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Optimal Scheduling of Demand Response in Pre-emptive Markets based on Stochastic Bilevel Programming Method

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***Abstract*—This paper proposes a new strategy for an independent system operator (ISO) to trade demand response (DR) with different DR aggregators while considering various operational constraints. The ISO determines the energy scheduling and reserve deployment in a pre-emptive market while setting DR contracts with the DR aggregators. The ISO applies a two-stage stochastic programming to cope with the uncertainty associated with wind power production. DR aggregators' behavior is modeled through a profit maximization function. Aggregators determine their DR trading shares with ISO and customers through three DR options, including load curtailment, load shifting and load recovery. A stochastic bilevel problem is formulated in which in the upper-level the ISO minimizes the total operation cost and in the lower-level the DR aggregator maximizes the profit. Afterwards, the problem is transferred to a single-level mathematical problem with equilibrium constraints (MPEC) by replacing the lower-level program with its Karush-Kuhn-Tucker (KKT) conditions. As a result, the total operation cost is reduced using the proposed method comparatively to running the program without considering the lower-level.**

***Index Terms*—demand response, day-ahead market, stochastic bilevel programming, two-stage programming.**

I. Nomenclature

A. Indices (sets) and abbreviations

DBK	Set of demand response offers between DR aggregator and customer.
DRK	Set of demand response offers between ISO and DR aggregator.
$g\ (NG)$	Index (set) of generating units.
gen	Generator units.
$k\ (NK)$	Index (set) of demand response offers.
$l\ (NL)$	Index (set) of transmission lines.
LC	Load curtailment option.
LS	Load shifting option.
LR	Load recovery option.
$n\ (NN)$	Index (set) of nodes.
$s\ (NS)$	Index (set) of scenarios.
$scen$	Superscripts for wind scenarios.
$shed$	Superscripts for load shedding.
$spill$	Superscripts for wind spillage.
$t\ (NT)$	Index (set) of hours.
TC, TS, TR	Set of times for load curtailment, shift and recovery options.
$\hat{X} \in LC, LS, LR$	Superscripts for LC and LS and LR.

B. Parameters

C_{tg}^{gen}	Production cost of generator units.
$C_{tg}^{up}, C_{tg}^{down}$	Up/down reserve cost of generator units.
$C_{g}^{strt.up}, C_{g}^{sht.dwn}$	Generator start-up/shut-down cost.
Cs_{tns}^{spill}	Wind spillage cost per scenario.
$Cs_{tgs}^{up}, Cs_{tgs}^{down}$	Up/down reserve cost per scenario.
Cs_{tns}^{voll}	Value of loss of load per scenario.
$DR_{tnk}^{Cost,\hat{X}}, DB_{tnk}^{Cost,\hat{X}}$	Cost of offer k from demand response option $\hat{X}$.
$DRK_{tnk}^{Min,\hat{X}}, DBK_{tnk}^{Min,\hat{X}}$	Minimum offer k from demand response option $\hat{X}$.
$DRK_{tnk}^{Max,\hat{X}}, DBK_{tnk}^{Max,\hat{X}}$	Maximum offer k from demand response option $\hat{X}$.
$LCD_{nk}^{\hat{X},\min}, LCD_{nk}^{\hat{X},\max}$	Min/max time for offer k from demand response option $\hat{X}$.
LD_{tn}	Forecasted load.
$MC_{nk}^{\hat{X}}$	Maximum number of calling DR option $\hat{X}$ per day.
$pf_{l}^{\max}, pf_{l}^{\min}$	Maximum/minimum transmission line capacity.
$P_{g}^{\max}, P_{g}^{\min}$	Maximum and minimum capacity of generating units.
$R_{g}^{\max,up}, R_{g}^{\max,down}$	Maximum up/down reserve.
$Rmp_{g}^{up}, Rmp_{g}^{dwon}$	Maximum ramp-up/-down.
X_{nl}	Transmission lines inductance.

C. Binary variables

u, y, z	Binary variables for on/off, start-up and shut-down status.
ub	On/off for demand response offers from DR aggregator viewpoint.

D. Variables

$CRK^{\hat{X}}, CBK^{\hat{X}}$	Total cost of demand response scheduling for demand response option $\hat{X}$.
$DRK^{\hat{X}}, DBK^{\hat{X}}$	Demand response scheduling for demand response option $\hat{X}$.
P	Thermal power generation.

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pf , pfs	Power line flows day-ahead/balancing.
$R_{tg}^{up}, R_{tg}^{down}$	Up/down reserve of units.
$Rs_{tgs}^{up}, Rs_{tgs}^{down}$	Up/down reserve of units for scenarios.
W	Wind power generation.
θ	Voltage angle.

II. Introduction

A. Motivation

DEMAND-SIDE management has been widely utilized in electricity markets especially after huge application of smart facilities like intelligent electric devices (IEDs) and advanced metering infrastructures (AMIs). These technologies enable independent system operators (ISOs) to implement demand response (DR) with more details and higher accuracy [1].

Aggregators for performing DR have been introduced to make an easier interaction between customers and ISO. Likewise, DR aggregators play an important role to achieve all targets of DR implementation such as reducing peak demand, improving the power systems security, decreasing the negative effects caused by the uncertainty of renewable energy sources (RESs) on power system operation and enhancing the economic aspects of electricity market [2].

In fact, DR aggregators serve as interfaces between customers and ISO and enable the participation of customers in the wholesale market [3]. Indeed, DR aggregators face two challenges including with customers in lower-level and with ISO in upper-level. In the upper-level, DR aggregator is challenged in selling DR products to ISO in a contract with the best quantity and the best price. In other words, DR aggregator seeks to define optimal trading options in the wholesale market. In the lower-level, DR aggregator buys DR from customers and looks for implementing DR with the highest profit, while precisely modeling the customers' limitations and constraints.

The best approach for scheduling of power systems from ISO's viewpoint with DR aggregators is considering both levels simultaneously. In other words, once an ISO is running a day-ahead market with DR aggregators, the lower-level (interaction between DR aggregators and customers) and the customers' constraints play an important role to make the final decisions related to DR precisely and economically. Hence, since most of the electricity markets are going to incorporate DR aggregators, considering this approach is desirable. Bilevel programming is one way to formulate both upper and lower-level [4], [5]. A bilevel program can be turned into a single-level mathematical problem by replacing the lower-level problem with its Karush-Kuhn-Tucker (KKT) [6] optimality conditions.

B. Literature review

Some markets, such as the ones in Singapore, ERCOT, PJM, Alberta, Ontario [7], have already allowed the participation of DR aggregators, and some others, such as Australian National Electricity Market (NEM) [8], are going to allow in the near future. Some researchers have tried to consider DR in the market with the concept of DR aggregators [9]–[12].

