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Multi-Objective Market Clearing Model with an Autonomous Demand Response Scheme

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Abstract: Demand response (DR) is known as a key solution in modern power systems and electricity markets for mitigating wind power uncertainties. However, effective incorporation of DR into power system operation scheduling needs knowledge of the price–elastic demand curve that relies on several factors such as estimation of a customer's elasticity as well as their participation level in DR programs. To overcome this challenge, this paper proposes a novel autonomous DR scheme without prediction of the price–elastic demand curve so that the DR providers apply their selected load profiles ranked in the high priority to the independent system operator (ISO). The energy and reserve markets clearing procedures have been run by using a multi-objective decision-making framework. In fact, its objective function includes the operation cost and the customer's disutility based on the final individual load profile for each DR provider. A two-stage stochastic model is implemented to solve this scheduling problem, which is a mixed-integer linear programming approach. The presented approach is tested on a modified IEEE 24-bus system. The performance of the proposed model is successfully evaluated from economic, technical and wind power integration aspects from the ISO viewpoint.

Keywords: customer's disutility; day-ahead market; demand response; multi-objective model; wind integration

1. Introduction

1.1. Aims and Motivations

The active participation of customers in modern electricity markets is considered as a potentially high impact with relatively low-cost alternative to achieve efficient and cost-effective operation [1]. In this regard, estimation of the flexible portion of demand due to both the technical ability to respond and a customer's eagerness is very crucial [2,3]. The challenges and benefits to each market entity using DR services are presented in [4].

The customer's technical ability depends on some control and communication infrastructure while their willingness to respond is mostly parameterized using the price elasticity of demand concept. The consumer's sensitivity to price changes can be measured by the coefficient of price elasticity. On this basis, estimating the price elasticity of demand has great importance for proper demand response (DR) implementation. However, the accurate calculation of demand elasticity is currently a major obstacle for incorporating DR into power system operation according to the main reasons described briefly below [5,6]:

(1) The elasticity estimation will be biased if the replacement of other inputs for the use of electricity occurs. Furthermore, this is disregarded by the models used to determine price elasticity. On the other hand, inclusion of such detailed information is not only hard to acquire but also increases the complexity of the model;
(2) The nonlinear structure of tariff plans and aggregation of metered behavior of the consumption over time creates associate simultaneity problems between marginal prices and consumption;
(3) The price elasticity may vary widely across various sectors (residential, commercial and industrial) and regions, so an exact estimation needs awareness of the mix of sectors and the disaggregation of the information which is intractable currently. For example, a methodology for day-ahead prediction and shaping of dynamic demand response is presented in [7], based on the application of Monte Carlo simulations and an artificial neural network.

According to the above, elasticity estimation depends on a chain of simplified assumptions which may create uncertainties in precise modeling of customer behavior and consequently lead to significant over- or under-estimation errors in the available responsive demand.

A practical solution to overcome the discussed challenges has been developed recently in the context of the autonomous DR (ADR) concept. ADR enables end-use consumers to automatically schedule their consumption based on price signals through appliance scheduling tools and also provides the possibility of information exchange with DR aggregators or load service entities (LSEs), simultaneously [8]. From this perspective, the end-use consumers can actively interact with DR aggregators or LSEs to plan their future demand. As a result, ADR eliminates the need for demand forecasting or estimating the price elasticity of demand and creates a new window of opportunity for proper DR planning and implementation.

1.2. Literature Review and Background

During recent years, DR has regained significant attention as a potential solution for tackling the economic, technical and environmental challenges of power grids [9–11]. In [12], a financial approach to incentivize customers to take part in the DR program is applied. On this basis, several models have been used to address customer behavior when integrated into electricity markets. The DR models can be categorized into two major groups as described below:

(1) DR models based on the price elasticity of demand definition; these models reflect the changes in customer demand in response to changing the electricity tariffs. To this end, the economic approach of responsive loads has been calculated based on the idea of price elasticity of demand curve to maximize the customer's utility function. In this respect, several papers considered fix price elasticity values [13,14], while others assumed flexible price elasticity factors [15,16]. Moreover, various relations of demand vs. price have been considered using linear, quadratic, exponential, and logarithmic functions to find out a conservative model for customer behavior in order to have less error in DR implementation [17,18]. However, the major challenge of the works in this category are related to the estimation of customer elasticity and participation level which restricts the applicability of these models due to significant errors in the accessible DR amount.
(2) DR models based on the DR aggregator or DR provider definition; these models aggregate small electricity customer responses and submit the aggregated offers on behalf of them in the electricity market in order to maximize its own profits as a virtual generation company. In such DR models, several constraints have been integrated into the model in order to meet the customer's needs and convenience. A decentralized approach is presented with price-based signals sent to consumers and demand-based signals sent to the aggregator from consumers in [19]. According to the

supply side, a function bidding model for DR is formulated [20]. A bidding strategy of the virtual power plants in the day-ahead market, the intra-day demand response exchange market, and the balancing market is modeled in [21]. The minimum and maximum load reduction duration (besides load reduction initiation cost) were considered in the participant's load reduction offer packages in [22]. DR treated as a virtual generation resource in [23] whose marginal cost and relevant constraints such as DR magnitude, duration and frequency were modeled according to customer information. The technical constraints of customers including the energy limit, minimum and maximum available capacities, maximum rate of energy change from one period to the next, minimum and maximum duration of the DR event, and the frequency of the DR events were integrated into the DR aggregator trading framework in [24]. In developing the power electricity market, there are different types of uncertainties that could change the day-ahead generation scheduling of the units. In the current paper, all the uncertainties about the behavior of the DR provider and elasticity of the customers are modeled for the independent system operator (ISO) to present secure generation scheduling with consideration of the all uncertainties on the side of the DR providers.

