Novel Customer-Driven Demand Response Model for Facilitating Roof-top PV and Wind Power Integration

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Abstract: Integrating wind and solar energy resources poses intermittency to power systems, which faces Independent System Operators (ISOs) with new technical and economic challenges. This paper proposes a novel model to integrate the uncertainties of wind power on the supply side and roof-top solar PV on the demand side. In order to cope with their uncertainties, a Demand Response (DR) aggregator is proposed, which is enabled to participate in reserve markets. To this end, a new DR model is developed considering both customers' options to reduce and increase load through the DR aggregator. As such, besides improving the existing DR models (load shifting and curtailment), two DR programs, i.e., load growth and load recovery, are mathematically modelled. Numerical studies indicate the effectiveness of the proposed model to reduce the total operation cost of the system and facilitate the integration of wind power and roof-top PV.

Keywords: Demand response, energy and reserve markets, load growth, load recovery, roof-top PV, wind power.

1. Introduction

1.1. Background, Motivation and Aim

Intermittent renewable resources are rapidly growing in power systems worldwide. Wind power producers (WPP) are dominant, where they are becoming matured enough in some countries such as Denmark and Germany. These producers impose uncertainty to the supply side, which may enforce ISOs to spill their power when the security of the system is jeopardized. On the other hand, solar PV penetration, mainly presented in the form of roof-top PVs in some countries such as Australia, adds uncertainty and variability to the demand side (e.g. see Fig. 1), being beyond the control for an ISO.

These uncertainties from both supply and demand sides enforce difficulties in market clearing by ISOs. Various solutions are proposed to facilitate renewable energy uncertainties, where the highest flexibility and the lowest cost belong to utilizing Demand Response (DR) programs [2, 3]. These benefits have extensively enhanced DR roles in electricity markets worldwide. Prior to others, Federal Energy Regulatory Commission (FERC) has established order 719, which requires market operators to accept DR offers in the US markets [4, 5]. While other electricity markets in Canada and Singapore allow DR participation in electricity markets, the Australian National Electricity Market (NEM) is investigating new rules to allow DR participation in ancillary services markets [6]. To this end, DR aggregators could procure DR from small consumers to sell it to electricity markets. This role requires a new model for DR aggregators through which they accurately model consumers' characteristics and thus provide their technical constraints when enrolling in electricity markets. Further, ISOs would encourage DR programs to help alleviate wind spillage, but also allow better utilize roof-top PVs during off-peak periods.

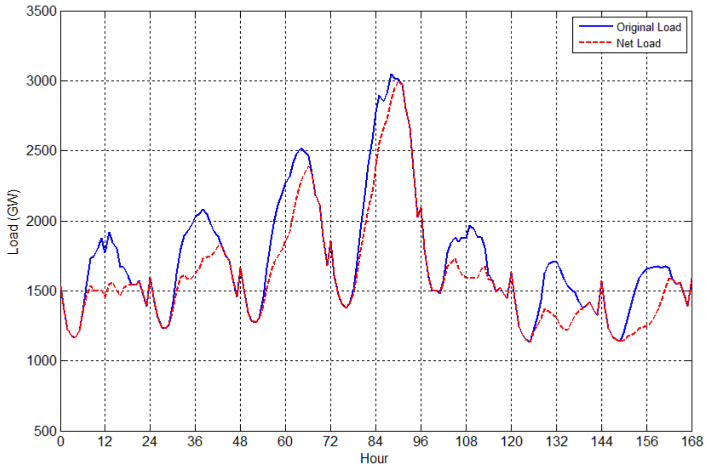


Fig. 1. *Original vs. net load profile (SA, 14-22 January) [1]*

This paper accordingly aims to study the problem of integrating wind and roof-top PVs. To this end, a stochastic unit commitment is mathematically formulated through which uncertainties associated with wind power production on the supply side, and roof-top PVs on the demand side are considered. Further, a novel DR model is formulated considering both load reduction and load increment programs. Moreover, consumers' constraints are comprehensively modelled through which DR aggregators could accurately capture consumers' behaviour when offering in reserve markets.

1.2. Literature Review

DR participation in electricity markets has recently received a great deal of attention [5, 7-9]. DR participation in reserve markets is studied in [5], where a deterministic unit commitment is modelled though which a DR aggregator employs only load curtailment and load shifting programs. Ref. [7] models demand bidding in energy markets, while it is assumed that DR does not enrol in reserve markets. Authors in [8, 9], respectively, use DR for ancillary services markets and critical peak pricing. The given studies disregard wind and solar energy impacts on electricity markets while formulating simple deterministic unit commitment models. There are some investigations addressing the benefits of employing DR to alleviate wind power uncertainty in electricity markets. These studies are mostly from the perspectives of wind power producers [10-14], while some papers deliver new models from an ISO's viewpoint [15-20]. A robust unit commitment is proposed in [15], which uses DR to overcome wind power uncertainty, while DR is modelled as an uncertain elastic demand. DR is allowed to participate in reserve markets in [16] to lessen wind power uncertainty. DR applications in high wind power systems such as in the UK and Germany are addressed in [17] and [18], respectively. Authors in [19] recommend coupling of deferrable load with wind power producers for easing their power uncertainties in the market. A joint energy and spinning reserve markets model is formulated in [20], where wind power uncertainties are covered using generation and demand side reserves. A network-constraint day-ahead market is proposed in [21] through which flexible load capability is used to facilitate wind power integration. Authors in [22] develop a new DR exchange model in which flexible load bidding is considered for participating in day-ahead markets with variable renewable resources. Technical and economic benefits of demand response to support systems integrating wind energy are validated through a day-ahead network-constraint market clearing formulation [23]. Load shifting programs are applied in [24] to facilitate network congestions and enhance wind utilization in the system. The abovementioned studies model wind power uncertainties only, while mostly modelling DR programs without considering the technical constraints of consumers.

The studies of roof-top PVs mainly investigate their impact on distribution networks while a few references model small-scale PV participation in electricity markets. Authors in [25] use storage systems along with an energy management strategy to enable PV participation in day-ahead and intraday markets. In [26], DR is employed to improve the power quality by reducing PV power fluctuations. A system with high penetration of PV is studied in [27], where DR and storage systems are employed to enable this integration. In [28], an isolated system including high penetration of wind and PV generation is studied while DR is not taken into account.

1.3. Contributions

Table 1 clearly compares the most relevant existing studies and the proposed model in this paper (all from the ISO's perspective). Overall, the contributions of the paper are listed as follows.

- This paper develops a comprehensive DR model, which on one hand considers the technical constraints of consumers and on the other hand formulates load increment programs to alleviate wind and solar power spillage. Our work contributes to the existing DR models such as the one presented in [5], by developing customer-driven constraints such as maximum and minimum valid duration for each program, maximum ramp rate, and energy limits to represents customers' behaviour in each DR program. Further, we mathematically formulate load growth and load recovery programs and illustrate their benefits in power systems integrating wind and solar PV.

- This paper formulates an energy and reserve markets auction which simultaneously models wind on the supply side and roof-top PV on the demand side, while utilizing the proposed DR model to cope with their uncertainties. A two-stage stochastic market dispatch is formulated in which the associated uncertainties of wind and solar are addressed through their plausible scenarios. Further, the given model allows DR aggregators participation in reserve markets as similar to conventional generators. As presented in Table 1, simultaneously considering DR aggregators, wind power producers and PV generation has not been reported.