In [9], small loads are aggregated to participate in the market for balance management in German balancing mechanism. In [10], domestic appliances of individual customers are considered as bottom-up aggregators which aggregate their reserve bids to offer in the day-ahead reserve market particularly in Portuguese territory reserve market. A game-theoretic framework for interaction between DR aggregators and electricity generators along with DR aggregator and customers is applied, separately to provide profit for all players in [11]. In [12], a bilevel method is applied which in the upper-level, local marginal prices are obtained through performing the unit commitment. In the lower-level, DR is scheduled by minimizing the total operation cost. DR aggregator in [13] solves a two-stage model in which in the first stage, distribution network operator (DNO) minimizes the power loss and in the second stage demand response providers (DRPs) minimize the electricity bill. Authors in [14] have studied three levels including an operator for the minimization of operation cost, DR aggregator for maximization of profit and end-user for maximization of payoff function. However, the network and its constraints have not been considered, and the problem was solved just by passing and exchanging the reward price to different players.

In [15], the authors only considered the upper-level for optimal hourly DR scheduling in a day-ahead market. They applied four options including load curtailment (LC), load shifting (LS), onsite generation and energy storage (ES) systems. They also implemented these options on lower-level in another work [16] to maximize the DR aggregators' profit. In [17], the optimal scheduling in day-ahead market has been conducted from wind power producer viewpoint. Indeed, DR aggregators deal with wind power producers in upper-level instead of ISO. In another work [18], a bilevel approach has been applied to consider upper-level including wind power producer-DR aggregator and lower-level including DR aggregator-customer. In upper-level, wind power producer wants to cope with their production uncertainty by making DR contract with DR aggregators. In lower-level, the DR aggregator tries to maximize its revenue. Reference [19] proposed a bilevel programming for DR scheduling, in which DR aggregator's profit for participation in the day-ahead and real-time markets is maximized in the upper-level, and the cost of providing power balance in the real-time market is minimized in the lower-level. The research in [20] considered both upper-level (ISO-DR aggregator) and lower-level (DR aggregator-customer) separately. This program has been run in a day-ahead market considering uncertain prices and tried to mix the results of each level to get the optimum solution. They also considered taking a risk using the conditional value-at-risk, although the two levels are not studied at the same time; therefore, the results are not reliable and accurate.

In Table I, key relevant references to the current work are summarized. For each reference, the point of view, the objective function of different levels (if there is any), and the difference (or deficits) of the reference compared with the current work are outlined. Accordingly, there is no study that has optimized the objective functions of ISO and DR aggregators at the same time, in a bilevel programming approach, in the presence of network constraints and considering the uncertainty of wind farms (WFs) from ISO's viewpoint.

C. Contributions and Aims

A new strategy for an ISO to trade DR with different DR aggregators while considering various operational constraints is proposed in this paper. ISO determines the energy scheduling and reserve deployment in a pre-emptive market while setting DR contracts with the DR aggregators. ISO applies a two-stage stochastic programming to cope with the

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uncertainty associated with wind power production. In this program, ISO makes the day-ahead decisions through having a look at the balancing market. DR aggregators' behavior is modeled through profit maximization function. Aggregators determine their DR trading shares with ISO and customers through three DR options including LC, LS and load recovery (LR). A stochastic bilevel problem is formulated which in the upper-level, ISO minimizes the total operation cost and in lower-level, DR aggregator maximizes the profit. Afterward, the problem is transferred to a single-level mathematical problem with equilibrium constraints through replacing the lower-level program with its Karush-Kuhn-Tucker (KKT) conditions.

Moreover, the nonlinearities of the derived problem are linearized through a proposed mathematical method. A 6-bus case study is utilized to assess the proposed strategy.

The uncertainty of wind power is considered through generating scenarios in the second stage of upper-level.

The main contributions of this paper are as follows:

- Modeling of the interaction between ISO and DR aggregators as well as the interaction between DR aggregators and customers for short-term scheduling in the presence of WFs.
- Solving a two-stage stochastic programming for minimizing the total operation cost while considering all network constraints and scenario generation for uncertainty handling of WF production and maximizing DR aggregator profit at the same time.
- Applying stochastic bilevel programming techniques for solving two objective functions for DR scheduling in a pre-emptive market from ISO's viewpoint.
- Linearizing the dual problem of the lower-level of DR scheduling problem for making decisions by the ISO through a mixed-integer linear programming (MILP) approach.

D. Paper organization

The remaining parts of the paper are as follows. Section III presents the framework of the proposed bilevel model. Section IV provides the corresponding mixed-integer linear problem of upper- and lower-level, the mixed-integer nonlinear problem of the duality of lower-level and its equivalent linear form. Numerical results illustrating the proposed method are provided in Section V. Section VI makes some concluding remarks.

III. Problem Statement

In this section, different aspects of the modeling in this paper are presented. The structure of DR aggregators, their contracts with customers and ISO are explained and formulated.

The strategy of ISO for the operation of the network is presented, and the market mechanism and the approach for uncertainty handling are outlined. Finally, the strategy for interaction among ISO, DR aggregator and customers at the same time is expressed as a bilevel model.

A. DR Aggregator's Perspective

The structure of proposed DR aggregator for the implementing DR scheduling is shown in Fig. 1.

Accordingly, the participation of customers in the electricity market is maximized through DR aggregator in a day-ahead market. In other words, DR aggregators provide some customer services in order to assess the DR provisions and make the customers aware of their flexible consumption value. Therefore, customers tend to participate in DR more than when they cannot evaluate the profitability of participation in DR.

DR aggregators can be the existing market participants such as load/serving entity, distribution network operators or microgrid operators [16].

According to Fig. 1, DR aggregators are supposed as non-profit independent organizations that each one serves customers located at an especial bus in the transmission network.

TABLE I
Taxonomy of key relevant papers and the differences with the current work

Reference	Viewpoint	Level 1	Level 2	Deficit
[14]	ISO	Minimization of total cost	Maximization of DR aggregators' profit & maximization of customers' payoff	Lack of considering network and its constraints and uncertainty handling
[15]	ISO	Minimization total cost	-	Lack of considering DR aggregator's objective function
[16]	DR aggregator	-	Maximization the DR aggregator's profit	Lack of considering ISO's objective function
[17]	Wind power producer	Minimization negative effect of WF uncertainty	-	- It is not from ISO's viewpoint - Considering just one level without DR aggregator objective function
[18]	Wind power producer	Minimization negative effect of WF uncertainty	Maximization the DR aggregator's profit	Lack of being ISO's viewpoint
[19]	DR aggregator	Maximizing DR aggregator profit for participation in day-ahead market and real-time market	Minimizing cost of power balance in real-time market	- Lack of being ISO's viewpoint - Different objective function in levels
[20]	ISO	Minimization of total cost	Maximization of DR aggregators' profit	Lack of solving two levels at the same time with a bilevel programming

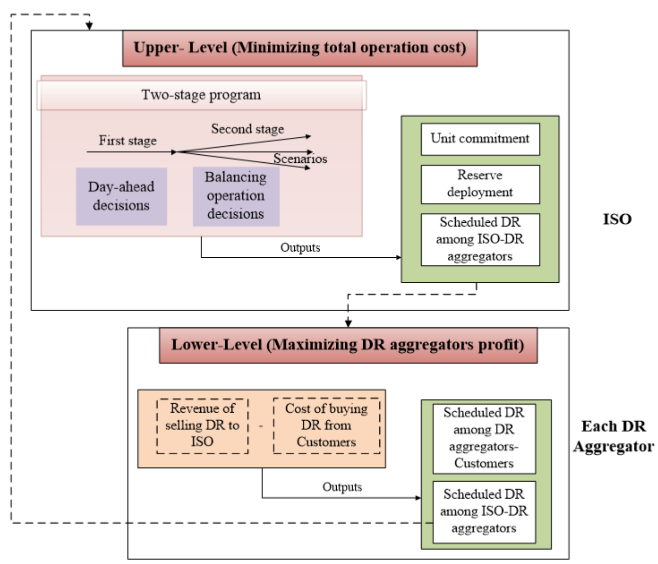

Fig. 1. Proposed bilevel model.

