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Real-Time Scheduling of Demand Response Options Considering the Volatility of Wind Power Generation

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***Abstract*—In this paper, a new methodology to unleash the potential of demand response (DR) in real-time is presented. Customers may tend to apply their DR potential in the real-time market in addition to their scheduled potential in the day-ahead stage. Thus, the proposed method facilitates balancing the real-time market via DR aggregators (DRAs). It can be vital once the stochastic variables of the network such as production of wind power generators (WPG) do not follow the forecasted production in real-time and have some distortions. Two-stage stochastic programming is employed to schedule some DR options in both day-ahead and real-time markets. DR options in real-time are scheduled based on possible scenarios that reflect the behaviors of wind power generation and are generated through Monte-Carlo simulation method. The merits of the method are demonstrated in a 6-bus case study and in the IEEE RTS-96, which shows a reduction in total operation cost.**

***Index Terms*—Optimal demand response, real-time market, two-stage stochastic programming, uncertainty handling, wind power generation.**

I. Nomenclature

A. Indices and sets

$g\ (NG)$	Thermal generators.
$k\ (NK)$	Offers of DR.
$l\ (NL)$	Branches.
$n\ (NN)$	Buses.
$s\ (NS)$	Real-time scenarios.
$t\ (NT)$	Time.

B. Abbreviations and superscripts

gen	Thermal Generators.
$scen$	Wind scenarios superscript.
TC, TS, TR	Time sets dedicated to load curtailment, shifting and recovery, respectively.
$\hat{X}$	LC, LS, and LR

C. Parameters

C_{tg}^{gen}	Thermal generation units cost.
$C_{tg}^{up}, C_{tg}^{down}$	Up and down thermal generators reserve cost, respectively.
$C_{g}^{strt.up}, C_{g}^{sht.dwn}$	Start-up/shut-down cost for thermal generators.
Cs_{tns}^{spill}	Cost of wind spillage for each scenario.
$Cs_{tgs}^{up}, Cs_{tgs}^{down}$	Cost of up/down reserve for each scenario.
Cs_{tns}^{voll}	Value of loss of load for each scenario.
$DR_{tnk}^{Cost,\hat{X}}$, $DRs_{tnk}^{Cost,\hat{X}}$	Cost of offering DR option $\hat{X}$ for offer k in day-ahead and in real-time market.
$DRK_{tnk}^{Min,\hat{X}}$, $DRKs_{tnk}^{Min,\hat{X}}$	Minimum possible DR option $\hat{X}$ for offer k in day-ahead and real-time market.
$DRK_{tnk}^{Max,\hat{X}}$, $DRKs_{tnk}^{Max,\hat{X}}$	Maximum possible DR option $\hat{X}$ for offer k in day-ahead market and real-time market.
$LCD_{nk}^{\hat{X},\min}, LCD_{nk}^{\hat{X},\max}$	Min/max possible time for offer k to be available from DR option $\hat{X}$.
LD_{tn}	Total Forecasted load at each hour for each bus.
$MC_{nk}^{\hat{X}}$, $MCs_{nk}^{\hat{X}}$	Maximum possible number of calling DR for each day and each scenario per day.
$pf_l^{\max}, pf_l^{\min}$	Maximum/minimum branch capacity.
$P_g^{\max}, P_g^{\min}$	Maximum/minimum capacity of thermal generators.
$R_g^{\max,up}, R_g^{\max,down}$	Maximum up/down reserve of thermal generators.
Rmp_g^{up}, Rmp_g^{dwon}	Maximum ramp-up and ramp-down of thermal generators.
X_{nl}	Reactance of branches.

D. Binary variables

u, y, z	On/off, start-up and shut-down states for the day-ahead market.
us, ys, zs	On/off, start-up and shut-down states for the real-time market.

E. Variables

$CDR^{\hat{X}}, CDRs^{\hat{X}}$	Total cost of DR scheduling for day-ahead and real-time market.
$DRK^{\hat{X}}$, $DRKs^{\hat{X}}$	DR scheduling in day-ahead and real-time market for DR option $\hat{X}$.

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P	Production of Thermal power generators.
pf, pfs	Load flows for day-ahead/real-time market.
$R_{tg}^{up}, R_{tg}^{down}$	Up/down reserve of thermal generators.
$Rs_{tgs}^{up}, Rs_{tgs}^{down}$	Up and down reserves of thermal generators for scenarios.
θ	Voltage angle.
W	The production of wind generators.

II. Introduction

With the deployment of demand response (DR) in distribution systems, the importance of making the best strategy to take full advantage of demand-side management is well acknowledged [1]. There are several programs for DR either in communication facilities like AutoDR, transactive controllers [2] or in different strategies like emergency DR program (EDRP) and time-of-use (ToU) pricing scheme [3]–[5] which should be applied in electricity markets to schedule and optimize the DR usage.

Meanwhile, customers recently play a key role in the market, and this issue should be considered by regulators and policy makers. In other words, the customers have been turned into active players from passive ones [6]. Accordingly, a new player has been introduced in the market called DR aggregator (DRA) in order to be placed as an interface among ISO and customers [7]. DRAs can be active in connection with customers in order to highly benefit from DR implementation either in the wholesale market or retail market.

In terms of wholesale market, the benefit of DRA is maximized for DR trading among ISO and customers in [8]. In [9], the day-ahead and intra-day markets have been considered for DR management by flexibility market operator. In [10] a model has been proposed to find the best bus for DRA and optimize DR to prevent line congestion in the day-ahead market. All above-mentioned papers have been focused on day-ahead market not real-time one.

Some articles have discussed DR issues in the balancing market. For example, in [11], DR bids are optimized in real-time balancing markets based on supply offers. The model developed by [12] tried to reduce the line congestion and operation cost by DR participation of cooling and heating systems in the real-time retail market. In [13], residential DR in the real-time market has been taken into account in order to schedule the consumption profile based on the price signal. These papers fail to consider DRAs in their model.

Some other investigations have considered DRAs in the real-time market. In [14], DR has been scheduled based on new real-time market dynamic prices for selling energy stored in storage from one aggregator to another in a competitive way. Moreover, references [15], [16] have worked on scheduling DR in the real-time market based on real-time pricing with DRAs. All these papers have not taken into account the unexpected events like the variability of production of wind power generators (WPGs) in real-time markets for DR scheduling.