Table 1. Comparison of the reported models in the literature

	[5, 7-9]	[15-25]	Our Model
Approach	Deterministic	Robust, Stochastic	Stochastic
Markets	Energy, Reserve	Energy & Reserve	Energy & Reserve
Uncertainties	No	Wind generation	Wind generation, Roof-top PV generation
Demand Response	Load reduction	Load reduction	Customer options for Load Reduction and Load Increment
WPP Model	-	Yes	Yes
PV Model	-	-	Roof-top PV

2. Proposed Model

The proposed model considers a joint day-ahead energy and reserve auction through which the key decisions are energy dispatch, reserve capacity, and reserve deployment from market participants. To this end, conventional generators are assumed to offer both energy and reserves in the market. Wind power producers offer in the energy market, while the ISO may spill their power in real-time for the sake of the system security. On the demand side, roof-top PV is considered as uncertain negative demand, which is subtracted from the original load. In addition, a DR aggregator is proposed which provides upward and downward reserves. The proposed problem is formulated in a stochastic unit commitment in which the uncertainties associated with wind power on the supply side and roof-top PV output on the demand side are considered.

2.1. Demand Response

The proposed DR aggregator offers capacity reserves in the day-ahead market, which is deployed in the real time according to the ISO's requirement. To this end, the DR aggregator considers four major DR programs as its resources. Load shifting is amongst the most popular DR programs, in which the DR aggregator requests its DR participants to reduce their load during a specific period of a day, while they can recover the reduced load in the remaining periods through load recovery programs. In addition, the DR aggregator may need to curtail customers load during predefined periods. Finally, the DR aggregator may need to encourage customers to consume more energy through a load growth program. This is specifically useful for integrating renewable resources into the grid, where the ISO might require more consumption to cope with their production uncertainty.

Each DR program has technical limitations such as the period to implement, minimum and maximum potentials, minimum and maximum durations, energy limit, maximum rate of change for one period to the next one, and the number of times that the DR aggregator can call them on a day. These constraints are modelled in the following terms.

$$F_{dra,w,t}(drp) \le F^{\max}_{dra,t}(drp).V_{dra,t}(drp).T^{On}_{dra,t}(drp) \qquad \forall drp, dra, w, t \tag{1}$$

$$V_{dra,t}(drp) - V_{dra,t-1}(drp) = I_{dra,t}(drp) - S_{dra,t}(drp) \quad \forall drp, dra, t \tag{2}$$

$$I_{dra,t}(drp) + S_{dra,t}(drp) \le 1 \quad \forall drp, dra, t \tag{3}$$

$$\sum_{k=t}^{k+D^{\min}_{dra}(drp)-1} V_{dra,t}(drp) \ge D^{\min}_{dra}(drp).I_{dra,t}(drp) \qquad \forall drp, dra, t \tag{4}$$

$$\sum_{k=t}^{k+D^{\max}_{dra}(drp)-1} S_{dra,t}(drp) \ge I_{dra,t}(drp) \;\; \forall drp, dra, t \tag{5}$$

$$\left| F_{dra,w,t}(drp) - F_{dra,w,t-1}(drp) \right| \le roc_{dra,t}(drp) \;\; \forall drp, dra, w, t \tag{6}$$

$$\sum_{w=1}^{NW} \pi(w) \sum_{t \in T^{On}_{dra,t}(drp)} F_{dra,w,t}(drp) \le E_{dra}(drp) \qquad \forall drp, dra \tag{7}$$

$$\sum_{t \in T^{On}_{dra,t}(drp)} I_{dra,t}(drp) \le N_{dra}(drp) \quad \forall drp, dru \tag{8}$$

The first constraint limits the maximum capacity of the DR program drp by the DR aggregator dra at time t. Note that $T^{On}_{dra,t}(drp)$ is the period in which the DR program is valid, and $V_{dra,t}(drp)$ indicates if the DR aggregator uses the given DR program. Constraints (2) and (3) respectively declare the status of the DR program drp at time t, and the initializing and stopping states of the given DR program. Equations (4) and (5) consider the minimum and maximum durations of the DR program drp, respectively. Constraint (6) imposes that load increase/decrease in two consecutive periods is limited by a maximum rate of change. The energy limit of the DR program is limited in constraint (7). Finally, the number of DR programs which can be carried out on a day is posed in (8). Accordingly, each DR program is defined as follows. Load curtailment and load shifting programs have the identical aim at reducing the load consumed by customers. These programs are modelled using (1)-(8). For load shifting, however, constraint (9) is required to illustrate the rate of the load recovery from load shifting programs. Note that the recovery volume depends on the recovery factor (RCF_{dra}) which is given by customers.

$$\sum_{w=1}^{NW} \pi(w). \sum_{\substack{t \in \\ T^{On,LS}_{dra,t}}} F_{dra,w,t}(ls) = \sum_{w=1}^{NW} \pi(w).RCF_{dra} \sum_{\substack{t \in \\ T^{On,LRC}_{dra,t}}} F_{dra,w,t}(lrc) \qquad \forall dra \tag{9}$$

Lastly, load recovery and load growth programs are formulated using (1)-(8), whose aim is to encourage consumers to use more energy during off-peak periods.

Overall, load shifting and load curtailment programs are used when the DR aggregator provides reserve up (see (10)), while load recovery and load growth programs are applicable in reserve down offers by the DR aggregator, as indicated by (11).

$$r_{dra,w,t}^{dr,u} = F_{dra,w,t}(lc) + F_{dra,w,t}(ls) \quad \forall dra, w, t \tag{10}$$

$$r_{dra,w,t}^{dr,d} = F_{dra,w,t}(lrc) + F_{dra,w,t}(\mathrm{lg}) \quad \forall dra, w, t \tag{11}$$

Note that several flexible load control programs match the proposed DR formulations. For instance, residential customers may adjust their air conditioners in a higher temperature to fulfil load curtailment programs (load curtailment). Or they may shift their pool pump or water heater usage from peak to off-peak periods (load shifting and recovery programs). Lastly, some large consumers may be encouraged to increase their consumption if utilities request (load growth). These are practical DR programs used in several countries such as Australia (e.g., in Australia, Energex as a distribution network service provider carries out the mentioned DR programs).

2.2. Market formulation

The ISO aims at minimizing the cost of the system, which is formulated in (12), followed by constraints (13)-(46).

Minimize

$$\begin{aligned}
&\sum_{t=1}^{T}\sum_{i=1}^{NG}(C_{i,t}^{SU} + C_{i,t}P_{i,t} + C_{i,t}^{RU}R_{i,t}^{U} + C_{i,t}^{RD}R_{i,t}^{D}) \\
&+\sum_{t=1}^{T}\sum_{wu=1}^{WU} C_{wu,t}^{W}P_{wu,t}^{W,S} \\
&+\sum_{t=1}^{T}\sum_{dra=1}^{DRA} C_{dra,t}^{DR,RU}R_{dra,t}^{DR,U} + C_{dra,t}^{DR,RD}R_{dra,t}^{DR,D} \\
&+\sum_{t=1}^{T}\sum_{w=1}^{NW}\pi(w)\left(\sum_{i=1}^{NG} c_{i,t}^{ru}r_{i,w,t}^{u} - c_{i,t}^{rd}r_{i,w,t}^{d}\right. \\
&\qquad + \sum_{dra=1}^{DRA} c_{dra,t}^{dr,ru}r_{dra,w,t}^{dr,u} - c_{dra,t}^{dr,rd}r_{dra,w,t}^{dr,d} \\
&\qquad \left. + \sum_{wu=1}^{WU} C_{wu}^{W,spill}P_{wu,w,t}^{spill} + \sum_{j=1}^{J} Voll_{j}L_{j,w,t}^{Shed}\right)
\end{aligned} \tag{12}$$

