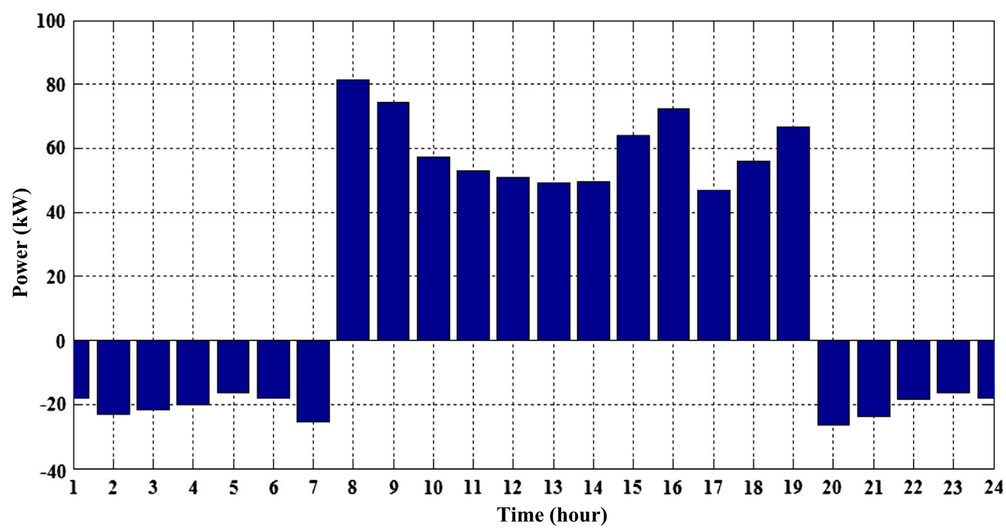

Fig. 9. The expected value of exchanged power between VPP and energy market for case 2.

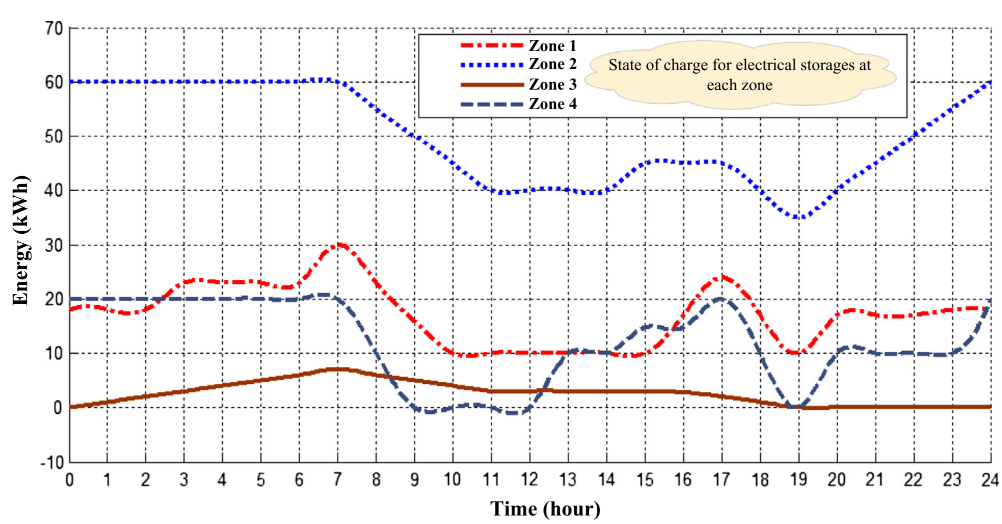

Fig. 10. The expected value of state of charge in electrical storages for case 2.