Stochastic behavior of WPG has been taken into account in our previous work [17] to schedule DR in aggregated-based DR and in day-ahead market, we only used the potential customers in the day-ahead market and not in real time. Similarly, some studies have considered real-time market beside the day-ahead market.

For example, reference [18] aims also to maximize DRA profit while considering customers' issues as well as day-ahead and real-time market clearing in the wholesale market. Definition of the volume of electricity purchased from the day-ahead market, as well as aggregator-based DR quantity has been conducted in [19] in a real-time trading strategy. Nevertheless, DR scheduling in the real-time market is not the aim of these papers.

Thus, there is no study in which, through the unpredicted potential of customers for DR participation in real-time, DRAs are able to optimize DR in the real-time market considering a variation of wind power generation as a stochastic factor in real-time.

In this paper, we consider both DRAs and customers as active players in the market. DRAs schedule the DR options involving LC/LS/LR and offer DR prices to customers for participation in the day-ahead market. Meanwhile, the customers may want to reduce or shift more loads in the real-time if an incentive is proposed by DRAs. For example, in the real-time market, customers are able to turn some more lights off or postpone the electric vehicle and washing machine usages, which all were supposed to be consumed according to the day-ahead scheduling.

This strategy is highly desired when some unpredicted events take place in the real-time, and the DRA can cope with the uncertainties. For example, when the wind power generation in real-time is different from the forecasted one or the market price does not live up the expectations or even, customers are able to help avoid any unbalances in the power or remarkable economic loss.

In this paper, wind power generation is a stochastic variable modeled based on scenario generation using Monte-Carlo Simulation (MCS) method. Thus, wind generation in real-time has been taken into account.

Based on these scenarios, new possible DR offers are decided in the real-time market with the new DR capabilities provided by customers.

A two-stage stochastic programming is applied to model the proposed strategy where in the first stage, DRA is scheduled in day-ahead market, and customers and DRAs are scheduled in second stage for new DR potential addition in real-time based on offered incentives and possible scenarios for wind generation.

The contributions of this work are briefly summarized as follows:

- Considering unpredicted potential of customers for DR participation in real-time markets.
- Employment of customers' potential for DR participation in the real-time market caused by unpredicted events in addition to their pre-defined potential in the day-ahead market.
- Offering the DR prices (incentives) to encourage customers for involving their extra DR potentials in the real-time market.
- DR quantity optimization in the real-time market through DRAs while considering the volatility of wind power generation as a stochastic factor in real time.

The rest of the paper is organized as follows. Section III introduces the DR offers and the way of DRA price bidding.

Likewise, scenario generation method and uncertainty handling are illuminated. Section IV presents the formulation of the proposed two-stage stochastic formulation in form of a mixed-integer linear program (MILP). Numerical results and case study are brought in Section V and finally section VI provides some concluding remarks.

III. Problem Statement

One of the key parts of the problem is dealing with the unexpected events in the real time. The way how to model and perform real-time events has the direct impact on the efficiency of this work. The details of the proposed mechanism for modeling the behavior of wind power production in the real-time market are outlined in this section. Moreover, the problem needs a market strategy to run the real-time market and day-ahead market at the same time in order to fulfill our requirements. Hence, a pre-emptive market is introduced in this section. Likewise, suitable demand-side management is a complementary stage to reach the best strategy. Therefore, DR options utilized based on the market structure and the proper framework for DRA as well as the method of price bidding for them are explained in this section as well.

A. Stochastic modeling

The behavior of wind power production in real time which is stochastic due to the variation of wind speed can be modeled and presented by different scenarios extracted from MSC. To this end, it is needed to produce suitable probabilistic distribution function (PDF) for wind speed. The most suitable PDF for wind speed is the Rayleigh distribution [20].

$$f(v)=\left(\frac{2v}{c^{2}}\right)e^{-\left(\frac{v}{c}\right)^{2}} \tag{1}$$

where c is a parameter, which is called the scale index and determines the shape of $f(v)$; v is the wind speed in (m/s).

Through historical data processing, some parameters of forming the probability distribution function (PDF) should be calculated. In this paper, scale index is obtained from the following acceptable approximation according to [21]:

$$c \approx 1.128 v_{mean} \tag{2}$$

where v_{mean} is the hourly average forecasted wind speed obtained from a time series. Likewise, generated electric power in the WPG is in associated with the wind speed as the following equation present [22]:

$$p_{w}=\begin{cases} 0 & v<v_{ci}\cup v_{co}\leq v \\ P_{r}.\dfrac{(v-v_{ci})}{(v_{r}-v_{ci})} & v_{ci}\leq v\leq v_{r} \\ P_{r} & v_{r}\leq v\leq v_{co} \end{cases} \tag{3}$$

where v_{ci}, v_{co}, v_{r} and P_{r} are cut-in, cut-out, rated wind speeds and rated power output of WT, respectively.

B. Scenario generation

In this paper, several scenarios for power generation of wind turbines are generated based on MCS. Using the constructed Rayleigh function, several scenarios that show the behavior of WPG in real-time are generated. The procedure of scenario generation is outlined in Fig. 1.

Accordingly, having some given and historical data of wind speed value, the mean value is obtained for a specific time period to get the parameters of Rayleigh probability distribution function. Using the cumulative function (CDF) of the obtained Rayleigh function, scenario generation process is conducted. A uniform random variable is fitted to the CDF to get the relative wind speed following by wind power production. This procedure is repeated until the number of desired scenarios which have the same probability generated. Finally, applying forward reduction method the numbers of scenarios are reduced with different probability to cope with the computational burden. Therefore, in this work ten thousand scenarios are generated for each time step and as we have 24 time steps, the total number of scenarios is 240,000. Applying the above-mentioned reduction procedure; the most important 10 scenarios are remained to study.

C. Market structure

A pre-emptive market scheme is run by ISO in this paper to solve the proposed model based on Fig. 2 [23]. This scheme is able to confront the renewable generation uncertainty by providing enough flexibility in real-time via day-ahead energy and reserve dispatch. Indeed, day-ahead economic dispatch decisions are considered for real-time operation via various scenarios that include different possible occurrences in the real-time market. Each Generation company (GENCO) transmits its offers for energy as well as upward and downward reserve capacities to the ISO. Likewise, the DR offers from DR aggregators (DRAs) are sent to ISO and DR scheduling for each hour is sent back to DRAs after market settlement. To solve this short-term management problem, a stochastic two-stage model is employed. The decisions regarding the first stage of the problem are DR scheduling for aggregators along with energy and reserve of GENCOs at each scheduling period which all are in associated with the day-ahead market.