Subject to:

A- Day-ahead constraints

$$\sum_{\substack{i=1,\\ i\in In}}^{NG} P_{i,t} + \sum_{\substack{wu=1,\\ wu\in WUn}}^{WU} P_{wu,t}^{W,S} - \sum_{\substack{j=1,\\ j\in Jn}}^{J} L_{j,t}^{S} - \sum_{\substack{l=1,\\ l\in Ln}}^{L} F_{l,t} = 0 \qquad \forall n,t \tag{13}$$

$$F_{l,t} = \frac{1}{X_l}(\delta_{ls,t} - \delta_{lr,t}) \quad \forall l,t \tag{14}$$

$$-F_{l}^{max} \le F_{l,t} \le F_{l}^{max} \quad \forall l,t \tag{15}$$

$$0 \le P_{wu,t}^{W,S} \le P_{wu,t}^{W,\max} \quad \forall wu,t \tag{16}$$

$$P_{i,t} + R_{i,t}^{U} \le P_i^{\max} \quad \forall i,t \tag{17}$$

$$P_{i,t} - R_{i,t}^{D} \ge 0 \quad \forall i,t \tag{18}$$

$$0 \le R_{i,t}^{U} \le RU_i \quad \forall i,t \tag{19}$$

$$0 \le R_{i,t}^{D} \le RD_i \quad \forall i,t \tag{20}$$

B- Real-time constraints

$$\begin{aligned}
&\sum_{\substack{i=1,\\ i\in In}}^{NG} (r_{i,w,t}^{u} - r_{i,w,t}^{d}) \\
&+ \sum_{\substack{wu=1,\\ wu\in WUn}}^{WU} (P_{wu,w,t}^{W} - P_{wu,t}^{W,S} - P_{wu,w,t}^{spill}) \\
&- \sum_{\substack{j=1,\\ j\in Jn}}^{J} (L_{j,w}^{Net} - L_{j,t}^{S} - L_{j,w,t}^{Shed}) + \sum_{dra=1}^{DRA} (r_{dra,w,t}^{dr,u} - r_{dra,w,t}^{dr,d}) \\
&- \sum_{\substack{l=1,\\ l\in Ln}}^{L} F_{l,w,t} = 0 \quad \forall n,w,t
\end{aligned} \tag{21}$$

$$F_{l,w,t} = \frac{1}{X_l}(\delta_{ls,w,t} - \delta_{lr,w,t}) \quad \forall l,w,t \tag{22}$$

$$-F_l^{max} \le F_{l,w,t} \le F_l^{max} \quad \forall l,w,t \tag{23}$$

$$0 \le L_{j,w,t}^{Shed} \le L_{j,w,t}^{N} \quad \forall j,w,t \tag{24}$$

$$0 \le P_{wu,w,t}^{spill} \le P_{wu,w,t}^{W} \quad \forall wu,w,t \tag{25}$$

$$P_{i,w,t} = P_{i,t} + r_{i,w,t}^{u} - r_{i,w,t}^{d} \quad \forall i,w,t \tag{26}$$

$$P_i^{\min} u_{i,t} \le P_{i,w,t} \le P_i^{\max} u_{i,t} \quad \forall i,w,t \tag{27}$$

$$u_{i,t}, I_{i,t}, SD_{i,t} \in \{0,1\} \quad \forall i,t \tag{28}$$

$$u_{i,t} - u_{i,t-1} = I_{i,t} - SD_{i,t} \quad \forall i,t \tag{29}$$

$$I_{i,t} + SD_{i,t} \le 1 \quad \forall i,t \tag{30}$$

$$C_{i,t}^{SU} \ge SUC_i (u_{i,t} - u_{i,t-1}) \quad \forall i,t \tag{31}$$

$$P_{i,w,t} - P_{i,w,t-1} \le RU_i u_{i,t-1} + P_i^{SU} I_{i,t} \quad \forall i,w,t \tag{32}$$

$$P_{i,w,t-1} - P_{i,w,t} \le RD_i u_{i,t} + P_i^{SD} SD_{i,t} \quad \forall i,w,t \tag{33}$$

$$(X_{i,t-1}^{on} - T_i^{on})(u_{i,t-1} - u_{i,t}) \ge 0 \quad \forall i,t \tag{34}$$

$$(X_{i,t-1}^{off} - T_i^{off})(u_{i,t} - u_{i,t-1}) \ge 0 \quad \forall i,t \tag{35}$$

C- linking constraints

$$0 \le r_{i,w,t}^{u} \le R_{i,t}^{U} \quad \forall i,w,t \tag{36}$$

$$0 \le r_{i,w,t}^{d} \le R_{i,t}^{D} \quad \forall i,w,t \tag{37}$$

D- DR constraints

$$0 \le R_{dra,t}^{DR,U} \le RU_{dra}^{DR} \quad \forall dra,t \tag{38}$$

$$0 \le R_{dra,t}^{DR,D} \le RD_{dra}^{DR} \quad \forall dra,t \tag{39}$$

$$0 \le r_{dra,w,t}^{dr,u} \le R_{dra,t}^{DR,U} \quad \forall dra,w,t \tag{40}$$

$$0 \le r_{dra,w,t}^{dr,d} \le R_{dra,t}^{DR,D} \quad \forall dra,w,t \tag{41}$$

Equations (10)-(11) for DR up and down reserves (42)

Equations (1)-(9) for Load Shifting (43)

Equations (1)-(8) for Load Recovery (44)

Equations (1)-(8) for Load Curtailment (45)

Equations (1)-(8) for Load Growth (46)

The objective function comprises the following terms. The first line represents the cost of energy and capacity reserves by conventional generators. Line 2 indicates the offer cost of wind power producers. The capacity cost of DR is formulated in line 3. The fourth and fifth lines respectively represent the expected deployed reserves costs from generators and DR. Finally, the last line provides the costs of wind spillage and involuntary load shedding. Constraint (13) ensures the demand balance at each bus in the day-ahead market. The transmission line flow is formulated in (14)-(15). Wind power scheduled in the day-ahead market is limited in (16). Constraints (17)-(20) limit the energy and capacity scheduled for conventional generators.

Demand balance in the real-time operation is ensured in (21), while the line flow is represented in (22)-(23). Load shedding and wind spillage volumes are respectively constrained in (24) and (25). Real-time generation is formulated in (26) and is limited in (27). Equations (28)-(30) declare the binary status of generators, if they are ON, starting up, or shutting down in period t. The cost of starting up a unit in each period is declared in (31). Ramp up and down limits are satisfied in (32) and (33), while minimum on and off times are represented in (34) and (35). Deployed reserves up and down from generators must not exceed their capacity volumes (see (36) and (37)). Finally, DR capacity and deployment for reserves up and down are imposed in (38)-(41). Note that the given formulations for DR programs, i.e. load shifting, load curtailment, load recovery, and load growth, are considered as the last set of constraints. Note also that the network losses are disregarded while the model considers a DC power flow. Considering DC power flow is commonly used in similar unit commitment studies.

The proposed problem is a two-stage stochastic programming approach in which first and second-stage decisions are as follows. First stage variables decided before the realization of scenarios and called *here-and-now* decisions, are: scheduled power of conventional generators and wind power producers, scheduled day-ahead load, scheduled reserves up/down of generators, and scheduled reserves up/down of DR aggregators. Second-stage variables are the deployed reserves up/down of generators and DR aggregators, wind spillage and involuntarily load shedding. These variables are independent of scenarios and called *wait and see* decisions.