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According to the framework, DR aggregators enroll customers for DR participation and submit DR offers with relative constraints to ISO.

In this model, DR aggregators actively communicate with ISO and customers to take the highest advantages of DR. In the day-ahead market for starting DR programs; ISO starts the DR programs through sending the required information to aggregators to register their DR bids. ISOs and DR aggregators can utilize a variety of systems and technologies to communicate demand response signals, ranging from internet-based protocols to dedicated networks communicating via DNP3. Moreover, the NAESB WEQ standards include requirements for all data flow from registration through to performance evaluation of demand sources involving deployment. Automated demand response (AutoDR) communication protocols, which are designed especially for large electricity customers and industrial customers, can be utilized for this purpose as well.

DR aggregators design the proper contract schemes for the customer and assess the DR capability of loads to help them for qualification themselves to participate in DR programs.

The contract between DR aggregator and customer is in a way that DR aggregator bids to the customer according to the assessment conducted on customers' capabilities through transferred data from customers to DR aggregator. Likewise, a range of load reduction quantity is determined in the contract, based on customers' physical load reduction strategies.

In the next stage, aggregators run DR contracts in day-ahead market to define optimal DR offer through maximizing their profit, and this data will be sent to ISO [16]. In the current paper, DR aggregators form DR offers of three load reduction options including LC, LS, and LR are considered.

B. *ISO's Perspective*

In this paper, the network is supposed to include renewable energy sources like WFs; therefore, the stochastic nature of wind power production should be modeled in a scenario-based method to show the possible events in the real-time.

Wind speed is an uncertain variable followed by unpredictable power generation of wind power generator. Wind speed profile in one area is conformed approximately to the Rayleigh distribution [21]. To form the probability distribution function (PDF), some parameters should be calculated from given historical data processing [22], [23]. The equation of converting wind speed to electric power is a linear one extracted from [23]. Based on Monte-Carlo Simulation method (MCS) and using constructed Rayleigh PDF, several scenarios are generated to illustrate the behavior of wind power generator in real-time. To this end, an uniform random variable is generated and assigned to the mentioned PDF. Afterwards, a wind speed with a probability is obtained followed by the amount of wind power generation. Finally, with a scenario reduction method (forward method) the desired amount of scenarios can be achieved. This procedure is demonstrated in Fig. 2.

Based on Fig. 1, ISO runs a pre-emptive market which describes an interaction among day-ahead market and balancing market [24]. This market framework can cope with the uncertainty of renewable generation why enough flexible capacity is made available for balancing through day-ahead energy reserve dispatch. The structure can be seen in Fig. 1.

In fact, day-ahead energy dispatch decisions account for balancing operation through different scenarios which contain possible events in real-time [24]. ISO receives generating companies (GENCOs) offers for energy and up/down reserve.

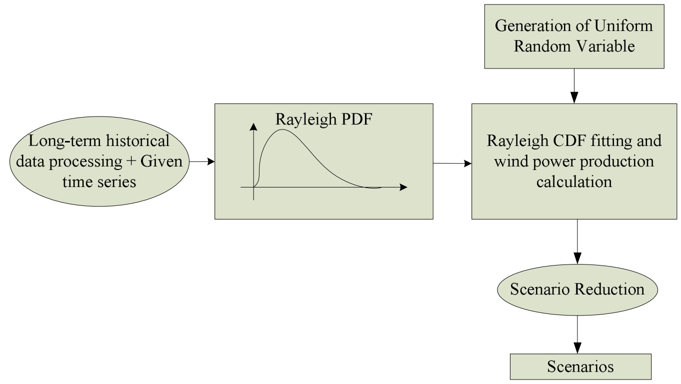

Fig. 2. Scenario generation flowchart.

ISO also receives the DR offers from DR aggregators, and when the ISO clears the market, hourly DR scheduling will be sent to DR aggregators. DR options, strategies and framework proposed to ISO are similar to ones are proposed to customers by DR aggregators. A two-stage stochastic model is applied for short-term scheduling. The first-stage decisions are those made for day-ahead market including energy and reserve of GENCOs as well as DR scheduling for aggregators in each scheduling hour. The second-stage decisions are those that related to the realization of scenarios including the deployment of the reserve, force load reduction and wind spillage.

C. *Demand Response Options*

DR aggregator can be designed for a specific class of customers [15], however, in this paper; we consider a comprehensive DR aggregator scheme which considers all customers and causes further reduction in a number of DR correspondence with consumers. Three load reduction strategies including LC, LS, and LR are utilized as DR options to participate in the day-ahead market and are expressed below.

1) *Load curtailment*

In LC option, customers reduce their consumption based on the program without shifting to other hours [15], [16]. The LC contracts include a number of offers k which each offer has a specific price according to an agreement among ISO and DR aggregators $DR_{tnk}^{Cost,LC}$ or DR aggregator and customers $DB_{tnk}^{Cost,LC}$. The DR cost is non-linear, however we apply price-quota curve approach for linearization and the customers react to different prices in a stepwise way. The price of each step is constant and the quantity is a decision variable in a special range for each step. The stepwise function is shown in Fig. 3. A similar price pattern is obtained for LS and for the lower-level contract between DR aggregators and customers.

Accordingly, the higher incentive the aggregator offers, the higher volume of load reduction will be selected by customers.

The LC contract also has a maximum and minimum quantity of load curtailment for each LC offer which is in equation (2) where u_{tnk}^{LC} is a binary variable to show if the LC offer is scheduled (equal to 1). The exact volume of LC quantity DRK_{tnk}^{LC} of offer k at time t for LC option is scheduled for DR aggregator bus n and the total cost for LC will be obtained by (1). The equation (3) indicates when the offer t will be started $y_{tnk}^{LC}=1$ and when it will be terminated $z_{tnk}^{LC}=1$. Equation (4) is for preventing any coincidence in

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starting and terminating. Minimum and maximum durations of load reduction are in (5) – (6) and the maximum number of LC in a day is given in (7).