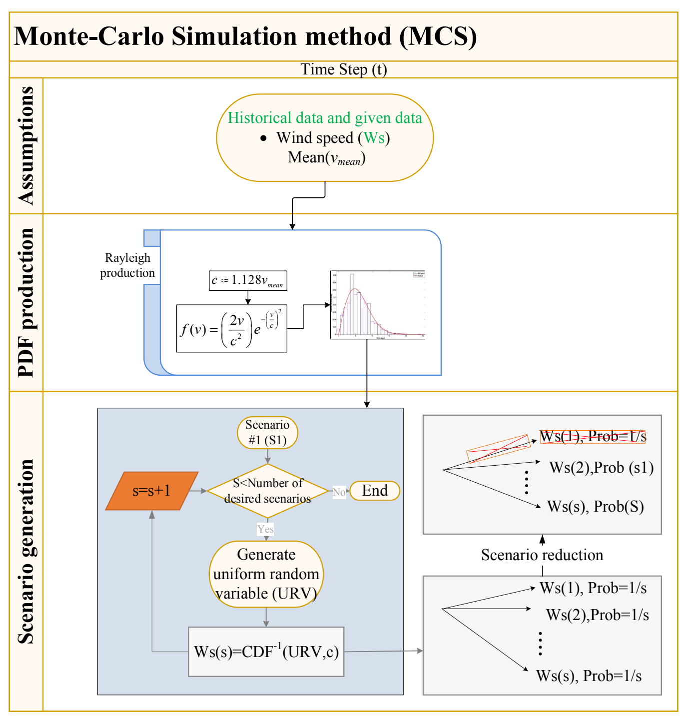

Fig. 1. The framework of scenario generation for WPG.

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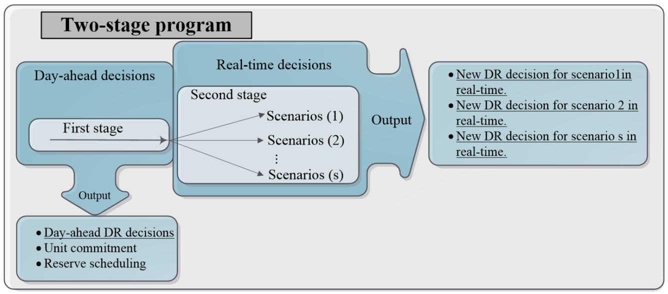

Fig. 2. Proposed model framework.

Furthermore, decisions obtained from the second stage of the problem are in connection with the scenarios realization involving the reserve deployment, wind spillage, and real-time DR decisions.

D. Demand Response Options

It is possible to design a DRA aiming at certain customers group [24], although DRA, here, is assumed as a general and comprehensive aggregator for all customers to reduce any extra correspondence among customers and DRA. Load reduction strategies utilized in this paper are LC, LR, and LS which are expressed in the following section.

1) Day-ahead DR decisions

For the day-ahead DR decisions, three load reduction strategies are considered. In LC option, a customer reduces its consumption without any shifting to other hours. For example, a residential customer can turn off the TV, or a commercial building can reduce its unnecessary consumptions [8]. The LC contract includes some offers named k that a certain price is dedicated to each one based on the agreement between ISO and DRA named $DR_{tnk}^{Cost,LC}$.

The LC contracts also have a limitation for the amount of load curtailment according to (5) where u_{tnk}^{LC} is the binary variable to express whether any LC offer is selected.

The exact amount of load curtailment related to LC, DRK_{tnk}^{LC}, for DRA is obtained in node n and its total cost achieved through (4). Meanwhile, (6) represents the starting time of the offer with $y_{tnk}^{LC}=1$ and terminating time $z_{tnk}^{LC}=1$. Eq. (7) is to prevent any coincidence in starting and terminating of DR programs.

The duration of load reduction process is limited by (8) – (9) and the maximum amount of load curtailment at each day is given in (10). For LS, all equations of LC will be repeated, and three other equations are needed shifting and recovery of curtailed loads which are introduced in Equations (11) – (13).

According to Equation (11), the volume of LR, DRK_{tnk}^{LR}, has a special margin determined in the contract. Furthermore, as Equation (13) states, the summation of LS and LR quantity has to be equal in a day. Meanwhile, according to (12) the LR and LS should not happen simultaneously.

$$CDR_{tn}^{\hat{X}} = \sum_{k\in KD} DRK_{tnk}^{\hat{X}} DR_{tnk}^{Cost,\hat{X}}, \forall t\in TC, \forall n \tag{4}$$

$$DRK_{tnk}^{Min,\hat{X}} u_{tnk}^{\hat{X}} \le DRK_{tnk}^{\hat{X}} \le DRK_{tnk}^{Max,\hat{X}} u_{tnk}^{\hat{X}}, \forall t\in TC, \forall n, \forall k \tag{5}$$

$$u_{tnk}^{\hat{X}} - u_{t-1nk}^{\hat{X}} = y_{tnk}^{\hat{X}} - z_{tnk}^{\hat{X}} \tag{6}$$

$$y_{tnk}^{\hat{X}} + z_{tnk}^{\hat{X}} \le 1 \tag{7}$$

$$\sum_{t}^{t+LCD_{nk}^{\max,\hat{X}}-1} z_{tnk}^{\hat{X}} \ge y_{tnk}^{\hat{X}} \tag{8}$$

$$\sum_{t}^{t+LCD_{nk}^{\min}-1} u_{tnk}^{\hat{X}} \ge LCD_{nk}^{\hat{X},\min}(u_{tnk}^{\hat{X}} - u_{t-1nk}^{\hat{X}}) \tag{9}$$

$$\sum_{t} y_{tnk}^{\hat{X}} \le MC_{nk}^{\hat{X}} \tag{10}$$

$$DRK_{tnk}^{LR} \le DRK_{tnk}^{\max,LR} u_{tnk}^{LR}, \forall t\in TR, \forall n, \forall k \tag{11}$$

$$u_{tnk}^{LR} + u_{tnk}^{LS} \le 1 \tag{12}$$

$$\sum_{t\in TR} DRK_{tnk}^{LR} = \sum_{t\in TS} DRK_{tnk}^{LS}, \forall n, \forall k \tag{13}$$

2) Real-time DR decisions

For real-time DR decision, according to the possible events which are determined in the scenarios, new decisions for DR which will be implemented in real-time will be made. DRAs provide this opportunity for the customer to participate even in the real-time market in order to use any possible potential of customers' consumption to shift or curtail which was not clarified in the day-ahead stage. Therefore, customers utilize this opportunity to propose any new possible potential for participation in DR within real-time. Having performed this strategy leads to not only profit for customers to sell DR with a higher price in real-time but also provide less expensive power balance for ISO followed by a profit for DRAs.

