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Risk-averse Probabilistic Framework for Scheduling of Virtual Power Plants Considering Demand Response and Uncertainties

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Abstract

In this paper, a risk-based stochastic framework is presented for short-term energy and reserve scheduling of a virtual power plant (VPP) considering demand response (DR) participation. The VPP comprises several dispatchable generation units, battery energy storage systems (BESSs), wind power units, and flexible loads. The proposed scheduling framework is formulated as a risk-constrained stochastic program to maximize the VPP's profit considering uncertainties of loads, wind energy and electricity prices as well as N-1 contingencies. The proposed model considers both supply and demand-sides capability for providing and deploying reserves in order to optimize the use of resources while satisfying N-1 security and other constraints. Moreover, the effect of risk-aversion on decision making of the VPP in the offering/bidding power and required reserve services is investigated by implementing conditional value-at-risk (CVaR) in the optimization model. The proposed scheme is implemented on a test VPP and the energy and reserve scheduling with and without DR participants is addressed in detail through a numerical study. Moreover, the effects of the operator's risk-averse behavior on the VPP energy and reserve management and its security indices are investigated.

Keywords: Virtual power plant (VPP), demand response (DR), energy storage system, energy and reserve scheduling.

Nomenclature

$(\bullet)_{t,s}$	At time t in scenario s.

$\overline{(\bullet)}$, $\underline{(\bullet)}$	Upper and lower limits of variable $(\bullet)$.
t , h	Indices of time intervals, t, h = 1, 2,…, T.
s	Index of scenarios, s = 1, 2,…, NS.
g	Index of DGs, g = 1, 2,…, NG.
w	Index of wind turbines, w = 1, 2,…, NW.
k	Index of BESS, k = 1, 2,…, NK.
j	Index of load groups, k = 1, 2,…, NJ.
b, n, r	Indices of buses
$a_{1,g}$, $a_{2,g}$	Cost coefficients of DG unit g.
Δt	Duration of time periods (hour)

Parameters and constants

$p_{j,t}^{DR}$	Power consumption of the j-th group of the flexible demand (MW).
η_k^c, η_k^d	Charging loss factor and discharge leakage loss factor of BESS unit k.
Pr_t^{DA} ($\mathrm{Pr}_{t,s}^{RT}$)	Day-ahead (real-time) market prices (\$/MWh).
$\mathrm{Pr}_{j,t}^{DR}$	The prices offered to the customers j (\$/MWh).
$E_{j,t,h}$	Elasticity of customers j.
α , β	Confidence level and risk parameter.
$\mathrm{Pr}_{g,t}^{up}$ ($\mathrm{Pr}_{g,t}^{dn}$)	Bid of up (down)-spinning reserve submitted by DG unit g at time t (\$/MWh).
$\mathrm{Pr}_{j,t}^{up}$ ($\mathrm{Pr}_{j,t}^{dn}$)	Bid of up (down)-spinning reserve submitted by loads j at time t (\$/MWh).
$\mathrm{Pr}_t^{buy,up}$ ($\mathrm{Pr}_t^{buy,dn}$)	Price of capacity bought from reserve market for up (down)-spinning reserve.
$\mathrm{Pr}_t^{sell,up}$ ($\mathrm{Pr}_t^{sell,dn}$)	Price of capacity sold to the reserve market for up (down)-spinning reserve.
$\mathrm{Pr}_{t,s}^{RT+}$ ($\mathrm{Pr}_{t,s}^{RT-}$)	Up (down)-regulation market prices (\$/MWh).
$\mathrm{Pr}_{g,t}^{dep}$ ($\mathrm{Pr}_{j,t}^{dep}$)	Price of deploying DGs (DR) reserve (\$/MWh).
$\mathrm{Pr}_{k,t}^{BESS}$	Price associated with operation of BESS unit k.
$VOLL_{j,t}$	Value of lost load (\$/MWh).
T^s	Spinning reserve delivery time.
ρ_s	Occurrence probability of scenario s.
$C_{g,t}^{DG}$	Operation cost of DG unit g (\$).
$SUC_{g,t}$,($SDC_{g,t}$)	Start-up (Shut-down) cost of DG unit g (\$).

RU_g ,(RD_g)	Ramp-up/down rates of DG unit *g*.
UT_g, (DT_g)	Minimum up (down) time of DG unit *g*.
G^l ,(B^l)	Conductance (Susceptance) of line *l*.

Variables

$p_t^{M,buy}$ ($p_t^{M,sell}$)	Power scheduled to buy (sell) from (to) the main grid (MW).
$p_{t,s}^{M,buy}$ ($p_{t,s}^{M,sell}$)	W&S active power bought (sold) from (to) the main grid (MW).
$\Delta p_{t,s}^{M,buy}$	Difference between p_t^{DA} and $p_{t,s}^{M,buy}$ in time *t* and scenario *s*.
$\Delta p_{t,s}^{M,sell}$	Difference between p_t^{DA} and $p_{t,s}^{M,sell}$ in time *t* and scenario *s*.
$p_{(n,r)}$, ($q_{(n,r)}$)	Active (reactive) power flow between bus *n* and *r* (MW).
$p_{w,t}$, ($q_{w,t}$)	Active (reactive) power of wind unit *w* (MW).
$p_{j,t,s}^{shed}$ ($q_{j,t,s}^{shed}$)	Active (reactive) power of load shedding of the *j*-th group of customers (MW).
$R_t^{sell,up}$ ($R_t^{sell,dn}$)	Capacity sold to the spinning reserve market for up/down reserve (MW).
$R_t^{buy,up}$ ($R_t^{buy,dn}$)	Capacity bought from the spinning reserve market for up/down reserve (MW).
$R_{g,t}^{up}$ ($R_{g,t}^{dn}$)	Up (down) reserve services provided by DG unit *g* (MW).
$R_{j,t}^{up}$ ($R_{j,t}^{dn}$)	Up (down) reserve services provided by customers in group *j* (MW).
$r_{g,t,s}^{up}$ ($r_{g,t,s}^{dn}$)	Up (down) spinning reserve deployed by DG unit *g* (MW).
$r_{j,t,s}^{up}$ ($r_{j,t,s}^{dn}$)	Up (down) spinning reserve deployed by customers in group *j* (MW).
$p_{k,t}^{BESS,c}$,($p_{k,t}^{BESS,d}$)	Charging (discharging) power of BESS unit *k* (MW).
$E_{k,t}^{BESS}$	Energy of BESS unit *k* (MWh).
$P_t^{h\&n}$	Profit of here and now stage ($).
$EP_t^{w\&s}$	Expected profit of wait and see stage ($).
$\theta_{t,s}$, $V_{t,s}$	Voltage angle and amplitude.
η_s , ζ	Auxiliary variable and value-at-risk for calculating the CVaR ($).
$u_{g,t}$,($u_{g,t,s}$)	Commitment status of DG unit *g*, {0, 1}.
$y_{g,t}$, ($y_{g,t,s}$)	Start-up indicator of DG unit *g*, {0, 1}.
$z_{g,t}$, ($z_{g,t,s}$)	Shut-down indicator of DG *g*, {0, 1}.
$\vartheta_{j,t,s}^{up}$	Binary variable, it is 1 if customer *j* is curtailed in time *t* in scenario *s*.
$\vartheta_{j,t,s}^{dn}$	Binary variable, it is 1 if customer *j* is recovering in time *t* in scenario *s*.
σ_t ,($\sigma_{t,s}$)	Binary variable for VPP total power exchanging, 1 denotes for buying power and 0 for selling

power.

$\chi_{k,t}^{BESS,c}$, ($\chi_{k,t}^{BESS,d}$) Binary variable denoting the charging (discharging) decisions of BESS unit *k*.

1. Introduction

The concept of a virtual power plant (VPP) was proposed to integrate and control different energy resources such as distributed generations (DGs), renewable energy generations, battery energy storage systems (BESSs), and controllable loads into a coordinated uniform power utility [1]. As an agent in the retail market, a VPP aggregates the capacity of many distributed energy resources (DERs) and creates a single operating profile, in order to participate in electricity market or to provide system support services [2]. By participating in electricity markets in a smart structure, a VPP can benefit from demand response (DR) or dynamic pricing program to shift or reshape the energy demand profile, contribute to reserve provision, and reduce peak periods [3]. A VPP can act as both power provider and customer and can offer to sell or bid to purchase its net power in the wholesale energy market. VPP's participation in the energy market and methods for determining its offering/bidding strategies have been proposed in several research works [4]. However, the uncertainties of market prices, renewable resources and customers' demand as well as contingency-based uncertainties introduce risk on the decision-making problem of a VPP that needs to be more investigated, especially when DR actions are considered.