2) Load shifting and load recovery

In LS option, customers' loads are curtailed with the potential of shifting to another time within the same day [15], [16]. The shifting and supplying total volume of curtailed loads with the potential of shifting (as LS) will be conducted in other hours of the day as an LR option. The modeling of LS contract is similar to LC which is given in (1) – (7) ($\hat{X} \in LS$). The modeling of a combination of LS and LR is presented in (8) – (10). According to (8), the volume of LR offer k at time t , DRK_{tnk}^{LR} has a limitation and should be lower than a specific amount defined in the contract. Moreover, as (10) shows, the total volume of LS in a day should be equal the total volume of LS. Meanwhile, the LR and LS should not be taken place at the same time given in (9).

In fact, LS presents how much load can be shifted in a certain peak time, while LR manages and controls to recover shifted loads through its precise program in order to avoid peak demand in off-peak hours and wind power spillage, especially in the morning when the wind speed is usually high.

$$CDR_{tn}^{\hat{X}} = \sum_{k\in KD} DRK_{tnk}^{\hat{X}} DR_{tnk}^{Cost,\hat{X}}, \forall t\in TS, \forall n \quad (1)$$

$$DRK_{tnk}^{Min,\hat{X}} u_{tnk}^{\hat{X}} \le DRK_{tnk}^{\hat{X}} \le DRK_{tnk}^{Max,\hat{X}} u_{tnk}^{\hat{X}}, \forall t\in TS, \forall n, \forall k \quad (2)$$

$$u_{tnk}^{\hat{X}} - u_{t-1nk}^{\hat{X}} = y_{tnk}^{\hat{X}} - z_{tnk}^{\hat{X}} \quad (3)$$

$$y_{tnk}^{\hat{X}} + z_{tnk}^{\hat{X}} \le 1 \quad (4)$$

$$\sum_{t}^{t+LCD_{nk}^{\max,LC}-1} z_{tnk}^{\hat{X}} \ge y_{tnk}^{\hat{X}} \quad (5)$$

$$\sum_{t}^{t+LCD_{nk}^{\min}-1} u_{tnk}^{\hat{X}} \ge LCD_{nk}^{\hat{X},\min}(u_{tnk}^{\hat{X}} - u_{t-1nk}^{\hat{X}}) \quad (6)$$

$$\sum_{t} y_{tnk}^{\hat{X}} \le MC_{nk}^{\hat{X}} \quad (7)$$

$$DRK_{tnk}^{LR} \le DRK_{tnk}^{\max,LR} u_{tnk}^{LR}, \forall t\in TR, \forall n, \forall k \quad (8)$$

$$u_{tnk}^{LR} + u_{tnk}^{LS} \le 1 \quad (9)$$

$$\sum_{t\in TR} DRK_{tnk}^{LR} = \sum_{t\in TS} DRK_{tnk}^{LS}, \forall n, \forall k \quad (10)$$

D. Bilevel Model

The decision-making problem pertaining to system operations that jointly minimizes the total operation cost and maximizes the DR aggregator profit can be formulated as a bilevel programming problem.

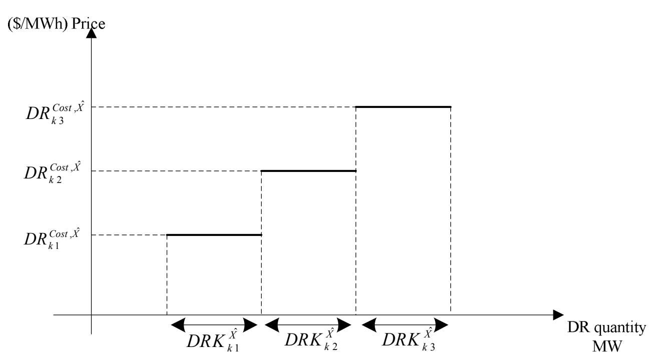

Fig. 3. DR price bidding.

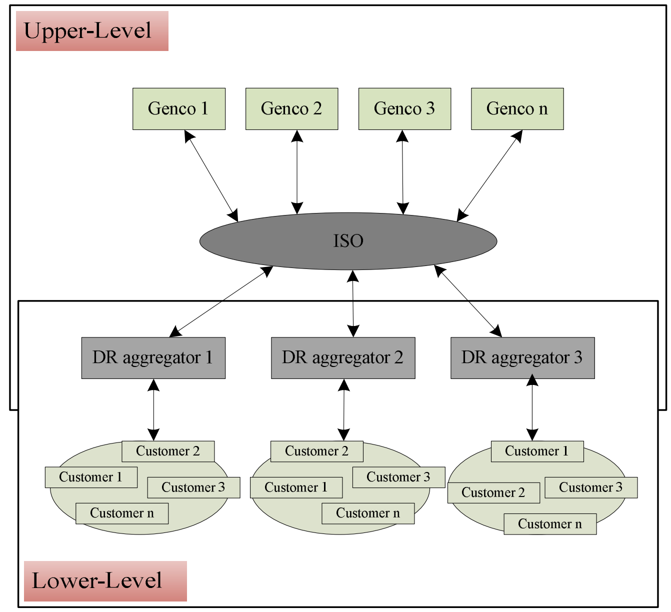

Fig.4. Interaction among different players.

The upper-level problem deal with decisions to be made by ISO with the goal of reducing operation cost in the presence of different DR options and considering different wind production scenarios for increasing system security.

The lower-level problem represents decisions to be made by DR aggregator and related to DR offers in contracts among ISO-DR aggregators as well as DR aggregators-customers with the target of maximization of DR aggregator profit.

Since contracts among ISO-DR aggregators are in both upper- and lower-level, they will be scheduled at the same time through this proposed bilevel stochastic programming.

The structure of this strategy and the interaction among different players are illustrated in Fig. 4.

IV. Problem Formulation

The stochastic day-ahead operation scheduling can be formulated as the stochastic bilevel model below:

A. Bilevel Programming

According to Fig. 1, the upper-level is the minimization of total operation cost through a stochastic two-stage programming as MILP problem which the objective function is in equation (11) and constraints are in (12) – (38).

The first and the second line of equation (11) is respect to first-stage of the program (here-and-now or day-ahead decisions) which includes generation cost of units, start-up and shut-down cost, units' capacity cost of up- and down- reserve as well as total cost of demand response options (LS and LC). The third and fourth line of (11) are linked to second-stage of the program (wait-and-see or balancing operation decisions) [24] which includes the energy cost of units' up- and down-reserve with wind spillage cost and forced load shedding in all scenarios.

First-stage constraints are in (12) – (23). Equations (12) – (13) are maximum/minimum capacity limitation of units. Day-ahead balance equation is in (14). Units' up-/down- reserve limitations are in (15) – (16). Units' ramp-up and down constraints are given in (17) – (18). Equations (19) – (20) represent the constraints that define the units' start-up/shut-down costs. DC power flow equation is presented in (21), and transmission line capacity is in (22). Equation (23) defines that

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the amount of scheduled wind power should be less than the expected volume which is the forecasted amount of wind power. Meanwhile, (1) – (10) are applied for calculation of DR costs that ISO should pay to DR aggregators in the day-ahead market.