The equations of real-time DR would be as follows:

$$CDRs_{tns}^{\hat{X}} = \sum_{k\in KD} DRKs_{tnks}^{\hat{X}} DR_{tnk}^{Cost,\hat{X}}, \forall t\in TC, \forall n \tag{14}$$

$$DRKs_{tnks}^{Min,\hat{X}} us_{tnks}^{\hat{X}} \le DRKs_{tnks}^{\hat{X}} \le DRKs_{tnks}^{Max,\hat{X}} us_{tnks}^{\hat{X}}, \forall t\in TC, \forall n, \forall k \tag{15}$$

$$us_{tnks}^{\hat{X}} - us_{t-1nks}^{\hat{X}} = ys_{tnks}^{\hat{X}} - zs_{tnks}^{\hat{X}} \tag{16}$$

$$ys_{tnks}^{\hat{X}} + zs_{tnk}^{\hat{X}} \le 1 \tag{17}$$

$$\sum_{t}^{t+LCD_{nk}^{\max,\hat{X}}-1} zs_{tnks}^{\hat{X}} \ge ys_{tnks}^{\hat{X}} \tag{18}$$

$$\sum_{t}^{t+LCD_{nk}^{\min}-1} us_{tnks}^{\hat{X}} \ge LCDs_{nk}^{\hat{X},\min}(us_{tnks}^{\hat{X}} - us_{t-1nks}^{\hat{X}}) \tag{19}$$

$$\sum_{t} y_{tnks}^{\hat{X}} \le MCs_{nks}^{\hat{X}} \tag{20}$$

$$DRK_{tnks}^{LR} \le DRKs_{tnk}^{\max,LR} us_{tnks}^{LR}, \forall t\in TR, \forall n, \forall k \tag{21}$$

$$us_{tnks}^{LR} + us_{tnks}^{LS} \le 1 \tag{22}$$

$$\sum_{t\in TR} DRKs_{tnks}^{LR} = \sum_{t\in TS} DRKs_{tnks}^{LS}, \forall n, \forall k \tag{23}$$

Equations (14) – (23) represents the real-time contract scheme and options for DR among DRAs and customers. The framework of DR options is similar to the day-ahead market, though the DR threshold and price in real-time would be different.

3) DR price bidding scheme

In fact, the DR cost is non-linear since both the price and DR quantity are variables. To prevent trapping in a local optimal point in solving nonconvex problems which leads to high financial losses, a method to achieve a linear problem is applied. To this end, we employ a stepwise price curve method that is precise enough in linearization, and a customer reacts to various prices in a stepwise approach. Therefore, each step has a fix price, and the reduced volume would be a decision variable with a certain range.

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In other words, DR prices/incentives are set as several fix values and different blocks are established based on these fixed values. Each block has a range of DR quantity assigned to one of those fix DR prices/incentives. The model selects one or several blocks for customers based on relative prices/incentives. At each block DR quantity can be scheduled within the relative limitation. Thoroughly, the model starts selecting the blocks/steps from lower prices/incentives to higher ones and the number of selected blocks/steps and DR quantity are based on their cost-efficiency. It means customers tend to select blocks and the relative DR quantities from the lower block to higher one according to the benefits it may bring them. The stepwise function is depicted in Fig. 3. It is noticed that the DR price bidding in the day-ahead market by DRA is usually less than that in the real-time market. Because in real-time market, customers expect a higher price for their DR offers and the market price would be higher as well.

IV. Two-Stage Stochastic Programming

To solve the proposed methodology, a two-stage stochastic programming is utilized which is the fittest model for this problem. The objective function (24) aims to minimize the total operation cost with different relative constraints as an MILP problem. The relative constraints are listed in Equations (25) – (36). The first and second lines of Equation (24) correspond to the first stage that involves units' power generation cost, start-up and shut-down costs for thermal units, upward and downward reserve capacities cost of units along with demand response options cost.

In (24), the third and fourth lines are in connection with the second stage (real-time decisions) that involves real-time total DR cost for all scenarios as well as energy cost, upward and downward reserve, and wind spillage cost in all scenarios. Equations (25) – (36) represent first-stage constraints. Units' capacity limitations are brought in (25) – (26). Day-ahead balance equality is given by (27). Reserve restrictions of units are given by Equations (28) – (29). Equations (30) – (31) indicate the ramp-up and ramp-down constraints of thermal units. The constraints regarding the start-up/shut-down costs of thermal units are presented in (32) – (33). DC load flow is brought in (34), and the capacity constraint of transmission line is given in (35). Equation (36) represents the limitation of scheduled power generation of WPG that ought to be lower than the forecasted amount of wind power.

Meanwhile, Equations (4) – (13) are employed to calculate DR costs in day-ahead market and (14) – (23) are utilized to obtain the DR cost in the real-time market.

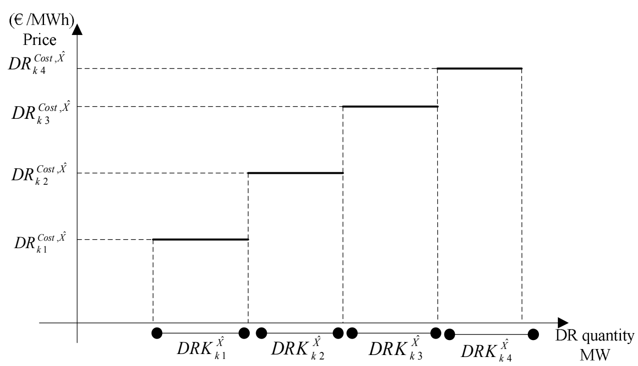

Fig. 3. DR price bidding for day-ahead and real-time market

The second-stage constraints are given by (37) – (42). The power balancing equation for the real-time market is brought in (37). Equations (38) – (39) indicates DC power flow constrain for real-time are given by Wind-spillage should be no greater than the available output in each scenario, which is shown in Equation (40). Limitations of upward and downward regulation in each scenario are provided by Equations (41) – (42).