Recently, energy management strategies have been presented for scheduling of a VPP considering DR. For instance, in [5], an energy management strategy has been presented for an unbalanced distribution system with a VPP including various DERs and participants in DR programs. A multiple optimization method has been deployed, but the uncertainties in the market prices and DG units are not considered. In [6], a novel approach has been proposed for VPP energy management in which uncertainties of market prices and renewable power outputs have been well characterized, but the risks of uncertainties in the optimization problem have not been addressed. Moreover, in [7], a mathematical model has been proposed for a bidding strategy of a VPP that participates in regular electricity market and intraday DR exchange market. In that study, uncertainties of renewable generation, energy prices, and customers' demand have been addressed without considering the risks associated with the uncertainties on the VPP's bidding strategy.

The uncertainties associated with the output power of renewable resources, electricity prices and customers' demand introduce a risk into VPP energy management problems. To address the risk in decision-making process, some efforts have been recently made by applying different risk measuring tools to provide valuable information to decision-makers. For instance, a risk-constrained two-stage stochastic program has been presented in [8] for energy management of a VPP, in which the risk-aversion of the VPP under uncertainties is provided by employing the conditional value at risk (CVaR) measure. In [9], an energy management problem has been presented for scheduling of VPP considering correlated DR to minimize the VPP operating cost while maintaining the power quality of the system. A risk-constrained two-stage stochastic program has been formulated to address uncertainties in day-ahead (DA) and real-time (RT) electricity prices, RESs generation processes, and the correlated DR relationship. In addition, in [10], a stochastic bi-level approach has been presented for optimal scheduling of VPP in DA energy market wherein uncertainties in wind generation and market prices are modeled with confidence bounds and scenarios, respectively. In addition, in [11], a centralized dispatch model of VPP has been introduced to improve the competitiveness of distributed energy resources in electricity market. To neutralize the side effect of RESs penetration, a bidding strategy optimization model considering DR and the uncertainty of RESs for VPP has been proposed. Also, scenario analysis method is applied to deal with the influence of elastic demand and potential risk, which are associated with utility users' consumption patterns and VPP's bidding preference, respectively. In none of [8]-[11], the reserve market trading as an important practical aspect in VPP scheduling has been ignored. Moreover, in none of them contingency-based uncertainties that can effect on the optimal offering strategy of the VPP has not been considered.

An optimal risk-averse offering strategy for a VPP trading in joint energy and reserve markets has been modeled in [12] using a two-stage stochastic programming approach. Although, the uncertainties associated with RES generation, loads as well as DA and real-time (RT) market prices are taken into consideration, the effects of participants in DR programs has not addressed in that study and the risks' effect on reserve services is not investigated. Also, that study has not addressed contingency-based uncertainties including random forced outages of generating units. Moreover, in [13], DA self-scheduling problem of a VPP trading in both energy and reserve markets has been modeled. In that study, the uncertainty associated with the VPP considered by the system operator to deploy reserves has been considered, but the effect of risk-aversion on the profit variability as well as the impacts of N-1 contingencies on the VPP scheduling are not investigated. Also, the problem of energy and reserve scheduling for autonomous microgrids has been addressed in [14] and [16], in which, the objective is to determine the optimal hourly energy and reserve scheduling with considering risk aversion and system security to maximize the operator's expected profit.

In contrast to previous studies, which were mainly focused on only energy management of the VPP, the current work develops the risk-averse stochastic programming to consider joint energy and reserve trading in a VPP scheduling in which DR based services can be purchased from several DR providers. Moreover, trading energy and reserve capacity sold (bought) to (from) the main grid as well as the effect of energy storage systems is covered in the proposed method. The objective of the proposed scheduling model is to maximize the VPP expected profit and optimal trading power with the main grid to ensure VPP power quality and satisfying N-1 security and other network constraints. Compared to the recent works in this area, there are main differences between this work and the others. First, a proper model of optimal energy bids and the reserve scheduling under various risk-averse behavior of VPP operator are determined where the demand side resources participate in reserve provision. As an extension of the concepts developed in prior works, in the proposed framework of this paper in addition of normal operation uncertainties including hourly load, RESs' output-power, DA and RT market prices and calls for reserve service, contingency-based uncertainties including random forced outages of VPP's components are also taken into accounts in the scheduling model. In addition, in this study the sensitivity of the profit and the VPP operator decision making in cases with and without the participation of responsive loads to DR price-based programs have been studied. Different cases for responsive loads are considered, and the effects of participation of customers in a price-based DR program on the offering/bidding strategies of VPP as well as DR effects on the reserve scheduling in different conditions has been investigated. As a whole, the main novel contributions of the work are three fold as follows:

- A risk-averse probabilistic framework is presented for modeling VPP's scheduling problem considering both normal operation uncertainties and N-1 contingencies. The proposed framework is formulated as a multi-objective optimization problem (MOOP) and Benders decomposition (BD) technique is employed to decompose the MOOP into a master problem which does not include N-1 security and reliability constraints and, and sub-problems where the solution of the master problem is checked for feasibility under different working scenarios.
- Impact of risk-averse behavior on the VPP profit and its optimal offering and bidding strategies is investigated through incorporation of CVaR metric into the problem formulation.
- Optimal energy bids and the reserve scheduling under various risk-averse behavior of VPP are determined where the demand side resources participate in reserve provision. The economic benefits of DR providers in providing reserve services and increasing profit of VPP are evaluated through a comparative study.

The rest of the paper is organized as follows. The proposed scheduling framework to characterize the normal operation uncertainty and N-1security, as well as the scenario generation and reduction methods is described in Section

2. The proposed stochastic model is formulated in Section 3 as a MOOP model. The numerical results of applying the proposed MOOP model on test VPP are presented in Section 4, and conclusions are provided in Section 5.

2. Description of the Proposed Scheduling Framework

This paper considers a commercial VPP, which consists of dispatchable DG units, battery energy storage systems (BESSs), wind power generators, and several groups of local electrical that is connected to the main grid. The VPP acts as a commercial aggregator that maximizes its revenue by exchanging energy with the main grid and selling energy to local customers. From the main grid perspective, the VPP acts similar to a large energy storage plant that plays both roles of a producer and a consumer. As an independent system operator, the VPP needs to optimally schedule its energy and reserve resources and to trade energy with the main grid. In this context, the VPP is exposed to risk of uncertain parameters such as wind energy, demand loads, market prices and outputs of DGs and BESSs which are limited by network conditions. Therefore, in such a risky condition, a proper risk-averse optimal scheduling model is needed to determine the offering/bidding strategy of the VPP participating in joint energy and reserve markets. In this model, it is assumed that the VPP is considered as a price-taker; i.e., its bids would not affect the market clearing prices. In addition, the local customers are equipped with energy management systems and exhibit elastic behavior in response to the VPP offering prices by adjusting their demand to reduce their consumption costs. To model the elastic behavior of the customers, economic DR model presented in [13], is used in this paper. The outcomes of the proposed model provide the optimal scheduling of DG units, the offering/bidding power to the main grid, up and down spinning reserve (SR) services allocated by DG units and DR actions, and also the offering price and load reduction (LR) for the customers.