The second-stage constraints are in (24) – (29). Equation (24) is balancing condition for real-time market. DC power flow equations for real-time are shown in (25) – (26). Wind-spillage should be lower than wind power of each scenario shown in (27). Limitations of up-/down-reserve for each scenario are shown in (28) – (29). The lower-level formulations are given in (30) – (44). The objective function, the maximization of DR aggregator profit as a linear problem, is given in (30). The first line of (30) is the revenue of DR aggregator from selling DR offers to ISO and the second line is the DR aggregators' expenditures of purchasing DR from customers. The constraints (31) – (37) are for selling DR to ISO and constraints (38) – (44) are related to buying DR from customers.

$$\begin{aligned} Minimize \sum_{t\in NT} \Bigg\{ & \sum_{g\in NG} (C_{tg}^{gen} P_{tg}^{gen} + SUC_{tg}^{gen} + C_{tg}^{up} R_{tg}^{up} + C_{tg}^{down} R_{tg}^{down}) \\ & + \sum_{n\in NN} (CDR_{tn}^{LC} + CDR_{tn}^{LS}) \\ & + \sum_{s\in S} \pi_s \Bigg[\sum_{g\in NG} (Cs_{tgs}^{up} Rs_{tgs}^{up} + Cs_{tgs}^{down} Rs_{tgs}^{down}) \\ & + \sum_{n\in NN} (Cs_{tns}^{spill} W_{tns}^{spill} + Cs_{tns}^{voll} Ls_{tns}^{shed}) \Bigg] \Bigg\} \end{aligned} \tag{11}$$

In (11), the here-and-now decision variables are $P_{tg}^{gen}, SUC_{tg}^{gen}, R_{tg}^{up}, R_{tg}^{down}, CDR_{tn}^{LC}, CDR_{tn}^{LS}$ and the wait-and-see decision variables include $Rs_{tgs}^{up}, Rs_{tgs}^{down}, W_{tns}^{spill}, Ls_{tns}^{shed}$. These variables are defined through minimizing (11) with considering following constraints:

$$P_{tg}^{gen} + R_{tg}^{up} \le P_g^{\max} u_{tg}^{gen}, \forall t, \forall g \tag{12}$$

$$P_{tg}^{gen} - R_{tg}^{down} \ge P_g^{\min} u_{tg}^{gen}, \forall t, \forall g \tag{13}$$

$$\sum_{g\in NG} p_{tg}^{gen} + W_{tn}^{sch} + \sum_{k\in KD} (DRK_{tnk}^{LC} + DRK_{tnk}^{LS} - DRK_{tnk}^{LR}) = LD_{tn} + \sum_{l\in NL} pf_{tl}, \forall t, \forall n \tag{14}$$

$$0 \le R_{tg}^{up} \le R_g^{\max,up}, \forall t, \forall g \tag{15}$$

$$0 \le R_{tg}^{down} \le R_g^{\max,down}, \forall t, \forall g \tag{16}$$

$$P_{t-1g}^{gen} - P_{tg}^{gen} \le Rmp_g^{up}, \forall t, \forall g \tag{17}$$

$$P_{tg}^{gen} - P_{t-1g}^{gen} \le Rmp_g^{down}, \forall t, \forall g \tag{18}$$

$$SUC_{tg}^{gen} \ge C_g^{strt.up} (u_{tg}^{gen} - u_{t-1g}^{gen}), \forall t, \forall g \tag{19}$$

$$SUC_{tg}^{gen} \ge C_g^{sht.dwn} (u_{t-1g}^{gen} - u_{tg}^{gen}), \forall t, \forall g \tag{20}$$

$$pf_{tl} = \sum_{n\in NN} \frac{1}{X_{nl}} (\theta_{nl}^1 - \theta_{nl}^0), \forall t, \forall l \tag{21}$$

$$pf_l^{\min} \le pf_{tl} \le pf_l^{\max}, \forall t, \forall l \tag{22}$$

$$0 \le W_{tn}^{sch} \le W_{tn}^{\exp}, \forall t, \forall n \tag{23}$$

$$\sum_{g\in NG} (Rs_{tgs}^{up} + Rs_{tgs}^{down}) + W_{tns}^{scen} - W_{tn}^{sch} - W_{tns}^{spill} + Ls_{tns}^{shed} = -\sum_{l\in NL} (pfs_{tls} - pf_{tl}), \forall t, \forall n, \forall s \tag{24}$$

$$pfs_{tls} = \sum_{n\in NN} \frac{1}{X_{nl}} (\theta_{nls}^1 - \theta_{nls}^0), \forall t, \forall l, \forall s \tag{25}$$

$$pf_l^{\min} \le pfs_{tls} \le pf_l^{\max}, \forall t, \forall l \tag{26}$$

$$0 \le W_{tns}^{spill} \le W_{tns}^{scen} \tag{27}$$

$$0 \le Rs_{tgs}^{up} \le R_{tg}^{up} \tag{28}$$

$$0 \le Rs_{tgs}^{down} \le R_{tg}^{down} \tag{29}$$

where

$$\begin{aligned} Maximize \sum_{t\in NT} \sum_{n\in NN} \sum_{k\in KD} & (DRK_{tnk}^{LC} DR_{tnk}^{Cost,LC} + DRK_{tnk}^{LS} DR_{tnk}^{Cost,LS}) \\ & -(DBK_{tnk}^{LC} DB_{tnk}^{Cost,LC} + DBK_{tnk}^{LS} DB_{tnk}^{Cost,LS}) \end{aligned} \tag{30}$$

subject to:

$$DRK_{tnk}^{LC} \le DRK_{tnk}^{Max,LC} u_{tnk}^{LC} : \alpha_{tnk}, \forall t\in TC, \forall n, \forall k \tag{31}$$

$$-DRK_{tnk}^{LC} \le -DRK_{tnk}^{Min,LC} u_{tnk}^{LC} : \beta_{tnk}, \forall t\in TC, \forall n, \forall k \tag{32}$$

$$DRK_{tnk}^{LS} \le DRK_{tnk}^{Max,LS} u_{tnk}^{LS} : \gamma_{tnk}, \forall t\in TS, \forall n, \forall k \tag{33}$$

$$-DRK_{tnk}^{LS} \le -DRK_{tnk}^{Min,LS} u_{tnk}^{LS} : \lambda_{tnk}, \forall t\in TS, \forall n, \forall k \tag{34}$$

$$DRK_{tnk}^{LR} \le DRK_{tnk}^{\max,LR} u_{tnk}^{LR} : \zeta_{tnk}, \forall t\in TR, \forall n, \forall k \tag{35}$$

$$u_{tnk}^{LR} + u_{tnk}^{LS} \le 1, \forall t, \forall n, \forall k \tag{36}$$

$$\sum_{t\in TR} DRK_{tnk}^{LR} = \sum_{t\in TS} DRK_{tnk}^{LS} : \mu_{tnk}, \forall n, \forall k \tag{37}$$

$$DBK_{tnk}^{LC} \le DBK_{tnk}^{Max,LC} u_{tnk}^{LC} : \sigma_{tnk}, \forall t\in TC, \forall n, \forall k \tag{38}$$

$$-DBK_{tnk}^{LC} \le -DBK_{tnk}^{Min,LC} u_{tnk}^{LC} : \rho_{tnk}, \forall t\in TC, \forall n, \forall k \tag{39}$$

$$DBK_{tnk}^{LS} \le DBK_{tnk}^{Max,LS} ub_{tnk}^{LS} : \varphi_{tnk}, \forall t\in TS, \forall n, \forall k \tag{40}$$

$$-DBK_{tnk}^{LS} \le -DBK_{tnk}^{Min,LS} ub_{tnk}^{LS} : \tau_{tnk}, \forall t\in TS, \forall n, \forall k \tag{41}$$

$$DBK_{tnk}^{LR} \le DBK_{tnk}^{\max,LR} ub_{tnk}^{LR} : \varepsilon_{tnk}, \forall t\in TR, \forall n, \forall k \tag{42}$$

$$ub_{tnk}^{LR} + ub_{tnk}^{LS} \le 1, \forall t, \forall n, \forall k \tag{43}$$

$$\sum_{t\in TR} DBK_{tnk}^{LR} = \sum_{t\in TS} DBK_{tnk}^{LS} : \omega_{tnk}, \forall n, \forall k \tag{44}$$