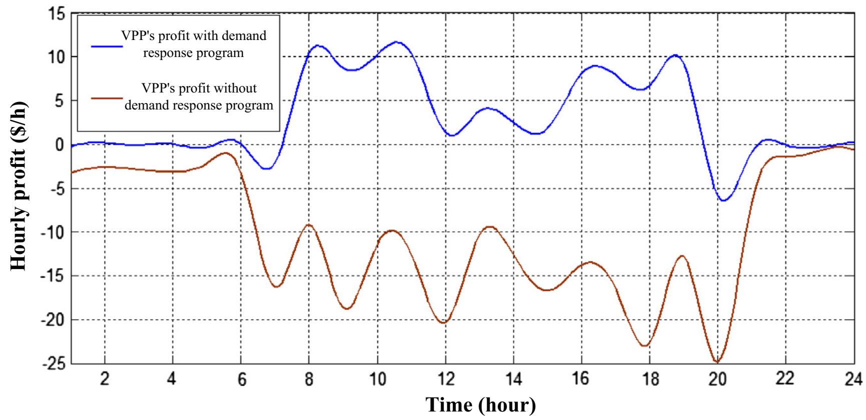

Fig. 11. The expected value of VPP's hourly profit for case 3.

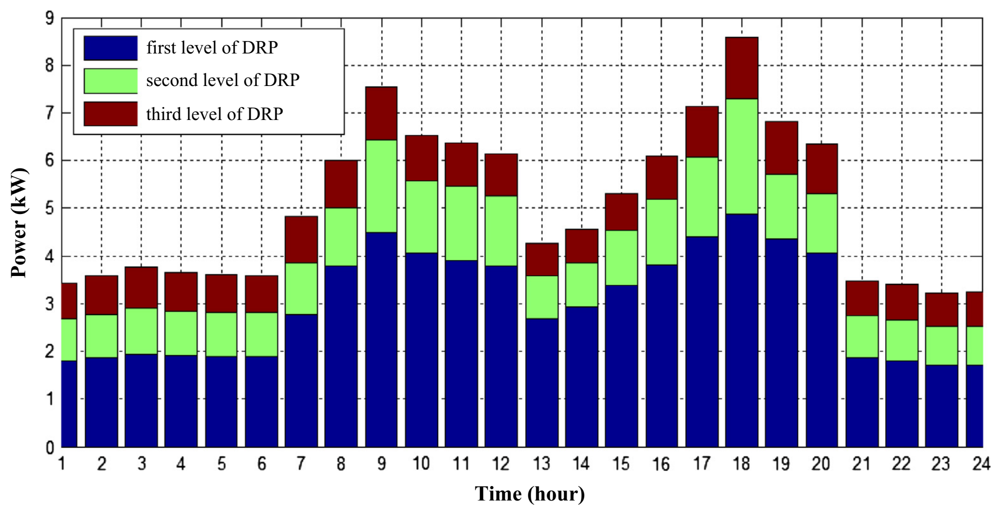

Fig. 12. The summation of curtailed power at each level of demand response program for all zones in case 3.

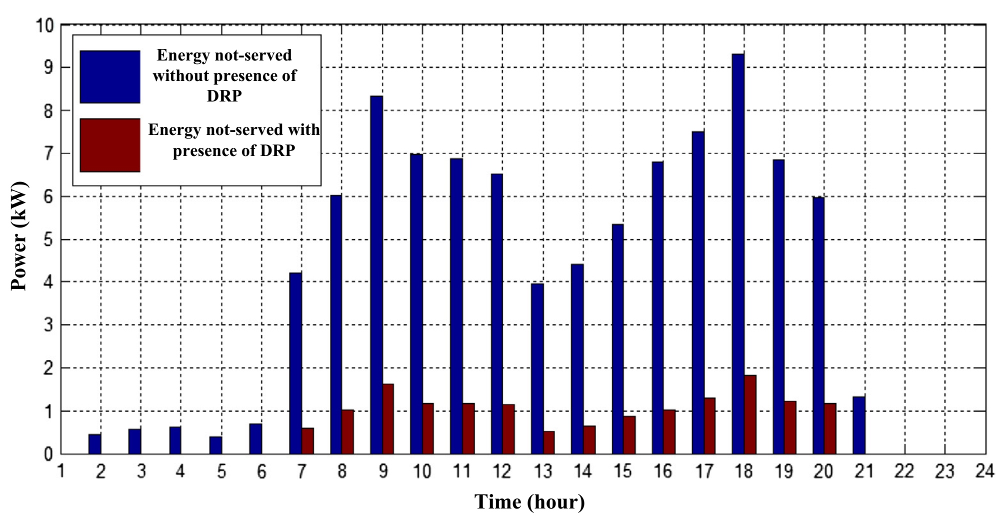

Fig. 13. The summation of energy not-served for all zones and case 3.