2.1 Market Framework

The market model of this paper is considered as a structure of joint DA and RT electricity market, that is common in European electricity pools such as the Nord and Dutch pools [16]. In DA market, the VPP schedules its energy and reserve resources and determines the offering/bidding power for each hour of the coming day before the gate closure (e.g. 12:00 pm). The VPP's energy imbalance due to unpredictable fluctuations in power production or consumption should be compensated in the RT balancing market on the basis of a regulation price. The RT balancing price, ($\mathrm{Pr}_{t,s}^{RT}$), is represented by a pair of positive and negative regulation price that can be calculated as a proportion of the DA market price as follow [17]:

$$\Pr_{t,s}^{RT} = \begin{cases} \Pr_{t,s}^{RT^+} = (1+\mu_t^+)\Pr_{t,s}^{DA} \\ \Pr_{t,s}^{RT^-} = (1-\mu_t^-)\Pr_{t,s}^{DA} \end{cases} \quad (1)$$

where, μ_t^+ and μ_t^- are positive constants that show relationship between the DA price and up-regulation and down-regulation prices, respectively. In particular, the power shortage is purchased at an up-regulation price, which is usually higher than the DA price, while, the power surplus is sold at a down-regulation price, which is usually lower than the DA price [17]. Therefore, the dual pricing policy for balancing markets that are widely used in European pool markets [3] is applied in the proposed framework of this paper.

2.2 Characterization of Uncertainty

The VPP may face two categories of uncertainties during scheduling process. Normal operation uncertainties including hourly load, wind power production, DA and RT market prices, and contingency-based uncertainties including random forced outages. To accurate model of these uncertainties a large enough set of scenarios is considered. In this paper, normal probability distribution functions (PDFs) are used for modeling the load, DA and RT electricity prices, and Weibull PDFs are used for modeling the wind power productions [19]. Moreover, for the security-constrained formulation, as in [20], without loss of generality, in this paper only outages involving the tripping of a dispatchable DG or BEES are taken into account as contingency-based uncertainties. By considering single outages for these elements and set of indices Γ^{DG} and Γ^{BEES} for representing DG and BEES outages. Therefore, there is a set of outages as $\Gamma = \{0\} \cup \Gamma^{DG} \cup \Gamma^{BESS}$, in which the " $\{0\}$ " shows the case of no outage.

Here, Monte-Carlo simulation (MCS) is used for scenario generation based on random sampling from PDFs of normal uncertainties[21], and then K-means algorithm [22] is applied to reduce the number of scenarios into a limited set of N_1 representing well enough the uncertainties. For each generated normal scenario, N_2 scenario is generated for contingency-based uncertainties. Finally, the obtained scenarios are combined by employing the scenario tree and as the result, a total number of $N_1 \times N_2$ scenarios are obtained that should be considered for stochastic scheduling.

Due to the existence of the uncertainties, the VPP decision making strategy has risky conditions. Therefore, to investigate the risk of VPP profit variability, uncertainties should be controlled in a proper way and also a suitable risk measure should be incorporated into the risk-neutral problem. In this context, CVaR is incorporated to the optimization model to evaluate the risk of profit associated with the VPP's decisions in different conditions.

3. Formulation of the MOOP

In this section, the MOOP for VPP energy management strategy is formulated to maximize the expected profit of the VPP participating in energy and reserve markets, simultaneously. The aim of MOOP is to determine the optimal energy and reserve volumes while guaranteeing that reserves are sufficient to tackle the plausible realizations of the normal operation uncertainties and N-1 contingencies. Therefore, the MOOP is developed as a two-stage stochastic programming problem. The first stage considering here-and-now (H&N) decisions would model the optimal scheduling of the VPP while the second stage considering wait-and-see (W&S) decisions represents the real-time operation of the VPP. The H&N constraints involve variables that do not depend on any specific scenario, while the W&S constraints describe relationships pertaining only decision variables that depend on scenario realizations.

In the H&N decisions, the status (on/off) of generating units and economic dispatch are defined as a MILP problem. Therefore, the H&N decisions decisions need to be made before realization of the system scenarios. This stage variables are consist of commitment states of the generating units ($u_{g,t}$), their scheduled active power ($P_{i,t}$), start-up and shut-down costs of generating units ($SUC_{i,t}$, $SDC_{i,t}$), up and down spinning reserve allocated by generating units ($R_{g,t}^{up}$ and $R_{g,t}^{dn}$), capacity sold to the spinning reserve market for up/down reserve ($R_t^{sell,up}$ and $R_t^{sell,dn}$), capacity bought from the spinning reserve market for up/down reserve ($R_t^{buy,up}$ and $R_t^{buy,dn}$), power scheduled to buy from the main grid ($p_t^{M,buy}$), power scheduled to sell to the main grid ($p_t^{M,sell}$), active and reactive power flow between bus n and r ($p_{(n,r)}$ and $q_{(n,r)}$), active (reactive) power of wind unit w ($p_{w,t}$ and $q_{w,t}$), load demand after implementing DR programs ($D_{j,t}^{DR}$), spinning and non-spinning reserves allocated by load demands ($R_{j,t}^{up}$, $R_{j,t}^{dn}$), charging (discharging) power of BESS unit k ($p_{k,t}^{BESS,c}$ and $p_{k,t}^{BESS,d}$) during each scheduling hour.

In the W&S decisions of the optimization process the MOOP solved for working scenarios. The decision variables of this stage are W&S active power bought from the main grid ($p_{t,s}^{M,buy}$), W&S active power sold to the main grid ($p_{t,s}^{M,sell}$), power generations of DG units in scenario ($P_{g,t,s}$), deployed reserves of DG units ($r_{g,t,s}^{up}$ and $r_{g,t,s}^{dn}$), load demand after implementing DR programs ($D_{j,t,s}^{DR}$), deployed reserves of DR ($r_{j,t,s}^{up}$ and $r_{j,t,s}^{dn}$), active and reactive power of load shedding of the j-th group of customers ($p_{j,t,s}^{shed}$ and $q_{j,t,s}^{shed}$), voltage angle and amplitude ($\theta_{t,s}$ and $V_{t,s}$), for scenario and 24-hours.

3.1 Objective Function

The objective of the VPP is to maximize the expected profit which is composed of three terms representing the profit associated with H&N and W&S decisions, and also the profit variability which is measured by CVaR.

$$Max \ \sum_{t=1}^{T}(P_t^{h\&n} + \rho_s \sum_{s=1}^{N_S} EP_{t,s}^{w\&c}) + \beta \times CVaR \tag{2}$$

$$\begin{aligned} P_t^{h\&n} = & \ p_t^{M,sell} \Pr_t^{DA} - p_t^{M,buy} \Pr_t^{DA} \\ & + \sum_{j=1}^{N_J} p_{j,t}^{DR} \Pr_{j,t}^{DR} \\ & - \sum_{g=1}^{N_G} C_{g,t}^{DG} + SUC_{g,t} y_{g,t} + SDC_{g,t} z_{g,t} \\ & - \sum_{k=1}^{N_K} (\Pr_{k,t}^{BESS} p_{k,t}^{BESS} + \Pr_{k,t}^{BESS} E_{k,t}^{BESS} \eta_k^d) \\ & - \sum_{g=1}^{N_G} R_{g,t}^{up} \Pr_{g,t}^{up} + R_{g,t}^{dn} \Pr_{g,t}^{dn} \\ & - \sum_{j=1}^{N_J} R_{j,t}^{up} \Pr_{j,t}^{up} + R_{j,t}^{dn} \Pr_{j,t}^{dn} \\ & - R_t^{buy,up} \Pr_t^{buy,up} - R_t^{buy,dn} \Pr_t^{buy,dn} \\ & + R_t^{sell,up} \Pr_t^{sell,up} + R_t^{sell,dn} \Pr_t^{sell,dn} \end{aligned} \tag{3}$$

$$\begin{aligned} EP_t^{w\&c} = & \ \rho_s \sum_{s=1}^{N_S} (\Delta p_t^{M,sell} \Pr_{t,s}^{RT-} - \Delta p_t^{M,buy} \Pr_{t,s}^{RT+}) \\ & - \sum_{g=1}^{N_G} \rho_s \sum_{s=1}^{N_S} \Pr_{g,t}^{dep} (r_{g,t,s}^{up} - r_{g,t,s}^{dn}) \\ & - \sum_{j=1}^{N_J} \rho_s \sum_{s=1}^{N_S} \Pr_{j,t}^{dep} (r_{j,t,s}^{up} - r_{j,t,s}^{dn}) \\ & - \sum_{j=1}^{N_J} \rho_s \sum_{s=1}^{N_S} p_{j,t,s}^{shed} VOLL_{j,t} \end{aligned} \tag{4}$$

Particularly, $P_t^{h\&n}$ denotes VPP's profit in H&N stage and comprises scenario independent components as follow:

The first term represents revenue of energy trading between the VPP and main grid in DA and the second term denotes revenue of selling energy to customers. The third term provides start-up and shut-down costs of DG units and their operating costs that is obtained as follow:

$$C_{g,t}^{DG} = \mathrm{a}_{1,\mathrm{g}} u_{g,t} + \mathrm{a}_{2,\mathrm{g}} p_{g,t} \tag{5}$$

The fourth term stands for the operational cost of BESSs depending on their lifecycle costs and the fifth and the sixth terms denote the cost of reserve allocated by generation and demand side, respectively. Also, the seventh and the eighth terms state the cost of provided reserve from the main grid and the revenue from providing reserve to the main grid, respectively. Likewise, $EP_t^{w\&c}$ in (4) denotes VPP's profit in W&S stage that includes scenario dependent components as follow:

The first term stands for the revenue which made through power exchange with the main grid, the second and the third lines denote the costs of deploying reserves from generation and demand side, respectively, and the fourth term represents the penalty cost of involuntary load shedding.