B. Implementing Duality Theory

In the bilevel problem, the lower-level problem can be turned into its dual problem. Since each primal constraints of the lower-level problem (30) – (44) is continuous and convex, it can be represented by its dual constraints and strong duality conditions [4]. The nonlinear dual problem of the lower level and its dual constraints beside strong duality conditions are given in (45) – (50). The nonlinear problem (45) can be transferred to the linear problem through equations (51) – (54). Equation (51) defines all nonlinear items which are a multiplication of a binary variable and positive variable like $\alpha_{tnk} u_{tnk}^{LC}$ as a single positive variable like α'_{tnk}.

In (52) a boundary is defined for the new variable α'_{tnk} where SPP_{tnk} is a large enough quantity compared with a range of α'_{tnk} (about more than 10 times). u'^{LC}_{tnk} is a new binary variable which determines if new variables (e.g. α'_{tnk}) are zero or equal to former variables (e.g. α_{tnk}). Eq. (52) determines that if $u'^{LC}_{tnk} = 0$, the variable $\alpha'_{tnk} = 0$ and consequently $\alpha_{tnk} = 0$. On the other hand, (53) – (54) specify that if $u'^{LC}_{tnk} = 1$ then $\alpha'_{tnk} = \alpha_{tnk}$. Therefore, the dual problem of lower-level will be turned into a linear problem.

$$\begin{aligned} Minimize \sum_{t\in NT} \sum_{n\in NN} \sum_{k\in KD} & \alpha_{tnk} u_{tnk}^{LC} DRK_{tnk}^{Max,LC} - \beta_{tnk} u_{tnk}^{LC} DRK_{tnk}^{Min,LC} \\ & + \gamma_{tnk} u_{tnk}^{LS} DRK_{tnk}^{Max,LS} - \lambda_{tnk} u_{tnk}^{LS} DRK_{tnk}^{Min,LS} + \zeta_{tnk} u_{tnk}^{LR} DRK_{tnk}^{\max,LR} \\ & + \sigma_{tnk} ub_{tnk}^{LC} DBK_{tnk}^{Max,LC} - \rho_{tnk} ub_{tnk}^{LC} DBK_{tnk}^{Min,LC} \\ & + \varphi_{tnk} ub_{tnk}^{LS} DBK_{tnk}^{Max,LS} - \tau_{tnk} ub_{tnk}^{LS} DBK_{tnk}^{Min,LS} + \varepsilon_{tnk} ub_{tnk}^{LR} DBK_{tnk}^{\max,LR} \end{aligned} \tag{45}$$

subject to:

$$\alpha_{tnk} - \beta_{tnk} \ge DR_{tnk}^{Cost,LC}, \forall t, \forall n, \forall k \tag{46}$$

$$\gamma_{tnk} - \lambda_{tnk} \ge DR_{tnk}^{Cost,LS}, \forall t, \forall n, \forall k \tag{47}$$

$$\sigma_{tnk} - \rho_{tnk} \ge -DB_{tnk}^{Cost,LC}, \forall t, \forall n, \forall k \tag{48}$$

$$\varphi_{tnk} - \tau_{tnk} \ge -DB_{tnk}^{Cost,LS}, \forall t, \forall n, \forall k \tag{49}$$

$$\alpha_{tnk}, \beta_{tnk}, \gamma_{tnk}, \lambda_{tnk}, \sigma_{tnk}, \rho_{tnk}, \varphi_{tnk}, \tau_{tnk} \ge 0 \quad \forall t, \forall n, \forall k \tag{50}$$

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Linearization:

$$\alpha_{tnk} u_{tnk}^{LC} = \alpha'_{tnk} \quad .... \quad \varepsilon_{tnk} ub_{tnk}^{LR} = \varepsilon'_{tnk}, \forall t, \forall n, \forall k \tag{51}$$

$$\alpha'_{tnk} \le SPP_{tnk} u'^{LC}_{tnk} \quad .... \quad \varepsilon'_{tnk} \le SPP_{tnk} u'^{LR}_{tnk}, \forall t, \forall n, \forall k \tag{52}$$

$$\alpha'_{tnk} \le \alpha_{tnk} + SPP_{tnk}(1 - u'^{LC}_{tnk}) \quad ..... \quad \varepsilon'_{tnk} \le \varepsilon_{tnk} + SPP_{tnk}(1 - u'^{LR}_{tnk}), \forall t, \forall n, \forall k \tag{53}$$

$$\alpha'_{tnk} \ge \alpha_{tnk} - SPP_{tnk}(1 - u'^{LC}_{tnk}) \quad ... \quad \varepsilon'_{tnk} \ge \varepsilon_{tnk} - SPP_{tnk}(1 - u'^{LR}_{tnk}), \forall t, \forall n, \forall k \tag{54}$$

C. *Equivalent Single-level Problem*

The stochastic bilevel problem of (11) – (44) can be turned into stochastic one-level problem through incorporating primal constraints of lower-level and its dual strong condition and constraints into upper-level.

The strong duality theorem states that a feasible solution of the primal problem and dual problem are obtained if and only if primal and dual objective functions are equal [6]:

$$\begin{aligned}
&\sum_{t \in NT} \sum_{n \in NN} \sum_{k \in KD} (DRK_{tnk}^{LC} DR_{tnk}^{Cost,LC} + DRK_{tnk}^{LS} DR_{tnk}^{Cost,LS}) \\
&-(DBK_{tnk}^{LC} DB_{tnk}^{Cost,LC} + DBK_{tnk}^{LS} DB_{tnk}^{Cost,LS}) = \\
&\sum_{t \in NT} \sum_{n \in NN} \sum_{k \in KD} \alpha'_{tnk} DRK_{tnk}^{Max,LC} - \beta'_{tnk} DRK_{tnk}^{Min,LC} \\
&+\gamma'_{tnk} DRK_{tnk}^{Max,LS} - \lambda'_{tnk} DRK_{tnk}^{Min,LS} + \zeta'_{tnk} DRK_{tnk}^{\max,LR} \\
&+\sigma'_{tnk} DBK_{tnk}^{Max,LC} - \rho'_{tnk} DBK_{tnk}^{Min,LC} \\
&+\varpi' \, DBK^{Max,LS} - \tau' \, DBK^{Min,LS} + \varepsilon' \, DBK^{\max,LR}
\end{aligned} \tag{55}$$

Single-level mixed integer linear problem equivalent to (11) – (44) is achieved by minimizing the upper-level objective function and considering all upper-level constraints as well as primal and dual constraints of lower-level constraints which are given below.

$$\text{Minimize } (11) \tag{56}$$

subject to:

$$(1) – (10), (12) – (29) \tag{57}$$

$$(31) – (44), (46) – (55) \tag{58}$$

V. Numerical Studies

A 6-bus system is applied to evaluate the proposed model in this paper; however, the model has been successfully tested on larger systems such as IEEE 24-bus system.