Fig. 2 depicts the scenario tree of the proposed problem. Uncertain parameters are wind and demand (including roof-top PV), which are represented through relevant scenarios.

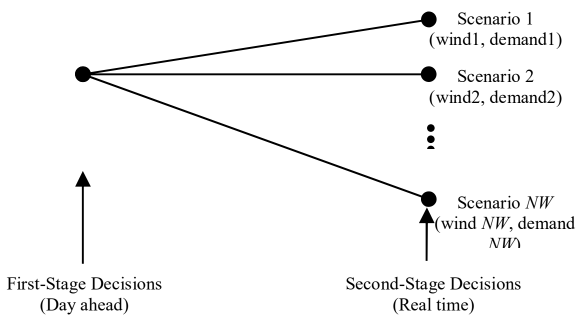


Fig. 2. *Scenario tree of the proposed stochastic problem*

Note that the stochastic programming approach is formulated individual weighting solutions associated with each input scenario, which gives a single solution representing the best of all input data. This objective function indeed represents the expect value of all solutions in a cost minimization form, which is mathematically modelled as a mixed-integer linear programming (MILP) problem.

2.3. Uncertainty characterization

2.3.1. Probabilistic model of wind speed

The generation of a wind power plant depends on wind speed and the characteristics of wind turbines. Weibull distribution function is a common function to model the wind speed [29], especially with the shape index of the so-called Rayleigh distribution functions [30]. On this basis, the hourly wind speed data has been employed for the generation of Rayleigh probability distribution functions (PDFs) formulated as follows:

$$f_r(v) = \left(\frac{2v}{c^2}\right)\exp\left(-\frac{v^2}{c^2}\right) \tag{47}$$

where $f_r(\cdot)$ denotes Rayleigh distribution function, and c is Rayleigh scale index that is determined from the historical data for each time period.

These continuous PDFs are sliced into several segments where each segment yields a mean value and a probability of occurrence. It should be noted that the probability of each segment at each hour is expressed as follows:

$$Prob_i^w = \int_{ws_i}^{ws_{i+1}} f_r(v)dv_i \tag{48}$$

where ws_i and ws_{i+1} indicate wind speed limits of segment i and $Prob_i^w$ represents the probability occurrence of segment i.

2.3.2. Probabilistic model of solar irradiance

The hourly solar irradiance data has been used to generate a Beta PDF [31] for each time period. Hence, the PDF of solar irradiance is formulated as:

$$f_b(x) = \begin{cases} \dfrac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} x^{(\alpha-1)}\left(1-x\right)^{(\beta-1)} & 0 \le x \le 1 \\ 0 & \text{Otherwise} \end{cases} \tag{49}$$

where $f_b(\cdot)$ is the Beta distribution function. s denotes the random variable. α and β are the parameters of the Beta function and are determined by the historical data.

In the same way, the Beta PDFs are split into several segments which the occurrence probability of each segment at each hour is expressed as follows.

$$Prob_i^s = \int_{s_i}^{s_{i+1}} f_b(s)ds_i \tag{50}$$

where s_i and s_{i+1} indicate solar irradiance limits of the interval i, respectively. $prob_i^s$ is the probability occurrence of interval i.

2.3.3. System Characterization

It should be noted that two different wind profiles (i.e., Wind 1 and Wind 2) are considered in this paper. The probabilistic generation of renewable power plants has been modelled according to the hourly historical data, during two whole years. In order to characterize the random behaviour of the renewable power plants, a typical day with 24-h time periods is considered. The data related to the same hours of the day are utilized to obtain the probability distribution functions (PDFs) corresponding to each time period, which also allows correlations of the distribution functions.

First, the PDFs for solar irradiance and wind speeds of Wind 1 and Wind 2 are obtained from the historical data. As discussed earlier, these continuous PDFs are sliced into several segments for each time period. Then, different realizations of the random variables, i.e., solar irradiance and wind speeds of Wind 1 and Wind 2, are generated using the roulette wheel mechanism (RWM) and Monte Carlo simulation (MCS) [32], separately. Therefore, N_s , $N_{wind\ 1}$ and $N_{wind\ 2}$ scenarios are generated for solar irradiance, wind speeds of Wind 1 and Wind 2, respectively. Note that each scenario process covers a 24-h time period of the typical day with its own probability of occurrence. A large number of scenarios may contribute to a more accurate model of the random variables. Nevertheless, it increases the computational burden of the problem. Thus, a fast forward scenario reduction method based on Kontorwish distance [33] is employed to decrease the number of scenarios while providing a reasonable approximation of random variable of the system.

3. Case study

The problem is a mixed-integer programming approach which is solved using CPLEX 11.1.1 under GAMS [34].

3.1. Six-bus system

A six-bus system is considered to assess the proposed problem as illustrated in Fig. 3. The information of this system is given in [35]. Three DR aggregators are considered at buses 3, 4 and 5. The data for demand response programs is provided in Tables 2 and 3. DR reserve offers are chosen in such a way to be close to that of conventional generators. Load recovery and load growth programs are considered for off-peak periods, where we have roof-top PV production and high wind power. Load shifting and load curtailment are assumed to be valid in the peak period. Two wind farms are modelled, where wind farm 1 is connected to bus 1 and wind farm 2 is located at bus 6. Wind power at each bus is assumed to have a capacity of 30% of the corresponding conventional power plant at that bus. The wind power production is taken from wind farms in the state of South Australia [36]. Roof-top PV is assumed to be 20% of loads at buses 3, 4 and 5. The realistic data of roof-top PV at the University of Queensland is used for the purpose of PV uncertainty modelling [37]. The uncertainty of wind and PV power is considered by ten scenarios as illustrated in Fig. 4. In this figure, cross-checks represent the scenarios, while solid lines present the expected values.

The VOLL is assumed to be $1000. In addition, we assume that the wind power producer places its offer price at zero. However, wind spillage cost is equal to $100/MW, as given in [38].

Seven cases (C1-C7) are considered to study the impacts of renewable energy resources and DR on the system.

C1: case 1 is carried out while only conventional generators are modelled.

C2: case 2 models the impact of wind and roof-top PV while DR is not considered.

C3: case 3 examines the impact of 5% DR on the system with wind and roof-top PV.

C4: case 4 is similar to C3, but considers 10% DR.

C5: case 5 is similar to C3, but considers 20% DR.

C6: case 6 is similar to case 4 (10% DR), but studies the system without roof-top PV.

C7: case 7 investigates how the higher penetration of roof-top PV affects the system (here also 10% DR is used).

The system cost is provided in Table 4. The total cost of the system declines as wind and PV are integrated to the system (see C2 vs. C1). This decrease is even further when the ISO uses DR to alleviate renewable uncertainties. The main reason behind this decline is the lower cost of wind spillage when DR is introduced (see C2 vs. C3-C5). Another interesting result is that the wind spillage cost increases as the penetration of PV grows (see C6 & C7), which is reasonable since the higher PV means the lower net load for the system. Finally, note that though the deployed DR cost is negative (due to further energy usage by consumers as a result of the load growth program), the overall capacity and deployed DR cost is positive for the system. Further, the cost of wind spillage due to conventional generation and line limits are provided in this table. The results indicate that negligible line congestions occur in the given system, while the majority of the spillage cost is due to conventional generation limits.