Finally, the last term in (2) denotes the CVaR multiplied by risk-aversion parameter β to show the relationship between the profit and the risk of the VPP's operator. It should be noted that, CVaR represents approximately the expected profit of the (1-α)×100 scenarios yielding the lowest profits and defined as follow [23]:

$$CVaR = \zeta - \frac{1}{(1-\alpha)} \sum_{s=1}^{N_S} \rho_s \eta_s \tag{6}$$

CVaR is incorporated in the model to take the risk associated with the volatility of the profit into account [24]. Also, the weighting factor β models the tradeoff between the expected profit and the profit variability which is measured by CVaR. If risk is not considered (risk-neutral case), the value of β is set to 0, and its higher values show the more risk averse VPP.

3.2 Constraints of Here and Now Stage

Power balance constraints: Active and reactive power balance between supply and demand at node *n* of the VPP is represented by the following constraints (7) and (8), respectively.

$$p_{g,t}^{n} + p_{w,t}^{n} - p_{j,t}^{DR,n} = \sum_{r=1}^{N_B} p_{(n,r),t} \tag{7}$$

$$q_{g,t}^{n} + q_{w,t}^{n} - q_{j,t}^{DR,n} = \sum_{r=1}^{N_B} q_{(n,r),t} \tag{8}$$

where, $p_{(n,r),t}$ and $q_{(n,r),t}$ can be obtained by using linearized power flow equations explained in (9) and (10), respectively [16].

$$\begin{aligned} p_{(n,r),t} &= G_{(n,n)}^{l}(2V_{n,t}-1) + \sum_{r(n\neq r)} G_{(n,r)}^{l}(V_{n,t}+V_{r,t}-1) \\ &\quad + B_{(n,r)}^{l}(\theta_{n,t}-\theta_{r,t}) \end{aligned} \tag{9}$$

$$q_{(n,r),t} = -B^{l}_{(n,n)}(2V_{n,t}-1) - \sum_{r(n\neq r)} B^{l}_{(n,r)}(V_{n,t}+V_{r,t}-1) + G^{l}_{(n,r)}(\theta_{n,t}-\theta_{r,t}) \tag{10}$$

To satisfy network constraints, the active and reactive power flow in (11) and the voltage magnitude and phase angle in (12) are also considered.

$$\underline{P}_{(n,r)} \le p_{(n,r),t} \le \overline{P}_{(n,r)}, \quad \underline{Q}_{(n,r)} \le q_{(n,r),t} \le \overline{Q}_{(n,r)} \tag{11}$$

$$\underline{V}_{n} \le V_{n,t} \le \overline{V}_{n}, \quad \underline{\theta}_{n} \le \theta_{n,t} \le \overline{\theta}_{n} \tag{12}$$

Constraints of DG units: DG units used in this study are only termed as gas-fired micro-turbines. The output of these units is constrained between a minimum and maximum value considering also the scheduled down and up SRs by (13) and (14), respectively. Also, feasible operational region of such generation units can be provided by start-up cost limit (15), shut down cost limit (16), power capacity limit (17) and ramping up/down limits (18)-(19), [14].

$$p_{g,t}u_{g,t} - R^{dn}_{g,t} \ge \underline{P}_{g} \tag{13}$$

$$p_{g,t}u_{g,t} + R^{up}_{g,t} \le \overline{P}_{g} \tag{14}$$

$$SUC_{g,t} \ge CU_{g}(u_{g,t} - u_{g,t-1}) \tag{15}$$

$$SDC_{g,t} \ge CD_{g}(u_{g,t-1} - u_{g,t}) \tag{16}$$

$$\underline{P}_{g}u_{g,t} \le p_{g,t} \le \overline{P}_{g}u_{g,t} \tag{17}$$

$$p_{g,t} - p_{g,t-1} \le RU_{g}(1-y_{g,t}) + \underline{P}_{g}y_{g,t} \tag{18}$$

$$p_{g,t-1} - p_{g,t} \le RD_{g}(1-z_{g,t}) + \underline{P}_{g}z_{g,t} \tag{19}$$

Moreover, for each DG unit *g*, the minimum-up time constraint (20) and the minimum-down time constraint (21) should be satisfied [14]. Furthermore, the scheduled up and down reserves are limited by (22)-(23), [25].

$$\sum_{h=t}^{t+UT_g-1} u_{g,t} \ge UT_{g}.y_{g,t} \tag{20}$$

$$\sum_{h=t}^{t+DT_g-1} (1-u_{g,t}) \ge DT_{g}(u_{g,t} - u_{g,t-1}) \tag{21}$$

$$0 \le R^{up}_{g,t} \le RD_{g}T^{s}u_{g,t} \tag{22}$$

$$0 \le R^{dn}_{g,t} \le RU_{g}T^{s}u_{g,t} \tag{23}$$

DR providers' constraints: The economic model for the participation of customers in DR programs is developed based on DR model in [16], in which the LR value depends on the demand elasticity of customers and electricity prices. When the customers *j* participate in DR program, its demand can be calculated as follow [16]:

$$p^{DR}_{j,t} = P^{\text{int}}_{j,t}.\exp\sum_{h=1}^{T} E_{j,t,h}.\ln[\frac{\Pr^{DR}_{j,t}}{\Pr^{DR,\text{int}}_{j,t}} + \frac{1}{1+E^{-1}_{j,t,h}}] \tag{24}$$

where, $P_{j,t}^{\text{int}}$ is the initial value of demand associated with customers *j* and $\text{Pr}_{j,t}^{DR,\text{int}}$ is the initial value of prices offered to the customers *j*. Also, it is considered that demand side resources may contribute to upward and downward reserves through appropriate coordination of the curtailment and the recovery periods. Providing up and down reserves from DR providers are limited by constraints (25)-(26), [25].

$$0 \le r_{j,t,s}^{up} \le \min(\vartheta_{j,t,s}^{up} p_{j,t,s}^{DR}, RU_{j,t}^{DR} T^s) \tag{25}$$

$$0 \le r_{j,t,s}^{dn} \le \min(\vartheta_{j,t,s}^{dn} p_{j,t,s}^{DR}, RD_{j,t}^{DR} T^s) \tag{26}$$

Constrict (25) states that the upward reserve scheduled by group of customers *j* are limited either by the minimum upward demand modification rate or by the load drop rate. Also, constraint (26) denotes that the downward reserve as a result of scheduled load recovery is limited either by the minimum downward demand modification rate or by the load pick-up rate.