Moreover, the constraint of scheduled DR in scenarios is brought in (43). Accordingly, there is a relationship among scheduled DR in day-ahead and real-time market implied DR in scenarios cannot be more than scheduled DR in the day-ahead market.

$$\begin{aligned} &Minimize \sum_{t\in NT}\Bigg\{\sum_{g\in NG}(C_{tg}^{gen}P_{tg}^{gen}+SUC_{tg}^{gen}+C_{tg}^{up}R_{tg}^{up}+C_{tg}^{down}R_{tg}^{down})\\ &+\sum_{n\in NN}(CDR_{tn}^{LC}+CDR_{tn}^{LS})\\ &+\sum_{s\in S}\pi_s\Bigg[\sum_{g\in NG}(Cs_{tgs}^{up}Rs_{tgs}^{up}+Cs_{tgs}^{down}Rs_{tgs}^{down})\\ &+\sum_{n\in NN}(Cs_{tns}^{spill}W_{tns}^{spill}+Cs_{tns}^{voll}Ls_{tns}^{shed})+\sum_{n\in NN}(CDRs_{tns}^{LC}+CDRs_{tns}^{LS})\Bigg]\Bigg\} \end{aligned} \tag{24}$$

In objective function, Equation (24), the day-ahead decision variables are $P_{tg}^{gen}, SUC_{tg}^{gen}, R_{tg}^{up}, R_{tg}^{down}, CDR_{tn}^{LC}, CDR_{tn}^{LS}$ and the real-time decision variables include. These variables are defined through minimizing Equation (24) by considering following constraints:

$$P_{tg}^{gen}+R_{tg}^{up}\le P_g^{\max}u_{tg}^{gen},\forall t,\forall g \tag{25}$$

$$P_{tg}^{gen}-R_{tg}^{down}\ge P_g^{\min}u_{tg}^{gen},\forall t,\forall g \tag{26}$$

$$\sum_{g\in NG}p_{tg}^{gen}+W_{tn}^{sch}+\sum_{k\in KD}(DRK_{tnk}^{LC}+DRK_{tnk}^{LS}-DRK_{tnk}^{LR})=LD_{tn}+\sum_{l\in NL}pf_{tl},\forall t,\forall n \tag{27}$$

$$0\le R_{tg}^{up}\le R_g^{\max,up},\forall t,\forall g \tag{28}$$

$$0\le R_{tg}^{down}\le R_g^{\max,down},\forall t,\forall g \tag{29}$$

$$P_{t-1g}^{gen}-P_{tg}^{gen}\le Rmp_g^{up},\forall t,\forall g \tag{30}$$

$$P_{tg}^{gen}-P_{t-1g}^{gen}\le Rmp_g^{down},\forall t,\forall g \tag{31}$$

$$SUC_{tg}^{gen}\ge C_g^{strt.up}(u_{tg}^{gen}-u_{t-1g}^{gen}),\forall t,\forall g \tag{32}$$

$$SUC_{tg}^{gen}\ge C_g^{sht.dwn}(u_{t-1g}^{gen}-u_{tg}^{gen}),\forall t,\forall g \tag{33}$$

$$pf_{tl}=\sum_{n\in NN}\frac{1}{X_{nl}}(\theta_{nl}^1-\theta_{nl}^0),\forall t,\forall l \tag{34}$$

$$pf_l^{\min}\le pf_{tl}\le pf_l^{\max},\forall t,\forall l \tag{35}$$

$$0\le W_{tn}^{sch}\le W_{tn}^{\exp},\forall t,\forall n \tag{36}$$

$$\begin{aligned} &\sum_{g\in NG}(Rs_{tgs}^{up}-Rs_{tgs}^{down})+W_{tns}^{scen}-W_{tn}^{sch}-W_{tns}^{spill}+\sum_{k\in KD}(DRKs_{tnks}^{LC}+DRKs_{tnks}^{LS}-DRKs_{tnks}^{LR})=\\ &-\sum_{l\in NL}(pfs_{tls}-pf_{tl}),\forall t,\forall n,\forall s \end{aligned} \tag{37}$$

$$pfs_{tls}=\sum_{n\in NN}\frac{1}{X_{nl}}(\theta_{nls}^1-\theta_{nls}^0),\forall t,\forall l,\forall s \tag{38}$$

$$pf_l^{\min}\le pfs_{tls}\le pf_l^{\max},\forall t,\forall l \tag{39}$$

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TABLE I
Units' Data

#	Bus	Generation Cost (€/kWh)	Minimum capacity (kW)	Maximum capacity (kW)	Start-up cost (€/kWh)	Shut-down cost (€/kWh)	Ramp rate (kWh)	Min on-time (h)	Min off-time (h)	Reserve-up limit (kWh)	Reserve down limit (kWh)	Reserve up cost (€/kWh)	Reserve down cost (€/kWh)
G1	1	13,5	100	220	100	50	100	4	4	110	110	15	10
G2	2	40	10	100	200	100	60	3	2	50	50	45	35
G3	6	17,7	10	40	0	0	30	1	1	15	15	20	15

$$0 \le W_{tns}^{spill} \le W_{tns}^{scen} \quad (40)$$

$$0 \le Rs_{tgs}^{up} \le R_{tg}^{up} \quad (41)$$

$$0 \le Rs_{tgs}^{down} \le R_{tg}^{down} \quad (42)$$

$$DRKs_{tnks}^{\hat{X}} \le DRK_{tnk}^{\hat{X}} \quad (43)$$

V. NUMERICAL STUDIES

To implement the proposed model in a network and assess the merits of the model two networks are employed including a 6-bus IEEE test system and RTS-96. The 6-bus system is demonstrated in Fig. 4. Thermal generation units' data, line data and DR prices are presented in Table I, Table II, and Table III, respectively. In Table III, DR prices for different options including LC, LS and different offers (5 offers, k1 to k5) in the day-ahead market and the real-time market are given. It is assumed that DR prices for LC and LS are the same.