The results for probabilistic analyzing (cases 2 and 3) are divided to three states based on the generated scenarios that are named as best scenario, worst scenario and expected value. As shown in the table, the gap of VPP's daily profit between the best and worst scenario in case 2 is lower than the ones corresponding to case 3; also, the expected value of VPP's profit for case 2 is more than the

Table 2
The VPP's daily profit (value of objective function) at each case and sampled scenarios.

Case 1	Case 2			Case 3					
Deterministic	Worst	Expected	Best	With DRP			Without DRP		
				Worst	Expected	Best	Worst	Expected	Best
Daily profit of VPP ($)									
191.44	−142	129.99	726	−1672	71.16	759	−4624	−254.8	775.56

ones obtained for case 3. As a reason, the used network for case 2 is stronger than the one used for case 3 and it demonstrates that the VPP's profit extremely depends on the network situations.

Conclusion

In this paper, a probabilistic model is proposed for optimal electrical/thermal scheduling of a virtual power plant to participate in both energy and spinning reserve markets. To this end, a stepwise scenario-based decision making method is developed for modeling of existing uncertainties in operation of a generic VPP. Moreover, simultaneous energy and reserve scheduling method considering demand response programs has been presented. The results evidenced that the optimal scheduling of VPP's resources by the proposed method leads VPP to make optimal decisions in the energy/reserve market and to play a dual role as a demand/generation unit from the perspective of the upstream network in some time periods. According to the results, VPP acts similar to a real power plant during high electricity prices periods and injects considerable energy to the upstream network.