Operation Constraints of BESS: The energy charging of BESS at time t is modeled by the state-transition equation as [19].

$$E_{k,t}^{BESS} = E_{k,t-1}^{BESS} + \eta_k^c p_{k,t}^{BESS,c} \Delta t - \frac{p_{k,t}^{BESS,d} \Delta t}{\eta_k^d} \tag{27}$$

where, $p_{k,t}^{BESS,c}$ and $p_{k,t}^{BESS,d}$ are both positive and limited by certain upper bounds, $\overline{P}_{k,t}^{BESS,c}$ and $\overline{P}_{k,t}^{BESS,d}$ as follow:

$$0 \le p_{k,t}^{BESS,c} \le \overline{P}_{k,t}^{BESS,c} \chi_{k,t}^{BESS,c} \tag{28}$$

$$0 \le p_{k,t}^{BESS,d} \le \overline{P}_{k,t}^{BESS,d} \chi_{k,t}^{BESS,d} \tag{29}$$

$$\chi_{k,t}^{BESS,c} + \chi_{k,t}^{BESS,d} \le 1 \tag{30}$$

To avoid any overcharging or over discharging, each BESS should be operated within its upper and lower limits as follow:

$$\underline{E}_{k,t}^{BESS} \le E_{k,t}^{BESS} \le \overline{E}_{k,t}^{BESS} \tag{31}$$

Constraints of Main Grid's Power Exchange and Reserve Services: The surplus/shortage power of the VPP should be traded with the main grid as the scheduled power in DA market. The trading power between the VPP and the main grid is limited as follows:

$$0 \le P_t^{M,buy} \le \overline{P}_t^{M,buy} \sigma_t \tag{32}$$

$$0 \le p_t^{M,sell} \le \overline{P}_t^{M,sell} (1-\sigma_t) \tag{33}$$

Moreover, the VPP can sell (buy) reserve capacity to (from) the reserve market. The amounts of reserve capacity sold to the reserve market for up and down reserves are limited by (34)-(35), while the reserves capacity bought from the market for up and down services are limited by (36)-(37), respectively.

$$0 \le R_t^{buy,up} \le \overline{P}_t^{M,buy} \sigma_t - p_t^{M,buy} \tag{34}$$

$$0 \le R_t^{buy,dn} \le p_t^{M,buy} - \underline{P}_t^{M,buy} \sigma_t \tag{35}$$

$$0 \le R_t^{sell,up} \le \overline{P}_t^{M,sell} (1-\sigma_t) - p_t^{M,sell} \tag{36}$$

$$0 \le R_t^{sell,dn} \le p_t^{M,sell} - \underline{P}_t^{M,sell} (1-\sigma_t) \tag{37}$$

3.3 Constraints of Wait and See Stage

Power balance constraints: Constraints (38) and (39) represent respectively, active and reactive power balance at node *n* in the wait and see decisions stage.

$$p_{g,t,s}^{n} + p_{w,t,s}^{n} - p_{j,t,s}^{DR,n} + p_{j,t,s}^{n,shed} = \sum_{r=1}^{N_B} p_{(n,r),t,s} \tag{38}$$

$$q_{g,t,s}^{n} + q_{w,t,s}^{n} - q_{j,t,s}^{n} + q_{j,t,s}^{n,shed} = \sum_{r=1}^{N_B} q_{(n,r),t,s} \tag{39}$$

where, $p_{(n,r),t,s}$ and $q_{(n,r),t,s}$ are obtained by equations (40) and (41) respectively [16].

$$\begin{aligned} p_{(n,r),t,s} = {} & G_{(n,n)}^{l} (2V_{n,t,s} - 1) + \sum_{r(n \neq r)} G_{(n,r)}^{l} (V_{n,t,s} + V_{r,t,s} - 1) \\ & + B_{(n,r)}^{l} (\theta_{n,t,s} - \theta_{r,t,s}) \end{aligned} \tag{40}$$

$$\begin{aligned} q_{(n,r),t,s} = {} & -B_{(n,n)}^{l} (2V_{n,t,s} - 1) - \sum_{r(n \neq r)} B_{(n,r)}^{l} (V_{n,t,s} + V_{r,t,s} - 1) \\ & + G_{(n,r)}^{l} (\theta_{n,t,s} - \theta_{r,t,s}) \end{aligned} \tag{41}$$

It should be mentioned that in order to satisfy the system constraints, the VPP operator can use inelastic load shedding as the last option. The amount of mandatory load shedding of customer *j* should be limited as given in constraint (42).

$$0 \le p_{j,t,s}^{shed} \le p_{j,t}^{DR} \tag{42}$$

Constraints of DG units: These constraints include the minimum and maximum limitation of output power of DGs in (43) as well as the ramp up and ramp down limits given in (44)-(45) for the actual generation in each individual scenario.

$$\underline{P}_g u_{g,t} \le p_{g,t,s} \le \overline{P}_g u_{g,t} \tag{43}$$

$$p_{g,t,s} - p_{g,t-1,s} \le RU_g (1 - y_{g,t,s}) + \underline{P}_g y_{g,t,s} \tag{44}$$

$$p_{g,t-1,s} - p_{g,t,s} \le RD_g (1 - z_{g,t,s}) + \underline{P}_g z_{g,t,s} \tag{45}$$

Risk measure constraints: The risk metric is considered with respect to the expected profit of each scenario as expressed in (46). Also, the auxiliary variable is nonnegative.

$$\eta_s + \sum_{t=1}^{T} (P_t^{h\&n} + EP_{t,s}^{w\&c}) \ge \xi \tag{46}$$

$$\eta_s \geq 0 \quad (47)$$

Constraints of demand-side reserve deployment: Constraints (48)-(50) enforce the requirement that a customer cannot reduce and increase its consumption simultaneously. Moreover, the left hand side of (48) denotes that a load reduction should be over a minimum amount of curtailment [25].

$$v_{j,t,s}^{up} R_j^{up,m} \leq r_{j,t,s}^{up} \leq RU_j^{DR} T^s v_{j,t,s}^{up} \quad (48)$$

$$0 \leq r_{j,t,s}^{dn} \leq RU_j^{DR} T^s v_{j,t,s}^{dn} \quad (49)$$

$$v_{j,t,s}^{up} + v_{j,t,s}^{dn} \leq 1 \quad (50)$$

A. ***Linking Constraints between the First and Second Stages***

Linking constraints couple the first stage decisions with possible realizations of stochastic processes. Constraints (51)-(53) couple the decisions of the scheduled power output of DGs with the actual power generation and deployed reserves. Likewise, constraints (54)-(56) couple decisions related to the scheduled power of demand side-resources with the actual power and deployed reserves of them.

$$p_{g,t,s} \leq p_{g,t} + r_{g,t,s}^{up} - r_{g,t,s}^{dn} \quad (51)$$

$$0 \leq r_{g,t,s}^{up} \leq R_{g,t}^{up} \quad (52)$$

$$0 \leq r_{g,t,s}^{dn} \leq R_{g,t}^{dn} \quad (53)$$

$$p_{j,t,s}^{DR} \leq p_{j,t}^{DR} - r_{j,t,s}^{up} + r_{j,t,s}^{dn} \quad (54)$$

$$0 \leq r_{j,t,s}^{up} \leq R_{j,t}^{up} \quad (55)$$

$$0 \leq r_{j,t,s}^{dn} \leq R_{j,t}^{dn} \quad (56)$$

$$p_{j,t,s}^{DR} \leq p_{j,t}^{DR} - r_{j,t,s}^{up} + r_{j,t,s}^{dn} \quad (57)$$

$$0 \leq r_{j,t,s}^{up} \leq R_{j,t}^{up} \quad (58)$$

$$0 \leq r_{j,t,s}^{dn} \leq R_{j,t}^{dn} \quad (59)$$

4. Solution Methodology

In this section, the proposed method to solve the MOOP including the objective function (2) subject to constraints (1) and (3)-(46) is discussed. Prior to solving this problem, the two categories of uncertainties including normal operation uncertainties and contingency-based uncertainties are modeled as stochastic processes. Subsequently, a set of 1000 scenarios is generated for each stochastic parameter of two categories using MCS method according to their probability distributions. The sets of generated scenarios are combined to build a scenario tree with 10^{12} scenarios. Then to achieve tractability, K-means algorithm as a proper scenario-reduction technique is applied to reduced scenario tree to 1000 scenarios. In the next step, these reduced scenarios are applied to a two stage optimization model to maximize the expected profit of the VPP as well as to minimize the total customers' consumption costs with the optimal scheduling of supply and demand-side energy and reserves resources, exchange power with the main grid while guaranteeing N-1 security of the VPP. In the first stage of the MOOP, decisions of here and now stage are made, while in the second stage, the feasibility and optimality of the first stage decisions under system contingencies are examined. In this study, Benders decomposition (BD) technique [26] is implemented for promoting the computational tractability of the MOOP.