Likewise, there are three DRAs. Each DR option in different DRAs has a boundary, which DR can be scheduled between these boundaries. It is noteworthy that LC and LS can be implemented in hours between 10 – 16 and 10 – 18, respectively. The maximum and minimum of DR contracts for all 5 offers are the same and for DRA #1 - #3, for LC, LS and in the day-ahead market can be obtained as follows:

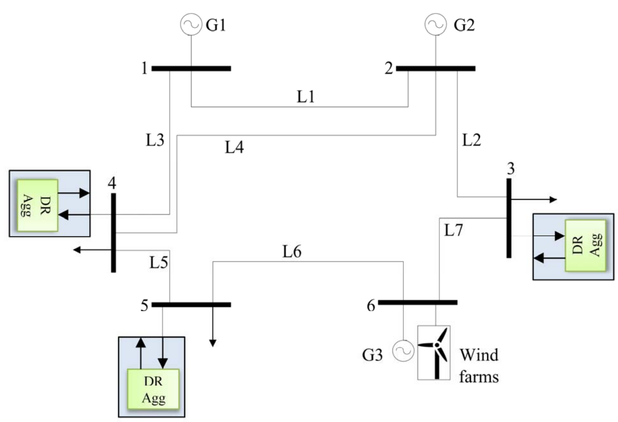

Fig. 4. The diagram of 6-bus network.

TABLE II
Transmission line data

Line	X	Capacity
L1	0.17	200
L2	0.037	100
L3	0.258	100
L4	0.197	100
L5	0.037	100
L6	0.14	100
L7	0.018	100

$$\begin{aligned} &DRK_{tnk}^{Max,\hat{X}} = \alpha \times LD_{tn} + \gamma, \\ &(\hat{X} \in LC, t \in 10-16 \cap \hat{X} \in LS, t \in 10-18), n \in 3,4,5. \end{aligned} \quad (44)$$

$$\begin{aligned} &DRK_{tnk}^{Min,\hat{X}} = \alpha \times LD_{tn} - \beta, \\ &(\hat{X} \in LC, t \in 10-16 \cap \hat{X} \in LS, t \in 10-18), n \in 3,4,5. \end{aligned} \quad (45)$$

According to Equations (44) – (45), the maximum of DR contract for LC and LS is a coefficient of load demand plus a parameter γ in the special bus that DRA is placed. $\alpha = 0.01$ and $\gamma = 0$ are used in this paper. The minimum of DR contract is the same coefficient of the load in the bus minus a parameter $\beta = 0.58$ in this paper. It should be noted that LC at periods 17 and 18 are not scheduled, while Equations (44) – (45) are taken into account for LS at these hours.

Limitation of DR contracts in the real-time market has the same equation like those in the day-ahead market, yet the parameters γ and β can take different values. Here β and γ are 0.48 and -0.01, respectively. Since in real-time the potential of customers to participate in DR is less, the boundary of DR contract is narrower than the day-ahead market. The general relationship among DR boundary in the day-ahead and real-time markets is like Fig. 5.

TABLE III
DR prices for 5 offers and two options

market		K1 (€/MWh)	K2 (€/MWh)	K3 (€/MWh)	K4 (€/MWh)	K5 (€/MWh)
Day-ahead	LC & LS price	10	11	12	13	14
Real-time	DR-Price1	6	7	8	9	10
	DR-Price2	8	9	10	11	12
	DR-Price3 (case 2)	11	12	13	14	15
	DR-Price4	14	15	16	17	18
	DR-Price5	20	21	22	23	24
	DR-Price6	24	25	26	27	28
	DR-Price7	30	31	32	33	34
	DR-Price8	35	36	37	38	39

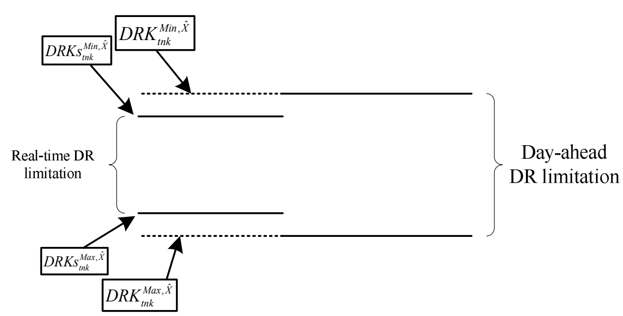

Fig. 5. The relationship between the limitation of DR quantity in the day-ahead and real-time markets

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TABLE IV
Case studies

Cases	Description	Output
Case1	6-bus system, DR employment just in day-ahead market.	DR quantity just in day-ahead market.
Case2	6-bus system, DR employment in both day-ahead market and real-time market.	DR quantity in day-ahead market and real-time market with 10 scenarios.
Case3	72-bus system, DR employment in both day-ahead market and real-time market.	DR quantity in day-ahead market and real-time market with 10 scenarios.

$DRK_{tnk}^{\max,LR}$ for LR option is considered 2 MW in day-ahead DR scheduling and 1.5MW in real-time DR scheduling. The CPLEX12 solver in GAMS [25] is applied to solve the problem utilizing a Laptop with Intel processor core i7, cache 2.7GHz, and random-access memory (RAM) 8 GB. It takes around 1 second to solve the problem. The CPLEX12 optimizer is designed to solve large and difficult linear or mixed integer programming (MIP) problems quickly. For problems with integer variables, CPLEX uses branch and cut algorithm that solves a series of linear problems and subproblems, since an MIP produces many subproblems following by intensive computation. The proposed model is an MIP, and CPLEX12 optimizer with branch and cut algorithm solves the problem. Based on GAMS solution report, the problem is feasible.

In this paper, the differences among scenarios after running DR options for them are mostly compared with each other as case 2. Though, case 1 includes the same method without running DR options in the real-time market for scenarios and the DR options run just in the day-ahead market. Finally, a larger network, RTS-96, is applied as the last case study to compare solving status among 6-bus system and 72-bus test system. All cases are presented in Table IV.

Through the proposed method to generate scenarios for WPGs, ten scenarios are generated. All ten scenarios along with forecasted wind power production are demonstrated in Fig. 6. Noted that in this paper, 3 DRAs for cases 1 and case 2 and 30 DRAs for case 3 are taken into account. Moreover, the problem considers network constraints as DC load flow.

As can be seen, scenario 2 has the minimum wind power production in a day. For example, the maximum production for scenario 2 is 5 MW out of 20 MW, and scenario 3 has the maximum wind power production in a way the maximum production is 19 MW for this scenario. The range of power production in scenarios 4 and 5 are between scenarios 2 and 3. Meanwhile, in Fig. 7, the result of real-time DR scheduling for these four selected scenarios along with day-ahead DR scheduling are presented.