The majority of the wind spillage occurs in wind farm 2. The results in Table 5 illustrate how DR alleviates the wind spillage in different periods. This is more obvious for the system with and without DR (C2 vs. C3), where the wind spillage declines to less than half when the ISO uses 5% DR. In addition, the wind spillage increase as a result of higher PV penetration is evident at hours 7-10 in case 7 compared to case 6. This indeed confirms the wind spillage cost growth mentioned in Table 4.

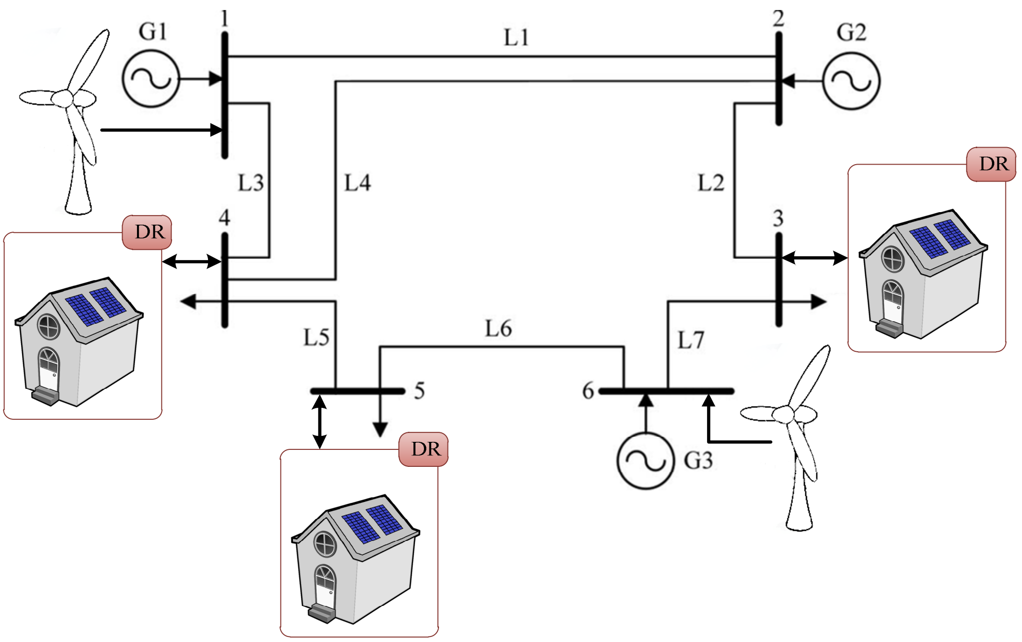


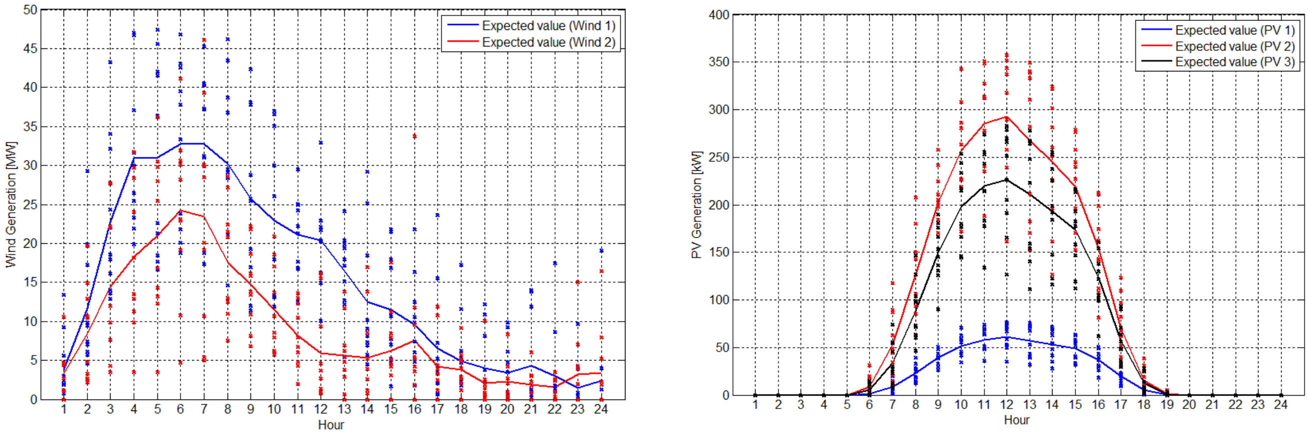
Fig. 3. *One-line diagram of the 6-bus system including wind power generation and roof-top PVs*

Table 2. The ramp up (RU) and ramp down (RD) reserves by DR

	RU Capacity Cost ($/MWh)	RD Capacity Cost ($/MWh)	RU Deployment Cost ($/MWh)	RD Deployment Cost ($/MWh)	RU Max Ramp (MW)	RD Max Ramp (MW)
DR Aggregator 1	20	20	30	30	5	5
DR Aggregator 2	50	50	70	70	15	15
DR Aggregator 3	15	15	25	25	5	5

Table 3. DR programs data

	Min Duration	Max Duration	Max Energy (MWh)	Valid Period
Load Shifting	4	7	30	15-22
Load Recovery	8	11	30	2-13, 23-24
Load Curtailment	4	6	20	15-22
Load Growth	4	6	20	2-14, 23-24



a) Wind power *b) PV*

***Fig. 4.** Generation scenarios*

Table 4. System cost ($)

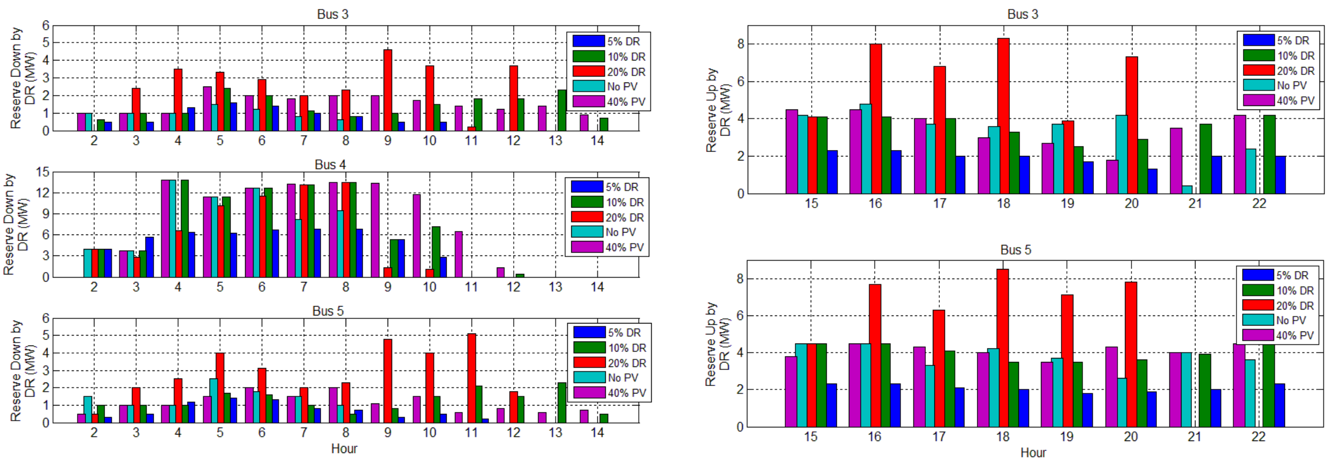
	Total	Energy	Cap. Res. Gen.	Cap. Res. DR	Dep. Res. Gen.	Dep. Res. DR	Wind Spillage due to generation limits	Wind Spillage due to line limits
C1: Conv.	168509	154859	5621	0	8030	0	0	0
C2: NO DR	153276	120062	14138	0	6212	0	12724	143
C3: 5% DR	144886	116773	14379	4548	6543	-2939	5522	62
C4: 10% DR	140988	120352	11647	8969	2980	-5144	2164	21
C5: 20% DR	139499	120345	10621	8847	2589	-3877	968	8
C6: No PV	154819	131482	11577	6186	6814	-3294	2035	20
C7: 40% PV	132889	109355	14255	9624	1900	-6302	4011	48