In order to accelerate the implementation of the MOOP, each stage of the problem is divided into a master problem and a sub-problem. In the master problem of the first stage, the vector of active power and outputs of committed DG units as well as reserves of different resources are obtained based on forecasted values of different input data. In the sub-problem, the system security is checked by running AC-power flow from feasibility viewpoint. If sub-problem fails to find a feasible solution, a feasibility and optimality cut based on the BD technique is created and included to the master problem to recalculate the decision parameters. The decisions of the first stage enter to the second stage where the problem for working scenarios is solved. In this stage, optimal decisions are made properly through a unit commitment algorithm and optimal power flow procedure by considering system's objectives and constraints. In the sub-problem of this stage, the system N-1 security constrains are checked by running AC-power flow and reliability is considered by index of allowed mandatory load shedding. Similar to the first stage, the feasibility and optimality cut are created and enter to the master problem to obtain decision variables. The iterative process continues till the violations are eliminated and a converged optimal solution is found.

5. Case Study and Numerical Results

5.1 Case Study Description

The presented scheduling approach is carried out on a 15-bus VPP test system depicted in Fig. 1, [19]. As shown, the VPP comprises three dispatchable DG units, four wind turbines, three BESS and 13 load buses. The total generation capacity is 8.1 MW including 2.7 MW of wind power and 5.4 MW of DGs. The forecasted values of total demand, output power of wind turbines as well as DA electricity prices are considered as depicted in Fig. 2. Also, the expected values of up and down regulation prices are assumed to be 1.1 and 0.9 of DA prices, respectively [8]. It is assumed that the forecasted errors of wind power, load and DA electricity prices follow normal distributions with standard deviations equal to 5%, 8%, and 10% of the forecasted values, respectively [27].

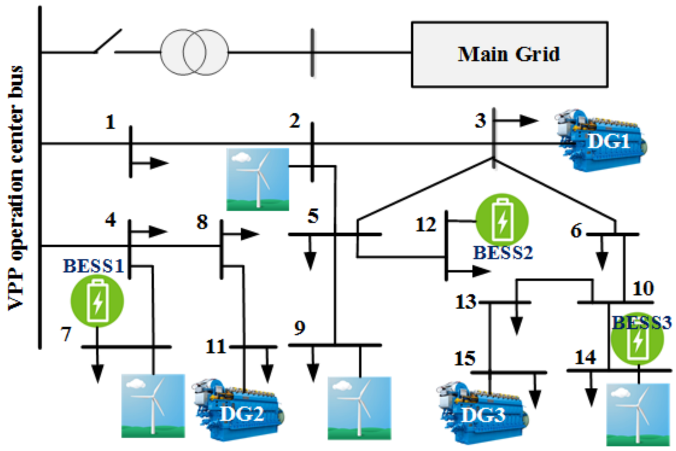

Fig. 1. *One-line diagram of the examined15-bus VPP system.*

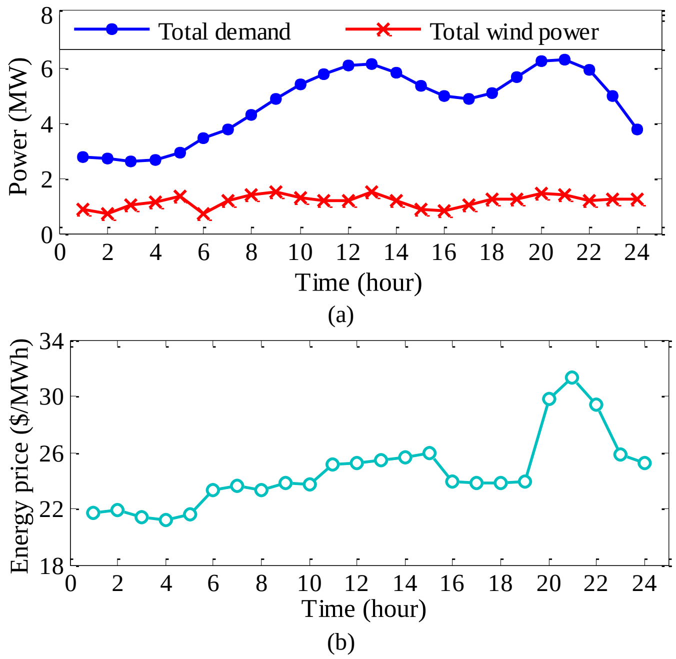

Fig. 2. *The forecasted values of (a) wind output power and demand, and (b) DA electricity price.*

Furthermore, technical data of DG and BESS units are depicted in Tables 1 and 2, respectively [9], [19]. For simplicity, the minimum up/down-time of all DGs are assumed to be 3 and 2 hours, respectively. Additionally, the VPP is connected to the main grid through a line that its maximum capacity of power is set as 2.4 MW. The MOOP model is solved using CPLEX solver under GAMS [28] on a PC with 4 GB of RAM and Intel Core i7 @ 2.60 GHz processor. The optimality gap of different cases of the optimization algorithm is set to 0.0, and computation times in all studies are less than 2 minutes with 39356 iterations in total.

Table 1 Technical data of DG units

DG Unit	$\underline{P}_g$ (MW)	$\overline{P}_g$ (MW)	$a_{1,g}$ ($)	$a_{2,g}$ ($/MWh)	SUC ($)	SDC ($)

DG_1	0.4	3	20	150	70	20
DG_2	0.2	1	25	320	70	20
DG_3	0.1	1.4	35	220	70	20

Table 2 Technical data of BESS units

BESS Unit	$\underline{E}_k^{BESS}$ (kWh)	$\overline{E}_k^{BESS}$ (kWh)	η_k^c, η_k^d	$\overline{P}_{k,t}^{BESS,c}$ (kW)	$\overline{P}_{k,t}^{BESS,d}$ (kW)
$BESS_1$	40	100	91.4%	50	50
$BESS_2$	80	200	91.4%	100	100
$BESS_3$	120	300	91.4%	150	150

5.2 Results and Discussions

In this section, the proposed scheduling model is applied to the VPP and its offering/bidding strategies are discussed and compared in different cases. In this comparison, the effect of risk-aversion parameter β on the profit of VPP is investigated by varying its values from 0 to 20. Moreover, the rate of participation of customers in DR program is assumed to be 50%. The simulations are conducted using the reduced 1000 scenarios in which the confidence level α, is considered to be 0.95. As shown in Table 3, for the same risk aversion level, participation of customers in DR, increases the expected profit of the VPP and reduces CVaR term. Also, by increasing risk-aversion β, the VPP profit decreases and the CVaR increases in both cases. When β varies from 0 to 20, the VPP profit in the cases with and without DR reduces by 11% and 7.2%, but their associated CVaR increases by 81% and 93%, respectively. These results indicate that a relatively high decrease in the VPP profit should be used to reduce efficiently the risk of profit variability. Moreover, a higher profit reduction is observed in the case of using DR that is due to the increased number of unfavorable scenarios with more negative profits.

To show the effect of DR participant and risk aversion on the VPP energy management, scheduled power of DGs, BESSs, Energy exchanged with the main grid as well as wind output power are compared in different cases in Fig. 3. In order to prevent crowding data in the figures, two cases with and without DR are investigated for only risk-neutral (β=0) and risk-averse (β =20) behaviors.

Table 3 The VPP profit and CVaR in different values of risk-aversion β

Risk-averse parameter β	Expected Profit ($)		CVaR ($)	
	No DR	With DR	No DR	With DR
0.0	8365	8811	-473	-533
0.1	8365	8810	-468	-527
0.2	8363	8809	-464	-524
0.5	8354	8802	-438	-502
1	8166	8653	-199	-312
2	8061	8565	-114	-232
5	7892	8323	-50	-135
10	7843	8241	-43	-125
20	7749	7838	-34	-100

Generally, demand loads must be satisfied even when the electricity prices are very high or the wind power generation is low. The DG units supply most of demand, especially during peak periods (i.e. 11:00-14:00 and 19:00-22:00), however, the surplus generation can be sold to the main grid or stored in BESSs. Also, the shortage generation should be provided by such resources. Therefore, BESSs are charged during off-peak hours when the DA prices are low (e.g. 2:00–5:00) and are discharge in peak times. However, by implementing DR actions, the responsive loads adjust their consumptions based on the electricity prices and more amount of LR occurs during peak hours, and as the result, trading energy with the main grid reduces. Moreover, as observed, in risk-averse cases, the energy exchanged with the main grid decreases compared to the risk-neutral case. In fact, the VPP with a more risky behavior tries to provide more energy from the reliable DG units instead of high uncertain electricity market.