The impact of running this model on load for these scenarios can be seen in Fig. 7. Moreover, the load profile after running the proposed method in case 2 for the day-ahead market is illustrated. The results of load after running DR in the day-ahead market for case 1 without running DR options in scenarios and real-time market are outlined in Fig. 7. For scenario 2, the load reduction is higher in peak hours, since it has the minimum wind power production compared with the forecasted one. Therefore, to compensate this shortage of production, DR options are applied to reduce the load, though the loads are recovered in off-peak hours. As a result, the highest load reduction occurs for scenario 2. On the other hand, less load reduction is observed in scenario 3, since it has the highest wind power production among all these scenarios.

Fig. 8 demonstrates the amount of reduced load as well as shifted loads for all DR aggregators per scenarios at each time step. Accordingly, the shifted and recovered loads have the negative sign and the reduced loads have the positive one. As a result, the real-time DR decisions for different scenarios are always less than day-ahead DR decisions which means DR for scenarios are related to DR in day-ahead and is scheduled based on what is decided for the day-ahead market.

A comparison among the DRAs cost for running DR options in all scenarios is performed in Fig. 9. In Fig. 9 a), there is no LC for scenario 3, since in this scenario the highest wind power generation is foreseen. Therefore, there is no need to reduce load, and all loads are served. Scenario 5 is nearly similar to scenario 3; hence, there is no DR cost for DRA 2 and for two other DRAs, it is too low, 100€ for DRA 3 and 250€ for DRA 1. Although, the DR cost for other scenarios and DRA for running the LC are nearly the same. DR cost, generally, for DRA 1 is lower than two other DRAs because the amount of load which is under control of DRA 1 is lower.

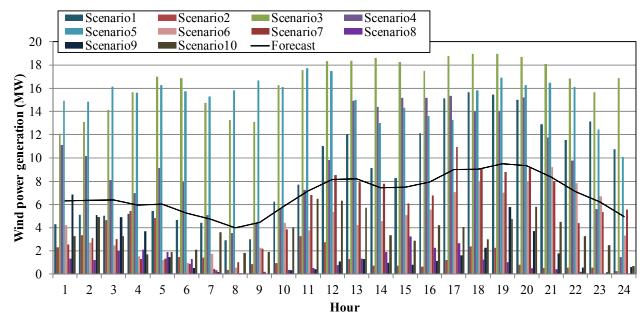


Fig. 6. Forecasted wind power generation and all scenarios extracted via the model.

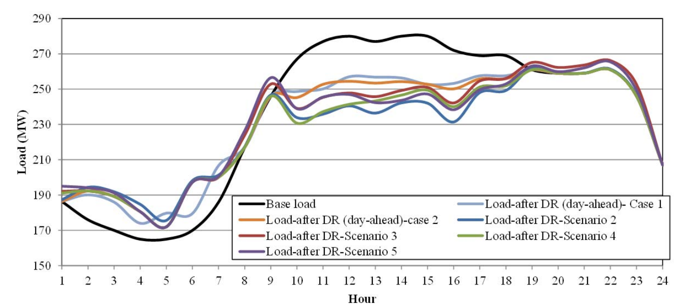


Fig. 7. Base load and loads after DR in different states.

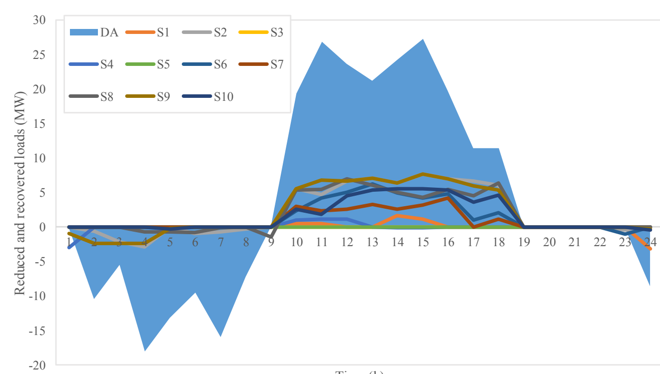
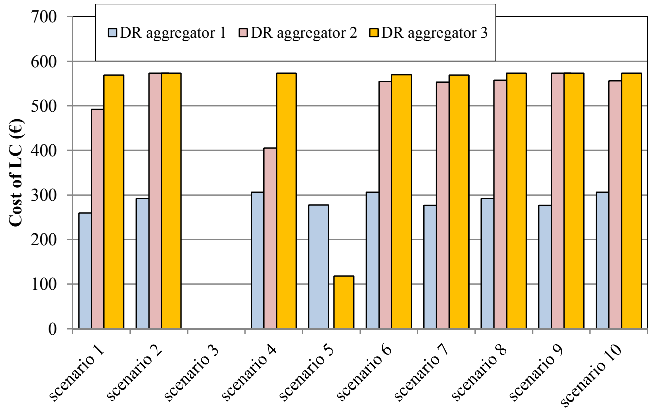


Fig.8. the quantity of DR for all three options LC, LS, and LR and all DR aggregators per scenarios and in the day-ahead market.

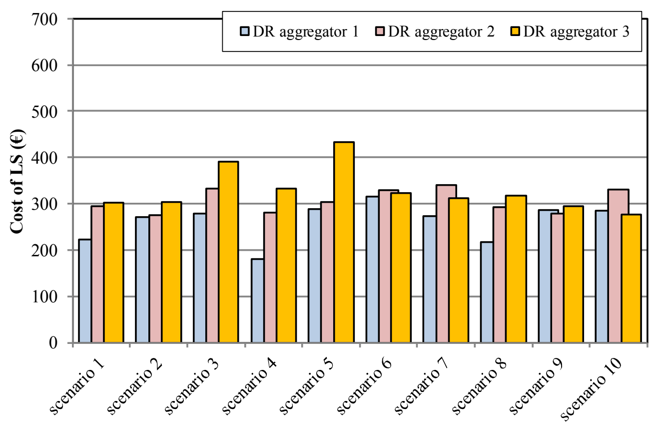
In Fig. 9 b), LS cost is considered. In all scenarios, LS is applied, yet LS cost is mostly less than LC cost. Generally, the LS cost is around 300€, although LS cost for DRA 3 is around 400€ in scenario 5 and LS cost is 150€ for DRA 1.