Table 5. Wind Spillage of Wind Farm 2 in different cases (MW)

Hour	2	3	4	5	6	7	8	9	10
C2: NO DR	1.4	4.6	10.2	13.3	14.8	10.2	4.7	0.5	0.1
C3: 5% DR	1.2	1.9	4.5	7.6	7.2	3.9	1	0.2	0
C4: 10% DR	0.9	1.5	1.9	2.3	2.4	1.1	0	0	0.1
C5: 20% DR	0.9	1	1.3	0.7	0.7	0.4	0	0	0
C6: No PV	1.4	1.5	1.9	2.3	2.2	1.1	0	0	0
C7: 40% PV	0.9	1.5	1.9	2.3	2.8	2.6	3.5	0.6	2.7

Fig. 5 delivers the reserves down and up deployed from DR aggregators at different buses. The main findings are as follows. Increasing the DR potential allows the ISO to deploy more reserve down in almost all hours. This is more obvious for the 20% DR case. This trend is also true for the case with 40% PV compared to the case without PV, where more reserve down is used as PV starts producing power. It is also illustrated that the DR volume employed at bus 4 is significantly higher than other buses. This is due to the higher load at this bus as well as the assumption that we consider the DR aggregator at this bus pays more for additional usage (see the reserve down cost of DR aggregator 2 in Table 2).

As for the deployed reserve up from DR aggregators (Fig. 5.b), increasing the DR potential leads to a higher reserve up deployed from DR aggregators 1 and 3. As it is expected, the DR aggregator at bus 4 has no contributions to the upward reserve, due to its expensive DR cost (See Table 2). In addition, it can be seen that PV has a slight impact on DR participation in the reserve up market. This is reasonable as main PV production is during 6am-6pm (Fig. 4.b).



a) Reserve Down

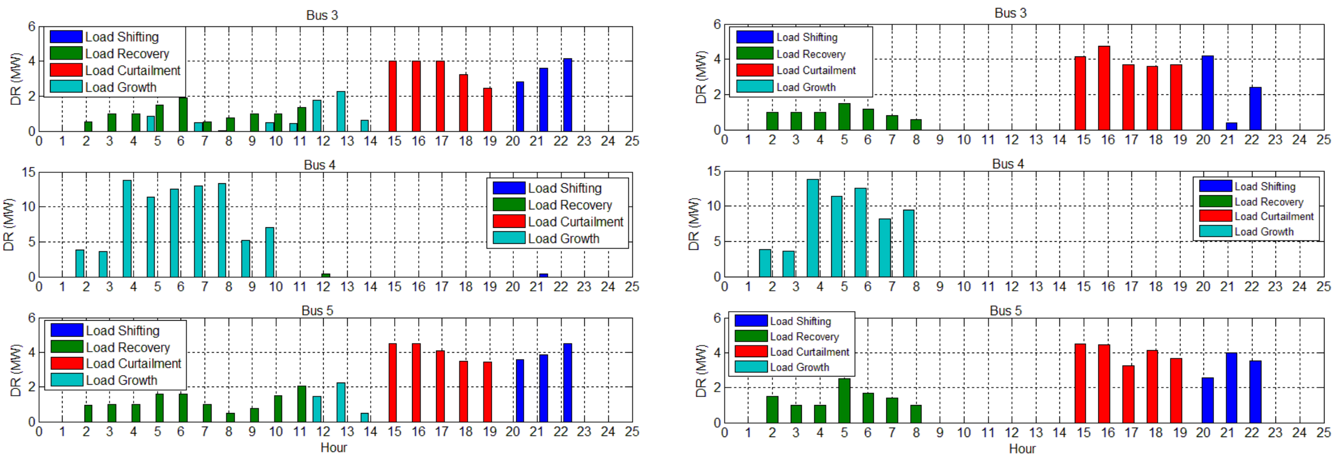
b) Reserve Up

Fig. 5. Reserve Up/Down by DR in different cases

To further investigate the contribution of DR on reserves up and down, Fig. 6.a displays the share of each DR program at each hour. The main results for buses 3 and 5 are as follows. Load curtailment is used during the early hours of period 15-22, while load shifting is used in late night.

In addition, load curtailment has a higher share in reducing load during hours 15-22 than does load shifting. This is sensible since load shifting has a limitation, through which the shifted load has to be recovered in other periods. Furthermore, the importance of modelling the load recovery program is obvious, where the ISO distributes the recovered load during hours 2-11, in order to facilitate wind and PV uncertainties during these hours. The same interpretation is true for the load growth program. Note that the results for bus 4 clearly confirm the reserves down and up shown in Fig. 5. Indeed, the load growth is the only program that provides reserve down, while almost no other DR programs (load shifting and load curtailment) providing the reserve up are used.

Fig. 6.b assesses the impact of PV on different DR programs. It is evident that PV leads to employing more DR (See Fig. 6.a vs. Fig. 6.b). This is particularly true for PV peak hours, i.e. 10-14, where no load growth and load recovery are required for these hours in the case without PV production. Also, the results indicate that PV has a negligible impact on load shifting and load curtailment programs, which confirms the reserve up outcome provided in Fig. 5.b.



a) 10% DR with PV

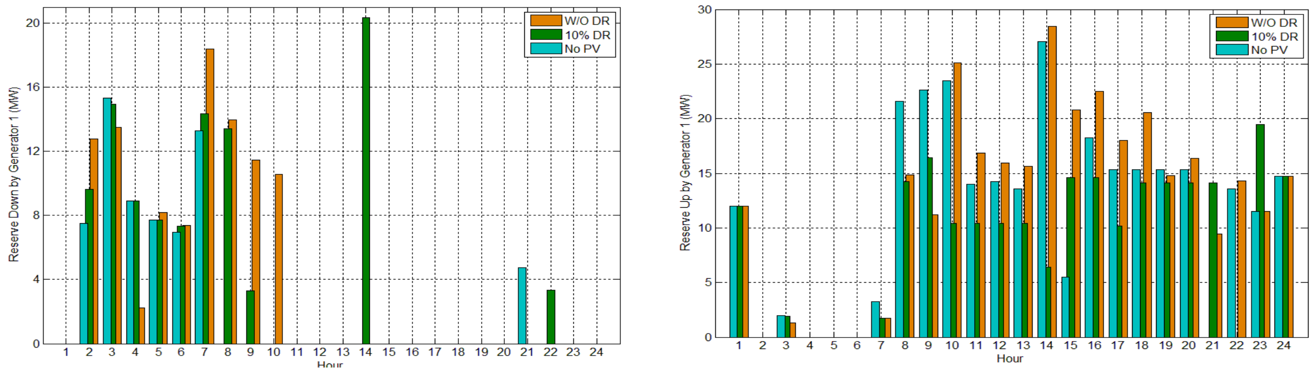
b) 10% DR without PV

Fig. 6. *DR programs outcome at each bus (10% DR with PV)*

The amounts of reserves down and up by generator 1 are shown in Fig. 7. Note that generator 1 is the only generator participates in the reserve market. One reason is that the DR aggregator close to this generator, i.e. DR aggregator 2, is expensive which makes the ISO to use conventional generation for reserve. From Fig. 7.a, it is evident that in early morning hours, when wind power is high, the need for the reserve down is high. It can also be stated that DR penetration changes the reserve down pattern provided by generator 1. This is because DR has a limited period of availability as well as a limited amount of energy, as per equation (7). Therefore, the ISO has to use the reserve down from generator 1 when DR is not available. In addition, it can be seen that PV desires the need for the reserve down deployment from generator 1 regardless the availability of DR. In cases with PV, the ISO deploys the reserve down from generator 1 during hours 8-14, while in the case of no PV, this reserve is not required.