The charging and discharging energy of BESSs within the scheduling horizon with and without DR actions is depicted in Fig. 4. By increasing β, the amount of charging and discharging reduces. That is because with a higher level of risk aversion (especially for $\beta > 1$), the VPP tries to supply more energy from reliable DG units instead of other uncertain energy resources. Therefore, in addition to a lower energy trading with the main grid, the amount of charging and discharging energy of BESSs decreases.

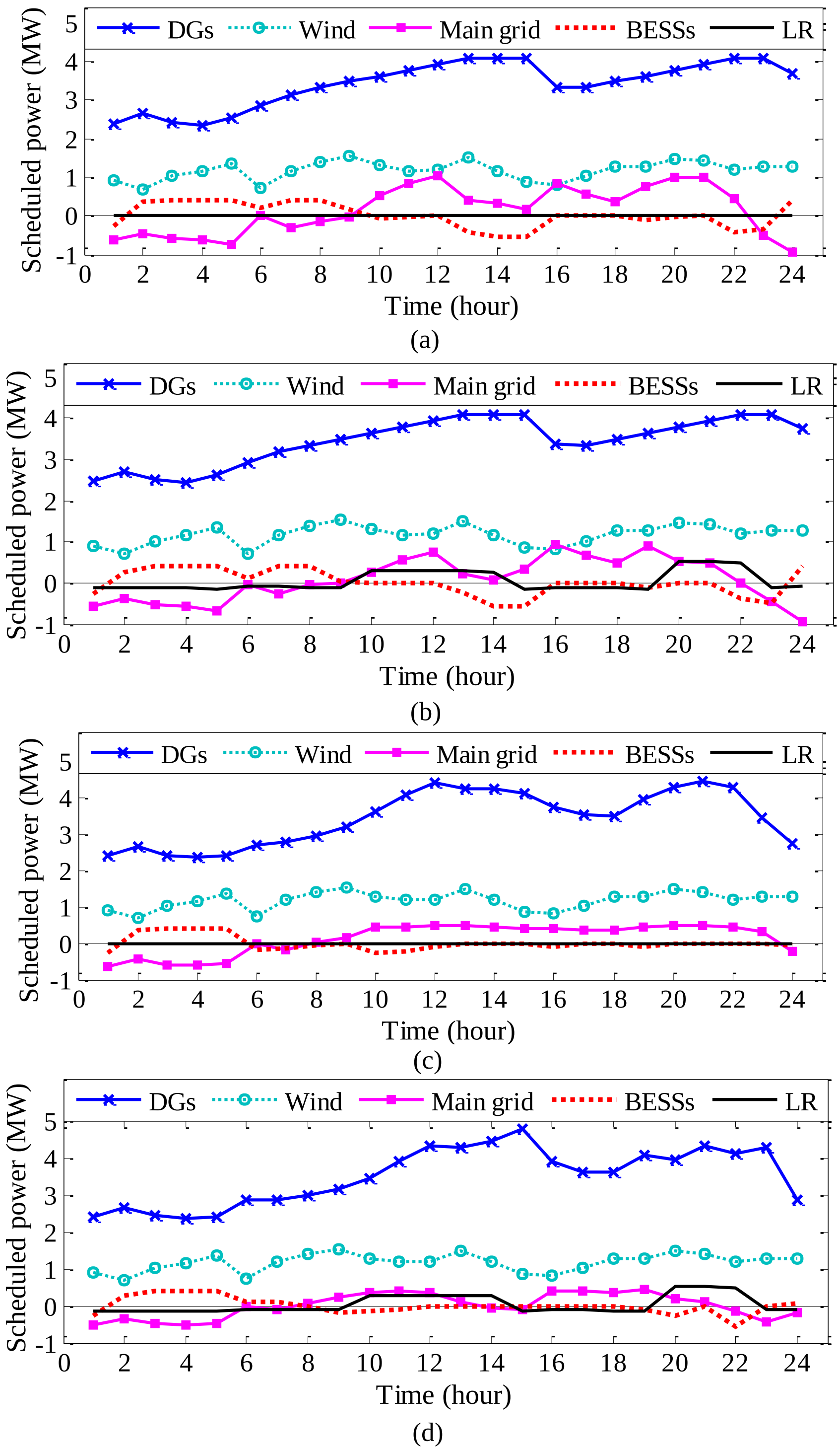

Fig. 3. *Scheduled power of the VPP's elements, (a) Without DR and β=0 (b). With DR and β=0, (c) Without DR and β=20, and, (d) With DR and β=20.*

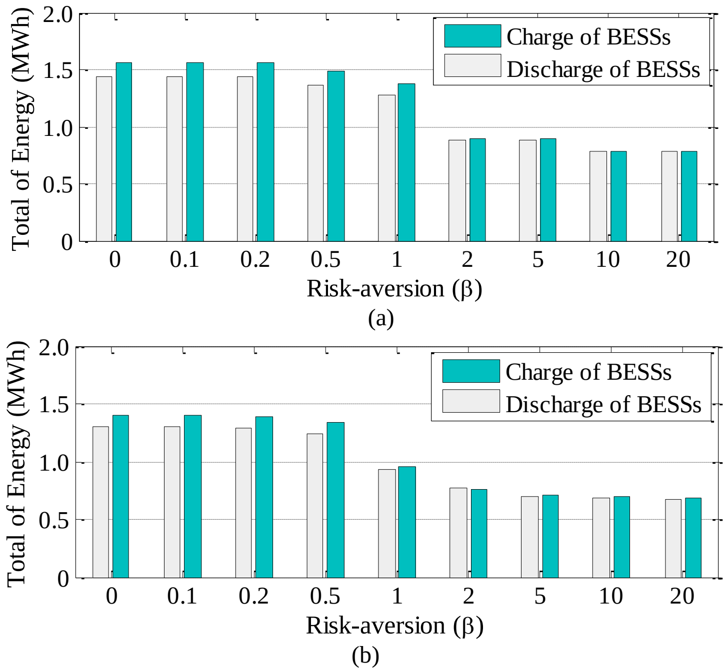

Fig. 4. *Total charge and discharge energy of BESSs, (a) no DR, (b) with DR.*

Fig. 5 illustrates the amount of total energy exchanged with main grid in cases with and without DR in different risk-aversion values of β. As it can be seen, energy trading with the main grid reduces when the VPP behaves more conservative. In fact, the VPP trades lower energy with the main grid to hedge against profit volatility while meeting its demand from more reliable DG units.

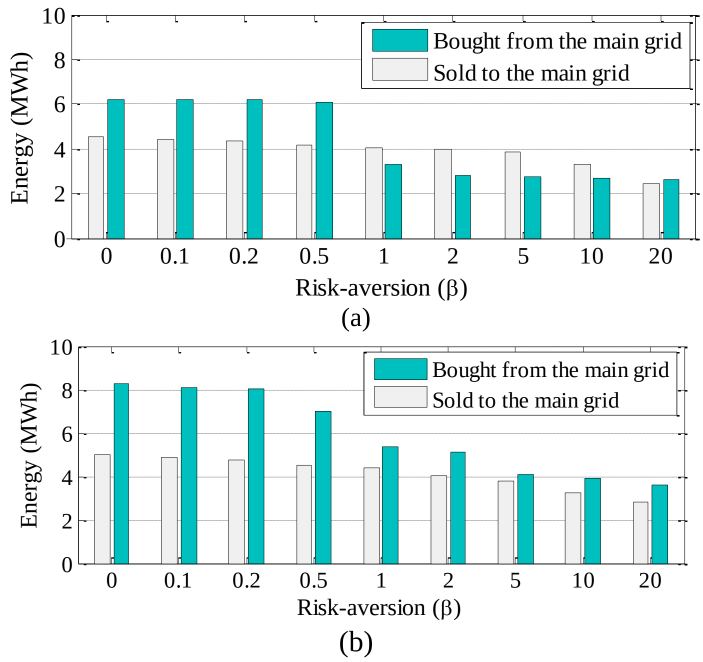

Fig. 5. *Expected energy traded with the main grid versus β, (a) Case without DR, (b) Case with DR.*