References

[1] Moutis P, Hatziargyriou ND. Decision trees aided scheduling for firm power capacity provision by virtual power plants. Electr Power Energy Syst 2014;63:730–9.
[2] Sucic S, Dragicevic T, Capuderb T, Delimarb M. Economic dispatch of virtual power plants in an event-driven service-oriented framework using standards-based communications. Electr Power Syst Res 2011;81:2108–19.
[3] Dabbagh SR, Sheikh-El-Eslami MK. Risk-based profit allocation to DERs integrated with a virtual power plant using cooperative Game theory. Electr Power Syst Res 2015;121:368–78. http://dx.doi.org/10.1016/j.epsr.2014.11.025.
[4] Bignucolo F, Caldon R, Prandoni V, Spelta S, Vezzola M. The voltage control on MV distribution networks with aggregated DG units (VPP). In: Proceedings of the 41st international universities power engineering conference. IEEE; 2006. p. 187–92.
[5] Katiraei F, Iravani R, Hatziargyriou N, Dimeas A. Microgrids management: controls and operation aspects of microgrids. Power Energy Magaz IEEE 2008;6(3):54–65.
[6] Mashhour E, Moghaddas-Tafreshi SM. Bidding strategy of virtual power plant for participating in energy and spinning reserve markets – part I: problem formulation. IEEE Trans Power Syst 2011;26(2):949–56.
[7] Mashhour E, Moghaddas-Tafreshi SM. Mathematical modeling of electrochemical storage for incorporation in methods to optimize the operational planning of an interconnected micro grid. J Zhejiang Univ Sci 2010;11(4):737–50.
[8] Mashhour E, Moghaddas-Tafreshi SM. Bidding strategy of virtual power plant for participating in energy and spinning reserve markets: part II: numerical analysis. IEEE Trans Power Syst 2011;26(2):957–64.
[9] Giuntoli M, Poli D. Optimized thermal and electrical scheduling of a large scale virtual power plant in the presence of energy storages. IEEE Trans Smart Grid 2013;4(2):942–55.
[10] Faria P, Soares J, Vale Z, Morais H, Sousa T. Modified particle swarm optimization applied to integrated demand response and dg resources scheduling. IEEE Trans Smart Grid 2013;4(1):606–16.
[11] Mazidi M, Zakariazadeh A, Jadid S, Siano P. Integrated scheduling of renewable generation and demand response programs in a microgrid. Energy Convers Manage 2014;86:1118–27.
[12] Nosratabadi SM, Hooshmand R, Gholipour E. Stochastic profit-based scheduling of industrial virtual power plant using the best demand response strategy. Appl Energy 2016;164:590–606.
[13] Sousa T, Morais H, Vale Z, Castro R. A multi-objective optimization of the active and reactive resource scheduling at a distribution level in a smart grid context. Energy 2015;85:236–50.
[14] Sousa T, Morais H, Soares J, Vale Z. Day-ahead resource scheduling in smart grids considering vehicle-to-grid and network constraints. Appl Energy 2012;96:183–93.
[15] Siano P, Sarno D. Assessing the benefits of residential demand response in a real time distribution energy market. Appl Energy 2016;161:533–51.
[16] Siano P. Demand response and smart grids – a survey. Renew Sustain Energy Rev 2014;30:461–78.
[17] Soroudi A. Taxonomy of uncertainty modeling techniques in renewable energy system studies. The first chapter of large scale renewable power generation. Green Energy Tech 2014:1–17.
[18] Tajeddini M, Rahimi-Kian A, Soroudi A. Risk averse optimal operation of a virtual power plant using two stage stochastic programming. Energy 2014;73:958–67.
[19] Niknam T, Golestaneh F, Malekpour A. Probabilistic energy and operation management of a microgrid containing wind/photovoltaic/fuel cell generation and energy storage devices based on point estimate method and self-adaptive gravitational search algorithm. Energy 2012;43:427–37.
[20] Li P, Zhou Z, Shi R. Probabilistic optimal operation management of microgrid using point estimate method and improved bat algorithm. In: 2014 PES general meeting conference & exposition. IEEE; 2014. p. 1–5.
[21] Peik-Herfeh M, Seifi H, Sheikh-El-Eslami MK. Decision making of a virtual power plant under uncertainties for bidding in a day-ahead market using point estimate method. Electr Power Energy Syst 2013;44:88–98.
[22] Atwa YM, El-Saadany EF, Salama MMA, Seethapathy R. Optimal renewable resources mix for distribution system energy loss minimization. IEEE Trans Power Syst 2010;25:360–70.
[23] Wu L, Shahidehpour M, Li T. Cost of reliability analysis based on stochastic unit commitment. IEEE Trans Power Syst 2008;23:1364–74.
[24] Mohammadi S, Soleymani S, Mozafari B. Scenario-based stochastic operation management of microgrid including wind, photovoltaic, micro-turbine, fuel cell and energy storage devices. Electr Power Energy Syst 2014;54:525–35.
[25] Atwa YM, El-Saadany EF, Salama MMA, Seethapathy R, Assam M, Conti S. Adequacy evaluation of distribution system including wind/solar DG. IEEE Trans Power Syst 2011;26(4):1945–52.
[26] Magness B, Seely CV. value of lost load literature review and macroeconomic analysis prepared for ercot by London economics international LLC. Public Utility Commission of Texas, project no. 40000; 2013.
[27] Lee J, Kim H. LP-based mathematical model for optimal microgrid operation considering heat trade with district heat system. Int J Energy Inf Commun 2013;4(4):13–22.
[28] Atwa YM, El-Saadany EF. Probabilistic approach for optimal allocation of wind-based distributed generation in distribution systems. Renew Power Gen IET 2011;5(1):79–88.
[29] Marwali MKC, Ma H, Shahidehpour SM, Abdul-Rahman KH. Short term generation scheduling in photovoltaic-utility grid with battery storage. IEEE Trans Power Syst 1998;13(3):1057–62.
[30] Lu B, Shahidehpour M. Short-term scheduling of battery in a grid-connected PV/battery system. IEEE Trans Power Syst 2005;20(2):1053–61.
[31] Wang MQ, Gooi HB. Spinning reserve estimation in microgrids. IEEE Trans Power Syst 2011;26(3):1164–74.
[32] http://www.ontarioenergyboard.ca/oeb/Consumers/Natural%20Gas/Natural%20Gas%20Rates.
[33] http://www.nrcan.gc.ca/energy/natural-gas/5641.
[34] http://weather.uwaterloo.ca/data.html.
[35] http://www.ontarioenergyboard.ca/OEB/Consumers/Electricity/Electricity+Prices.