Moreover, as can be seen in part c) the total DR cost, i.e., the summation of LS and LC cost, is minimum for scenario 3 and 5 which have the highest possible wind power productions. Although the price for other scenarios are approximately the same with 900€ for DRA 2 and 3, and 500€ for DRA 1.

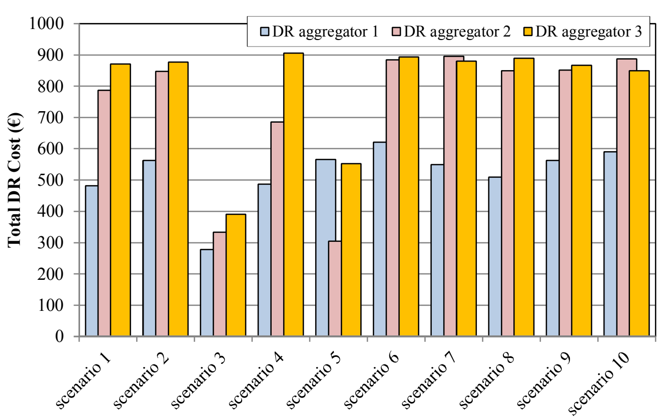
Finally, the most interesting part of results regards to Table V. Based on this table, the proposed method has less total operation cost compared with case 1 where there is no DR scheduling for scenarios in real-time.



a) LC cost for different DRAs in all scenarios



b) LS cost for different DRAs in all scenarios



c) Total DR cost for different DRAs in all scenarios

Fig. 9. DR cost in different DRAs and different scenarios a) total cost b) LS cost c) LC cost.

Nevertheless, the day-ahead DR scheduling for case 2 is more. The reason behind this is why the need for a reserve of units in different scenarios is reduced because of applying a new methodology for DR in real-time, which is less costly than units' reserve.

To show the impacts of real-time DR price on the total operation cost and the DR cost, a sensitivity analysis is conducted. To this end, some variable real-time DR prices with lower and higher values than the base case 2 (DR-Price3) are taken into account which are introduced in Table III in real-time stage. In this Table, DR prices for case 2 is assigned as DR-Price3. The results are demonstrated in Fig. 10.

In Fig. 10, eight real-time DR prices are considered to make a comparison among different total operation costs and total DR costs. As can be seen in Fig. 10, with increasing the DR price, total operation cost always has an incremental trend. This increase occurs from 88100€ in DR-Price1 to 88700€ in DR-Price8 which is the highest real-time DR price in this package. The reason behind this phenomenon is why rising the real-time DR price causes more expense for aggregators. In other words, aggregators have to spend more money to buy DR participation of customers in both real-time and day-ahead market. On the other hand, DR cost has a decrement trend in a way that with increasing the real-time DR price, DR cost is dropped. Once the DR price is high, DRA tries to buy less DR from customers. Therefore, despite the fact that the DR price is going to increase, the DR cost tends to be lower. This attitude is depicted in Fig. 11.

TABLE V
Different costs in all cases

Cases	Total cost (€)	DR cost (€)
Case 1	90158.04	2142.35
Case 2	86054.1	2336.683

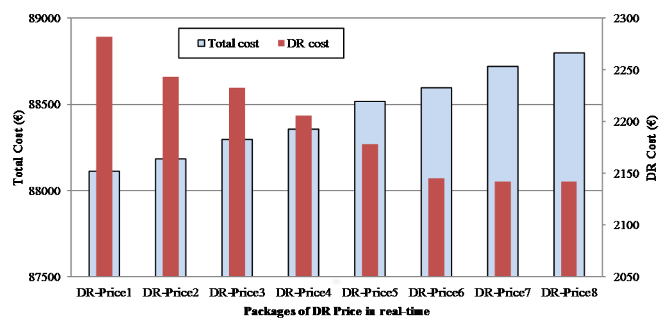


Fig. 10. Sensitivity analysis for different real-time DR price for total cost and DR cost.

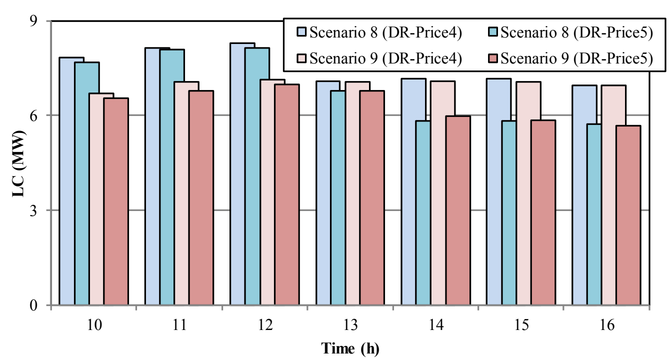


Fig. 11. Differences of LC scheduling in two scenarios for two DR prices.

TABLE VI
Comparison the results of performing the model on 6-bus system and RTS-96

	6-bus system	RTS-96
Number of variables	229	872
Number of iterations	2598	63175
Total cost (objective function)	89217.89	693751.09
Execution time	0.91 Seconds	165.5 Seconds

In Fig. 11, the effect of real-time DR price packages DR-Price4 and DR-Price5 on LC scheduling for scenarios 8 and 9 are compared. According to the figure, for scenario 8 and 9, the LC in DR-Price5 is scheduled always less than DR-Price4 which leads to a lower DR cost.

The proposed model is also implemented in the large-scale network, i.e. IEEE RTS-96, to demonstrate the possibility and applicability of running the model on real networks. Therefore, the results of the model implementation on IEEE RTS-96 with 72 buses are brought in Table VI and compared with 6-bus system. The comparison is conducted between the number of variables, iterations, execution time and total cost as the objective function. Noted that we assumed 35 demand response aggregators and 30 wind farms in the new case study. Accordingly, in RTS-94, it just takes more time to solve the model due to higher number of iterations and variables.

VI. CONCLUSIONS

In this paper, a two-stage MILP stochastic model was applied to schedule the real-time DR options, including LC, LR and LS. Ten scenarios have been generated through the MCS method to show the different possible amount of WPG at each hour. Through this methodology, in addition to day-ahead DR scheduling by coordination of DRAs and customers, DR options in real-time market are scheduled for DRAs based on each scenario, which shows shortage or enough wind power production. Hence, the more wind power is produced in each scenario, the less DR is applied in that scenario. Moreover, this method has lower total operation cost compared to when there is no option for DR scheduling in the real-time market. Considering uncertainty in demand side and DR as well as customers' comfort are offered as future works.

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