Also, it is observed that in a specific value of risk aversion, the amount of energy transaction with the main grid in the case with DR support is lower than that of without DR. This is because when customers participate in DR, a part of surplus/shortage VPP production is compensated by adjusting energy consumption of responsive loads. The total amount of up and down-SR in different risk levels is shown in Fig. 6. It is worth noting that the reserve service is mainly provided by DG units and the main grid if no DR is considered; however, such a reserve capacity can be reinforced by DR support. It is also observed that in both cases, the total amount of required reserve decreases when the uncertainties are highly handled. In fact, in correspondence of lower levels of risk aversion, the VPP should allocate more reserve to avoid non-desirable profit distributions due to various worst scenarios. But, in correspondence of higher risk aversion, the available resources are scheduled in such a way that the probability of mismatch between supply and demand mitigates and therefore, the required reserve decreases. In other word, in a more risk-averse case, the VPP is willing to sacrifice high profits in the best scenarios in the hope of avoiding low profits or even losses in the worst scenarios.

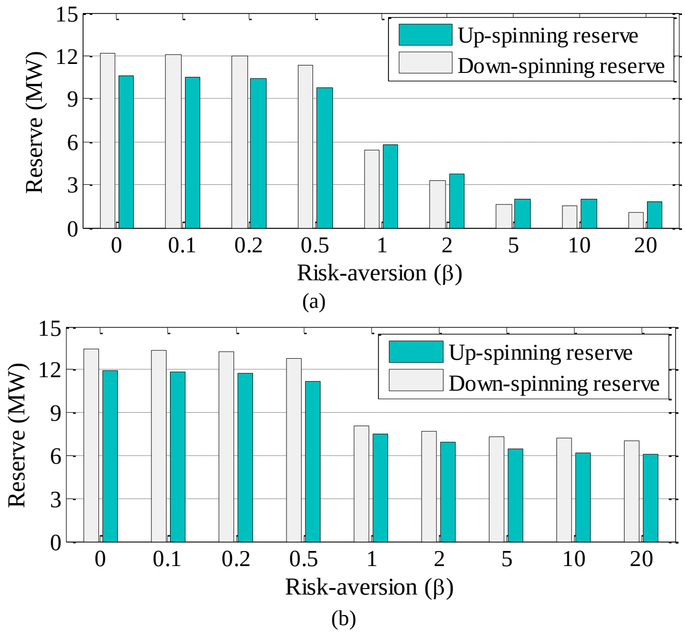

Fig. 6. *Total scheduled up- and down-SRs, (a) Case without DR, (b) Case with DR.*

Furthermore, the comparison of two cases shows that when considering the contribution of customers in providing reserve services, a higher reserves capacity is required in order to accommodate unpredictable variability of responsive loads. Hourly up and down-SRs in different cases are depicted in Fig. 7. As observed, in the risk-averse case, the amounts of both up and down- SRs substantially reduce during all hours compared to those in the risk-neutral case. That is because when considering a higher risk aversion, DG units are scheduled in order to mitigate the probability of mismatch between supply and demand. In such condition, the number of worst scenarios reduces and as the result, lower reserve is required to be scheduled to accommodate the uncertainties of the VPP. Moreover, when DR is called to provide up and down-SRs, the commitment of DG units decreases.

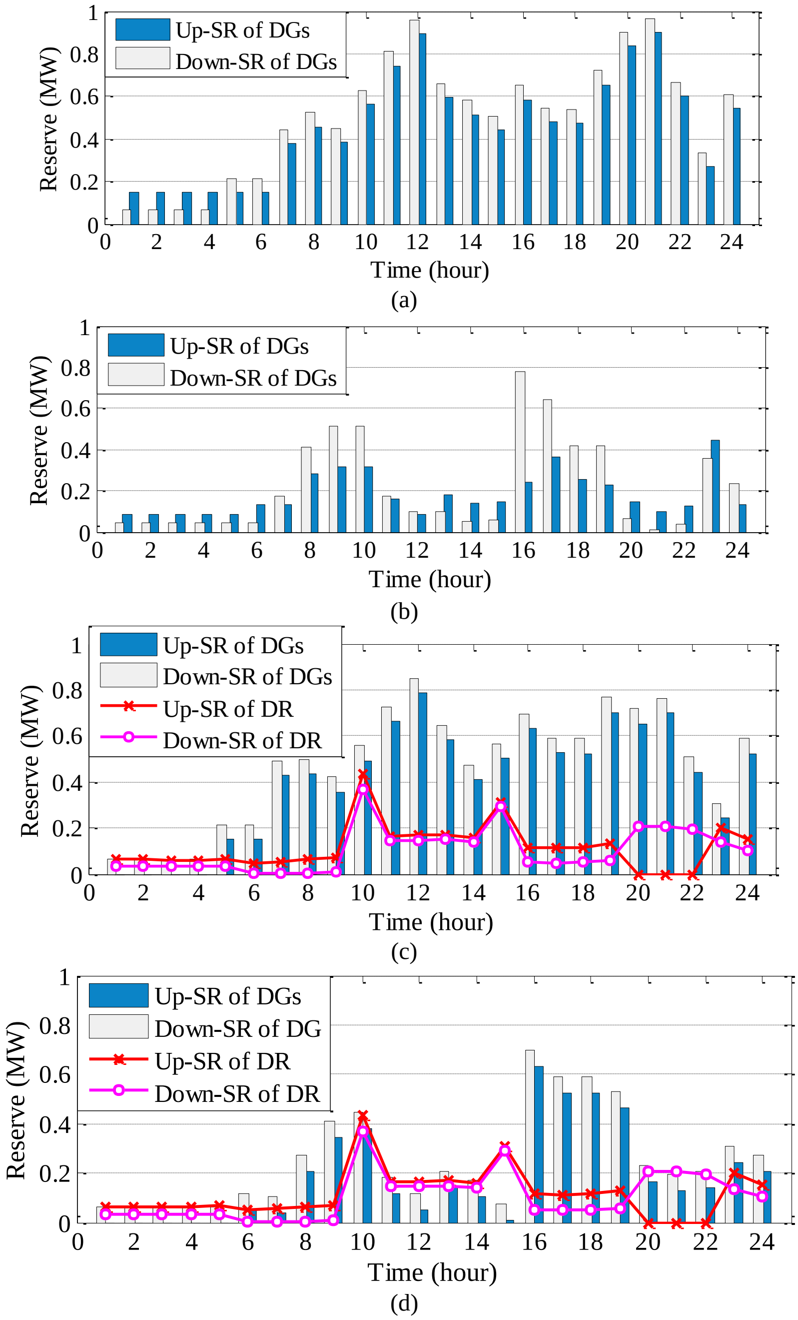

Fig. 7. *Hourly up and down SR (a) without DR and in risk-neutral case, (b) without DR and in risk-averse case, (c) with DR and in risk-neutral case, and, (d) with DR and in risk-averse case.*

6. Conclusions

This paper presented a stochastic framework for joint energy and reserve scheduling of a VPP considering DR participation. The VPP optimized its hourly scheduling strategy through a risk-constrained stochastic optimization model, in order to maximize the total profit. To capture profit variations imposed by uncertainties related to wind generation, demand and electricity prices, CVaR term was incorporated into the model. The proposed model was applied to the 15-bus VPP and different cases were investigated. Numerical results demonstrated that as the risk aversion increases, the expected profit of the VPP decreases, while the value of CVaR augments. In the risk-averse case, the VPP could provide more energy from reliable DG units rather than the main grid, and therefore, trading energy with the main grid as well as providing SRs decreases, significantly. Furthermore, simulation results showed that participation of customers in price-based DR program could lead to more negative profits in the worst scenarios; hence, the VPP schedules more reserve to mitigate the impacts of uncertainties in this condition. Moreover, supplement of scheduled reserves depends on the VPP risk perspective meaning that a higher risk-aversion behavior yields a lower required reserve capacity.

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