The system shown in Fig. 5 includes 3 conventional generation units and a WF with the maximum capacity of 20 MW. Each load bus has a DR aggregator.

Three cases are considered to study the different states of this problem. The cases contain DR Price variation to show the effect of DR price on the outputs. In each case, the proposed model is compared with the case when DR aggregator-customer contract is not considered which we called here as being the model disregarding DR aggregator's viewpoint (DDRV). In other words, since the proposed method has two levels and the second level is from DR aggregator's viewpoint, in DDRV, the second level has been omitted and only the first level, which is the minimization of the total operation cost with DR options, has been considered.

Hence, the impact of simultaneously considering ISO-DR aggregator contract and DR aggregator-customer contract is investigated versus considering only ISO-DR aggregator contracts, demonstrating the merits of the proposed model.

Case 1 includes the main price scheme, which is placed as a reference to compare other cases. In case 2, the DR prices are 20% higher than the first case, and in case 3, conversely, DR Price is 20% lower than case 1. DR offer prices for load reduction of case 1 are categorized in Table II. DRC is relevant to DR offers of the ISO-DR aggregator contract, and DBC is related to offers of DR aggregators-customers contract. These DR prices are identified based on the price difference between selling and buying DR in the upper level and lower level. In fact, DR aggregator should take the advantages of DR price difference when buying from the customer and selling to ISO. Hence, the DR selling price has to be more than the DR buying price so that the DR aggregator can benefit from this market. These offers for all DR aggregators are the same. Other information about constraints of DR offers and options as well as 6-bus case study data are given in [25]. The problem is solved by solver CPLEX in GAMS [26] using a computer with 6 GB RAM and 2.6 GH, core i7 processor. The computation time is less than 1 second.

The impact of the proposed model on load profile for the case 1 is demonstrated in Fig. 6. As can be seen, after running DR programs, LC, LS, and LR are applied to the load profile. Between hours 10 to 18, LR and LS are called. Therefore, the load curve for peak hours is shaved. However, this LC for proposed model is more than when just interaction between ISO and DR aggregator is considered as a DDRV method. The reason behind this is why unlike the DDRV method, in the proposed model is considering the interaction of both ISO-DR aggregator and DR aggregator-customer. Hence, the model includes the detail information of DR aggregator contract with customers, and it gives more precise results. Moreover, the curtailed loads are shifted to off-peak hours between hours 1 to 8 and customers will consume their voluntary curtailed load in off-peak hours as LS and LR options. As a result of the previous phenomenon for LC, more load demands are shifted and recovered to the off-peak hours through the proposed model in compared with the DDRV method.

In Table III, the impact of the proposed model on unit commitment in case 1 is illustrated. Accordingly, by implementing the proposed bilevel model, there is no need for committing the generator number 2 until hour 11. It causes a decrease in energy cost which is units' generation and reserve cost following by a drop in total operation cost which is demonstrated in Table V. It is due to the fact that since the proposed model has a closer look at details of customer constraints and decision-making variables, the cheapest unit (G1) produces more power in proposed model to supply the both shifted and regular loads.

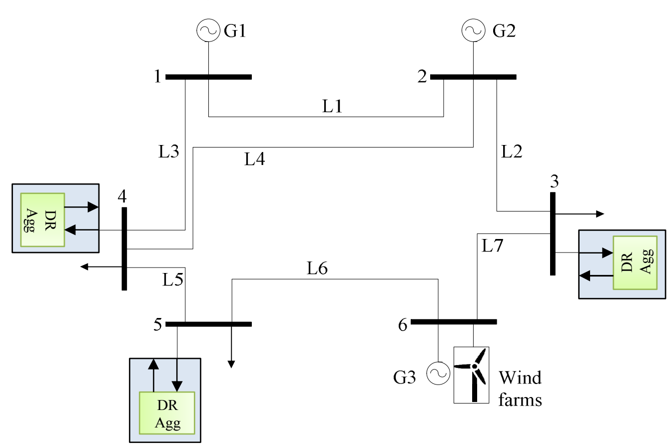

Fig. 5. One-line diagram of studied 6-bus network.

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TABLE II
DR prices for 5 offers and two options in case 1

CASE1		K1 (€/MWh)	K2 (€/MWh)	K3 (€/MWh)	K4 (€/MWh)	K5 (€/MWh)
DRC	LC price	10	11	12	13	14
	LS Price	10	11	12	13	14
DBC	LC price	8	9	10	11	12
	LS Price	8	9	10	11	12

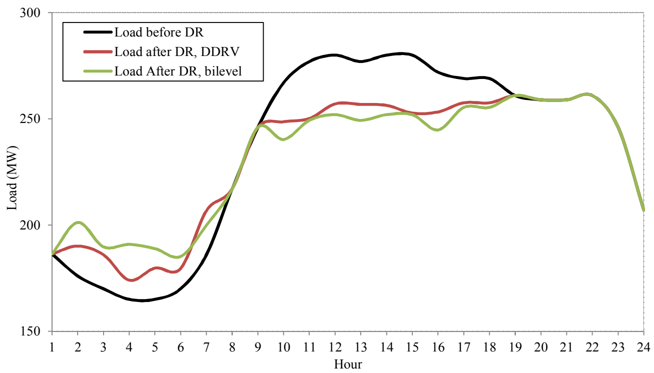

Fig. 6. Impact of proposed DR model on load profile for case 1.

TABLE III
Unit commitment status of units comparison among proposed bilevel model and conventional method for case 1

unit	DDRV method (Hours 1 to 24)
G1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
G2	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
G3	0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
unit	Proposed bilevel method (Hours 1 to 24)
G1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
G2	0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1
G3	0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1

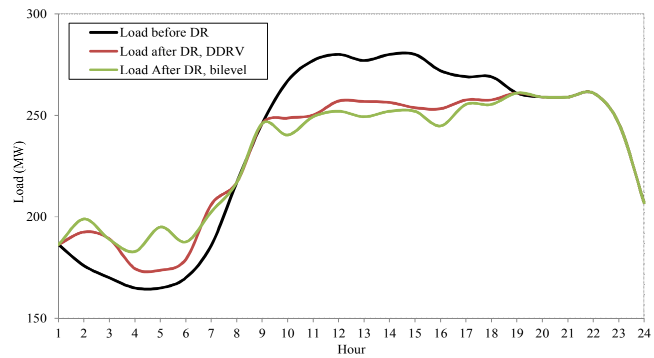

Fig. 7. Impact of proposed DR model on load profile for case 2.