As for the reserve up deployed from generator 1, it can be said that both introducing DR and a higher penetration of PV reduce the share of this generator in the reserve up in most periods.

In order to further investigate the effectiveness of the load growth program, the wind spillage volumes with and without this program are compared, which is shown in Fig. 8. The results clearly demonstrate that the load growth program significantly decreases the amount of wind spillage, which is particularly evident at hours 4, 7 and 8.



a) Reserve Down *b) Reserve Up*

Fig. 7. *Reserve Up/Down by Generator 1*

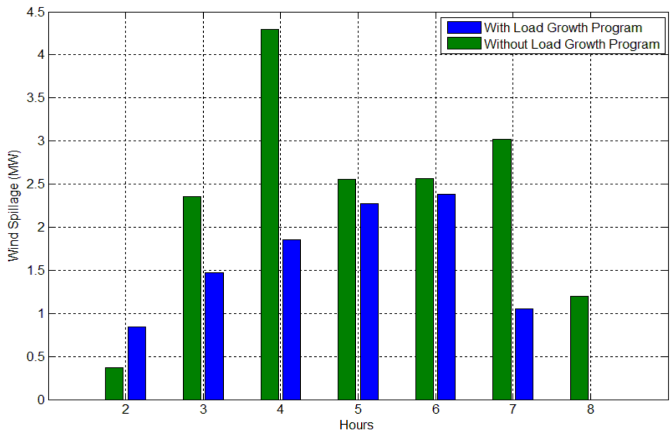


Fig. 8. *Wind spillage with and without the load growth program*

3.2. The IEEE RTS

This section validates the results using the IEEE RTS 24-bus system. The data is obtained from [38]. The capacity and deployment costs of reserves up and down by generators are assumed 30% and 100% of their highest incremental cost of energy, respectively. Table 7 shows the buses to which wind, roof-top PV and DR are connected. DR reserve capacity and deployment costs are assumed in such a way to be close to the relevant cost of conventional generators. Table 7 presents the data of DR aggregators. Note that the duration and valid periods for each program are similar to that of the 6-bus system. Wind and PV scenarios are also similar to the 6-bus system.

Table 6. Bus connections of new wind, roof-top PV and DR

	Bus numbers
Wind farms	1,2,4,6,9, 15,16,18,19,21
Roof-top PV	1,2,6,7,8,10,15, 16,18,19,20
DR	1,2,4,6,9,10, 15,16,18,19,20

Table 7. DR cost and energy limits for various programs

	Capacity Cost of RU	Capacity Cost of RD	Deployment Cost of RU/RD	Energy Load Shifting (MWh)	Energy Load Recovery (MWh)	Energy Load Curtailment (MWh)	Energy Load Growth (MWh)
DR 1	3.5	1	15	60	60	50	81
DR 2	3.5	1	15	54	54	45	72
DR 3	3.5	1	15	41	41	34	55
DR 4	3.5	1	15	76	76	64	102
DR 5	3.5	1	15	97	97	81	129
DR 6	3.5	1	15	108	108	90.1	144.2
DR 7	2.5	0.6	10	176	176	147.1	235.3
DR 8	2.5	0.6	11	56	56	46.38	74.2
DR 9	1	0.2	5	186	186	155	248
DR 10	2.5	0.6	11	102	102	84.8	135.7
DR 11	2.5	0.6	11	72	72	59.63	95.4

Five cases are studied here.

Case 1: Conventional system without wind, PV and DR;

Case 2: System with wind and PV, but no DR;

Case 3: The system integrates wind, PV and 10% DR;

Case 4: Similar to case 3, but without PV;

Case 5: Similar to case 2, but with 20% DR.

Table 8 represents the total cost of the system as well as the wind spillage cost for each case. The result clearly validates the outcome obtained from the 6-bus system. Overall, the system cost declines if we integrate wind and roof-top PVs, and this decrease is even more when using DR. In addition, wind spillage cost decreases with the higher employment of DR. This is also true for roof-top PV whose disintegration increases the wind spillage cost by around 10% in this study (see C3 vs. C4).

Table 8. Total system and wind spillage costs

	Expected Cost ($)	Wind Spillage Cost ($)
C1: Conventional System	452751	0
C2: W/O DR	381458	40225
C3: 10% DR	377679	37652
C4: W/O PV	405082	36586
C5: 20% DR	374860	34392

Fig. 9 depicts the volume of the wind spillage in different cases. This indeed confirms the discussion mentioned earlier on how DR and roof-top PV affect wind power which is spilled by the ISO. Increasing DR penetration significantly declines the wind spillage volume. That is, when integrating 10% DR, the wind spillage declines by around 15% while 20% DR employment leads to a wind spillage decrement of around 14%. Note that, roof-top PV has less impact on wind spillage as its peak production does not correlate with wind peak periods (see Fig. 4).

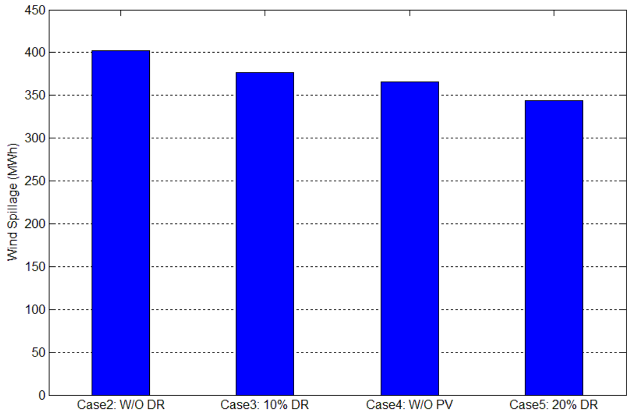


Fig. 9. Wind spillage volume in various cases

3.3. Computational issues

The issue of computational burden of stochastic programming models is discussed in similar investigations [7, 38]. One reason is the number of scenarios, which can be overcome using sufficient small numbers to make the problem tractable. The other reason is the large number of binary variables, which does not increase the computational time significantly, since the problem is linear [7]. Table 9 compares the running time for the 6-bus and IEEE RTS cases. Note that the problem is solved using a personal computer with the processor of Intel® core™ i7 at 3.4 GHz and RAM of 8 GB. The model statistics (6-bus, IEEE RTS) are as follows: blocks of equations and variables are (89,88) and (51,52), respectively. Single variables are (11599, 46927) and discreet variables are (1080, 4032).