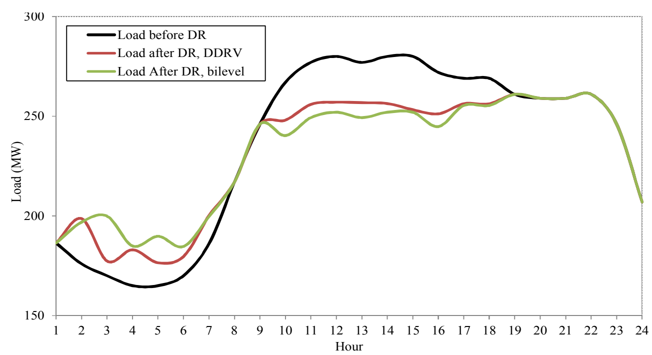

Fig. 8. Impact of proposed DR model on load profile for case 3.

In the second case, with increasing the DR offer price for both ISO-DR aggregator contracts and DR aggregator-customers, no change for load reduction is taken place based on Fig. 7. However it was expected that higher DR price leads to less scheduled load reduction. Therefore, it can be concluded that increasing DR price at least up to 20% has no negative impact on customers' DR participation. Moreover, the amount of load that should be recovered based on LR at each off-peak hour is different in case 2 compared with case 1 for both DDRV and the proposed method. Because according to the model, the consumption can be freely shifted to each off-peak hour up to 2 MW. Hence, loads are generally shifted to hours with more generation. For example, at hour 5, G1 generates 193.78 MW in case 2 in the proposed bilevel model, while this generation is 187.69 MW in case 1. Therefore, as can be seen in Fig. 7, the recovered loads at hour 5 in case 2 are more than this volume in case 1. In addition, there is no difference between unit commitment status of cases 1 and 2 because the higher DR price does not aid to improve system operation condition. As it was expected, the higher price for DR offer is considered, the higher total operation cost, DR implementation cost and energy cost take place which is illustrated in Table V.

The load profile in case 3 for the proposed bilevel model has no remarkable changes compared with cases 1 and 2. This reflects the fact that DR price variation within ±20% has no impact on the load reduction pattern for the proposed method. On the other hand, load reduction in DDRV method in case 3 at hour 11 is less than case 1 and case 2 according to Fig. 8, while the DR price in case 3 is lower and the load reduction is supposed to be equal or higher than other cases. The reason is due to lack of enough accuracy for the DDRV model. Another difference is in the amount of load that is shifted and recovered at hours 1 to 8; the reason is similar to what happens in case 1 and case 2 in this term. On the other hand, in this case, according to Table IV, the unit commitment status in both conventional and proposed bilevel methods is the same, because the DR price is low and it is better to apply DR instead of turning on the generators, even for DDRV. In other words, unlike the case 1, generator number 2 is not scheduled and committed for the first 8 hours even in the DDRV method.

Moreover, according to the Table V, the total operation cost of two methods in case 3 are relatively the same. It is concluded that low price of DR offers is not able to demonstrate the positive impact of the proposed bilevel method, because in reality, too low DR prices cannot be reasonable and applicable for DR implementation.

Security cost, which is the cost of dealing with balancing market scenarios in the second stage, is lower in the proposed bilevel method in case 1 and 2; however, this cost is the same in the third case based on Table V.

A sensitivity analysis for DR prices is conducted for the proposed model which is demonstrated in Fig. 9. Accordingly, case 1 is assumed as the base of DR price. The DR price will vary between $\pm 5\%$ and $\pm 30\%$. Meanwhile, the impact of different WF maximum capacities is studied. As expected, with increasing DR prices, total operation cost generally grows for each WF capacity. Moreover, the larger WF is installed, the lower total operation cost is obtained. However, installing more than 22 MW WF will cause an increase in total operation cost due to and increase the wind spillage cost.

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TABLE IV
Unit commitment status of units comparison among proposed bilevel model and conventional method for case 3

unit	DDRV method (Hours 1 to 24)
G1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
G2	0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1
G3	0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
unit	Proposed bilevel method (Hours 1 to 24)
G1	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
G2	0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1
G3	0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1

TABLE V
Different costs in all cases based on two methods

Case	Method	Total operation cost (€)	Energy cost (€)	Security cost (€)	DR cost (€)
Case1	DDRV	90158	88878	862	2142
	Bilevel	88475	86664	835	2646
Case2	DDRV	90574	88881	862	2554
	Bilevel	89004	86664	835	3175
Case3	DDRV	87740	86876	835	1699
	Bilevel	87946	86664	835	2117

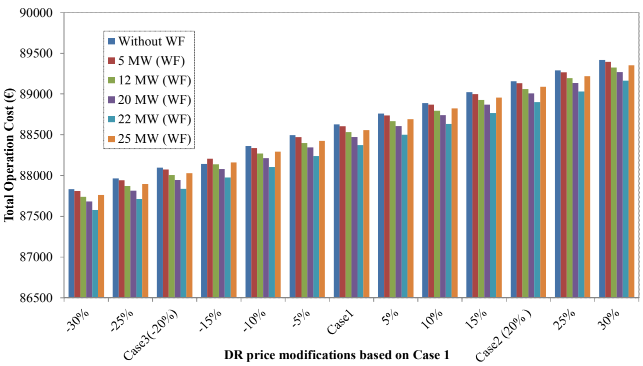

Fig. 9. The impact of DR prices and WF capacity on total operation cost.

VI. CONCLUSIONS

A stochastic bilevel problem has been formulated in which the upper-level problem aims to minimize the total operation cost of the ISO and the lower-level problem seeks the maximum profit of DR aggregators. A two-stage stochastic programming is applied to cope with the uncertainty of wind power production. DR aggregators' behavior was modeled through profit maximization functions. Aggregators determine their DR trading shares with ISO and customers through three DR options, namely LC, LS, and LR. Comparisons among the proposed bilevel model and the DDRV method as well as different prices for DR offers were performed in a 6-bus system. The results demonstrated that the proposed method could reduce more loads in peak hours followed by more load recovery in off-peak hours. Moreover, the total cost was reduced compared with the DDRV method. These improvements and differences among the proposed bilevel method and DDRV method are due to the fact that the scheduling in the proposed method was performed based on more information related to DR and had a closer look at details of customer constraints. However, when the prices of DR offers were low, there was no remarkable difference between operation costs in the proposed method and DDRV method. Likewise, the operation cost was reduced when a higher capacity of WF was used; however, after a specific higher capacity of WF the operation cost increased due to wind spillage cost. Enabling the customers for choosing the DR aggregator and making a competition among DR aggregators can be a very interesting suggestion for future work. Moreover, a more detailed modeling for load reduction can be performed with considering ramp rate constraint of load reduction as a future work. Another future work can be considering the DR uncertainty within the model.

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