Table 9. Problem computational time

Case	Time
6-Bus system	1:51min
IEEE RTS	2:42min

3.4. Impact of modelling DR constraints

This section further assesses the impact of modelling customers' constraints for each DR program (i.e., Equations (1)-(8)) on the outcome which the ISO expects from DR. To this end, the problem is solved while disregarding all constraints and only considering energy limit that each DR program can provide (this is the case modelled in other DR modelling investigations). The cost results are compared in Table 10. Although disregarding customers' constraints has a slight impact on the total cost of the system, the cost reduction for wind spillage is considerable. That is, if the ISO ignores customers-driven constraints, it may expect lower wind spillage and consequently lower cost, while this may not be achievable in practice.

Table 10. System and wind spillage costs with and without modelling consumers constraints

	Total Cost ($)	Wind Spillage Cost ($)
C3: 10% DR	377679	37652
No DR constraint	377562	34111

Further, we compare the DR usage in both cases in Table 11. Disregarding DR constraints lead to a higher DR usage of around 6%, while this potential may not be available in the real case. This significant increment is primarily due to a considerable increase of using load curtailment and load growth programs, though load shifting and consequently load recovery shares decrease in the case of having no DR constraints. Note that one reason for this decline is that the reserve up/down constraints for the DR provided in the reserve market (i.e. Equations (38)-(41)) still exist, which limit the overall DR usage.

Table 11. DR usage with and without modelling consumers' constraints

	Total DR	Load Curtailment	Load Growth	Load Shifting	Load Recovery
No DR Constraint	561.07	147.74	245.95	83.691	83.691
Full Model	529.72	89.41	156.26	142.02	142.02

4. Conclusions

This paper proposes a novel DR model through which an ISO mitigates wind and PV power uncertainties. The model formulates load shifting and load curtailment programs as upward reserve providers, and load growth and load recovery programs for meeting downward reserve commitments. The main findings are as follows.

1- Integrating wind and PV decreases the total cost of the system. The cost further declines when DR is enabled to participate in the reserve market. This is mainly due to a lower wind spillage volume when modelling DR.

2- While roof-top PV integration increases the need for the reserve down by DR, it has an insignificant impact on the upward reserve provided by the DR aggregator.

3- Load recovery and load growth programs have key roles in enhancing PV integration into the system. This is particularly true for load growth due to its more flexibility compared to the load recovery program (e.g. the share of load growth is three times as that of load recovery in out 24-bus case study).

4- Load growth can reduce the wind spillage during early morning when the wind power production is high.

5- One contribution of the work is proved, where the results indicate that disregarding the proposed DR constraints may mislead the DR aggregator in its potential DR obtained from consumers (up to 6% in our case study).

The proposed model in this paper can be further improved in following aspects. First, the integration of battery storages and electric vehicles as the key distributed energy resources in future power systems is essential to study as they may have high impacts on intermittent wind and solar PV. Given this, the stochastic model could be complex, which may need developing new approaches such as Bender Decompositions methods to make it solvable using commercially-available optimization tools.

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Nomenclature

Indices

t	Index of time periods $t=1,\ldots,T$
i	Index of conventional units $i=1,\ldots,NG$
wu	Index of wind power units $wu=1,\ldots,WU$
dra	Index of DR aggregators $dra=1,\ldots DRA$
drp	Index of DR program $drp=1,\ldots DRP$
j	Index of loads $j=1,\ldots,J$
w	Index of scenarios $w=1,\ldots,NW$
l	Index of lines $l=1,\ldots,L$
lc	Index of load curtailment programs
ls	Index of load shifting programs
lrc	Index of load recovery programs
lg	Index of load growth programs

Parameters

$C_{i,t}$	Production cost of conventional units
$C_{i,t}^{RU}$	Offer capacity cost of up-reserve of conventional units

$C_{i,t}^{RD}$	Offer capacity cost of down-reserve of conventional units
$C_{wu,t}^{W}$	Offer cost of wind power units
$C_{dra,t}^{DR,RU}$	Offer capacity cost of up-reserve of DR
$C_{dra,t}^{DR,RD}$	Offer capacity cost of down-reserve of DR
$c_{i,t}^{ru}$	Offer energy cost of up-reserve of conventional units
$c_{i,t}^{rd}$	Offer energy cost of down-reserve of conventional units
$c_{dra,t}^{dr,ru}$	Offer energy cost of up-reserve of DR
$c_{dra,t}^{dr,rd}$	Offer energy cost of down-reserve of DR
$C_{wu}^{W,spill}$	Cost of wind spillage of wind power units
$D_{dra}^{\max}(drp)$	Maximum ON time of DR program drp
$D_{dra}^{\min}(drp)$	Minimum ON time of DR program drp
$E_{dra}(drp)$	Max energy which can be provided by program drp
$F_{dra,t}^{\max}(drp)$	Max available DR volume by program drp
F_{l}^{max}	Maximum capacity of line l
$L_{j,w,t}^{N}$	Net load j in period t
$N_{dra}(drp)$	Maximum number of DR program drp
$P_{i,w,t}$	Real power output of conventional units
$P_{wu,t}^{W,\max}$	Maximum capacity of wind power units
$P_{wu,w,t}^{W}$	Power production of wind power units
$P_{i}^{\max}$	Maximum capacity of conventional units
RU_{i}	Ramp-up limit of conventional units
RD_{i}	Ramp-down limit of conventional units
RU_{dra}^{DR}	Ramp-up limit of DR aggregators
RD_{dra}^{DR}	Ramp-down limit of DR aggregators
RCF_{dra}	Recovery factor of load recovery programs
$roc_{dra,t}(drp)$	Maximum rate of change of DR program drp between two consecutive periods
SUC_{i}	Start-up cost of conventional unit i
T_{i}^{on}	Minimum ON time of conventional unit i
T_{i}^{off}	Minimum OFF time of conventional unit i
$Voll_{j}$	Value of lost load j
$X_{i,t}^{on}$	ON time duration of conventional units
X_{l}	Reactance of line l
$X_{i,t}^{off}$	OFF time duration of conventional unit
$\pi(w)$	Probability of scenario w

Variables

First-Stage Decisions:

$C_{i,t}^{SU}$	Start-up cost of conventional units

$L_{j,t}^{S}$	Scheduled load j
$P_{i,t}$	Scheduled power of conventional units
$P_{wu,t}^{W,S}$	Scheduled power of wind power units
$R_{i,t}^{U}$	Scheduled up-reserve of conventional units
$R_{i,t}^{D}$	Scheduled down-reserve of conventional units
$R_{dra,t}^{DR,U}$	Scheduled up-reserve of DR aggregators
$R_{dra,t}^{DR,D}$	Scheduled down-reserve of DR aggregator
$u_{i,t}$	Binary variable indicating the on/off status of conventional units
$I_{i,t}$	Binary variable indicating the start-up status of conventional unit i at the beginning of period t
$SD_{i,t}$	Binary variable indicating the shut-down status of conventional unit i at the beginning of period t

Second-Stage Decisions:

$F_{dra,w,t}(drp)$	DR volume by program drp
$L_{j,w,t}^{Shed}$	Load shedding of load j
$P_{wu,w,t}^{spill}$	Wind power spillage of wind power units
$r_{i,w,t}^{u}$	Deployed up-reserve of conventional units
$r_{i,w,t}^{d}$	Deployed down-reserve of conventional units
$r_{dra,w,t}^{dr,u}$	Deployed up-reserve of DR aggregators
$r_{dra,w,t}^{dr,d}$	Deployed down-reserve of DR aggregators
$V_{dra,t}(drp)$	Binary variable indicating the on/off status of deployed DR program drp in period t
$I_{dra,t}(drp)$	Binary variable indicating if DR program drp in period t is started
$S_{dra,t}(drp)$	Binary variable indicating if DR program drp in period t is stopped

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