Although many constraints were employed in order to satisfy customer requirements, there are some drawbacks to these works. On one hand, customer requirements in various sectors (i.e., residential, industrial and commercial) are different according to their own characteristics and hence satisfying the particular needs of each sector is very complicated due to the difficulty in separating the data among the mentioned sectors. On the other hand, as opposed to the former DR category, the customer's utility function is not incorporated in the model explicitly and just addressed by a limited set of constraints.

It is noticed that a number of studies have modeled the DR uncertainty in order to have a more precise DR estimation [25–30]. For instance, the unknown price–elastic demand curve has been modeled in the reliability unit commitment problem to be run by the independent system operator (ISO) using the robust optimization method in [25]. The uncertainty in the realization of DR provided by DR providers in the day-ahead electricity market clearing process has been investigated in [26,27]. The authors in [28–30] have modeled the fail in customer's behavior by proposing a two-state reliability model for DR resources including the availability and unavailability of DR resources.

1.3. Contributions

According to the above discussion, the current DR models deal with several practical limitations which may affect the proper DR implementation from an ISO point of view. In fact, the main challenge for DR development in power system operation is that the price–elastic demand curve is not exactly known in advance. On this basis, this paper proposes a novel DR model (so-called ADR) for the ISO that omits the need for forecasting customer participation level in DR programs as well as estimating the price elasticity of demand. To reach a reliable scheduling for power plants that any changes to the different behavior of the DR provider could do not have any profound influence on the operation of the power plants. In the proposed framework, the DR providers who participate in the electricity market submit several ranked daily load curves to the ISO according to their preference order so that the high-ranked offered load curves have less customer disutility and vice versa. This is one of the novelties of the manuscript that all of these different uncertainties such as customer reaction of the each DR providers to the submitted programs will be modeled in the day-ahead scheduling and finally the output will be the most reliable program to all of these uncertainties. The ISO decision making problem is defined as a bi-objective problem including operation cost and customer disutility goals. In this regard, the ISO aims to minimize the operation cost with a minimum customer disutility level. This is mainly due to the fact that although the participation of customers in DR programs may decrease the operation cost, it causes some difficulty for customers since they are forced to change their typical consumption pattern. Therefore, it is important for the ISO to minimize operation cost with respect to the customer disutility function.

In short, the main contributions of the current paper are summarized below:

- We propose a novel DR framework that eliminates the need to estimate customer reactions in response to DR programs with the aim of reducing DR uncertainty and consequently enhancing DR development in power system operation from the ISO point of view in the presence of renewable units;
- To present a bi-objective approach including among its objective functions the operation cost and customer disutility in order to gain a cost-efficient generation dispatch in energy and reserve markets, taking into account customer disutility as a result of participation in DR programs.

1.4. Paper Organization

This paper will be continued as follows: Section 2 deals with the proposed DR scheme modeling. The stochastic market clearing formulation in the presence of variable wind generation is modeled using a bi-objective decision-making approach in Section 3. Section 4 is devoted to numerical results and discussion, and finally, Section 5 concludes the paper.

2. ADR Scheme Modeling

The scheduled amount of DR depends on customer behavior, specifically customer participation level in DR programs as well as the customer's price elasticity of demand. Accurate estimation of such factors is impossible for ISOs which causes failed assessments of DR potential in the electricity market. In order to avoid such a challenge and promote the role of DR in power system transactions, this paper proposes a novel DR scheme called ADR. From this perspective, DR providers who participate in the electricity market submit a number of ranked daily load profiles based on their preference order in the context of the day-ahead market. According to the market and network conditions, the ISO selects one of the load profiles of each DR provider in order to not only minimize the total operation cost but also minimize the customer's disutility as a result of violation in the customer's priority order. After the market clearing procedure, the ISO notifies the DR providers of their individual final chosen load profile. The DR providers are then assumed to obey the selected daily load profiles. Incentive and compensative cost for shaving and shifting of the load curve and customer price–demand elasticity are related to the DR providers side, but when we look at the problem from the ISO point of view in the power market, they just showed them in the load balance constraint. When the ISO is responsible for shaving and shifting of the load curve by direct cooperation with the demand side, incentive and compensative cost should be modeled in the operation cost of the ISO. In this paper, the ISO receives a different load curve from DR providers and incentive cost for the customer will be the problem of the DR providers and not the ISO.

The individual final selected load profile for each DR provider is formulated as shown in (1). It is worth noting that $x_{drp,n}$ is a binary variable that indicates which one of the candidate load profiles is selected by the ISO. Constraint (2) ensures the selection of only one load profile for each DR provider. The customer's disutility realized by each DR provider depends on the selected load profile and the profile rank as formulated in (3) [31]. The profile rank of DR providers is considered as a matrix given in (4) [31]. The logic behind such a matrix is that when the top-ranked profile is selected, it is assumed that the disutility is equal to zero because it will be considered as the main load profile as ISO input. For lower ranked profiles, there are higher coefficients that make the disutility higher. The ISO has many different proposed load curves from many different DR providers. By considering of all of these different proposed loads for the power network, the ISO should be able to publish a day-ahead generation schedule with strong reliability. The DR providers try to present their most profitable load curves, so it will be logical that they have less disutility to it, and it is modeled in the manuscript by coefficients that could allocate to other suggestion the lighter degree of the disutility consequently. DR providers will send NN number load curves to the ISO and the ISO should consider all of them so that weighting of the load curves is done in comparison with the selected load curve. The DR provides seek to more profit and they are concern about their competitive edge in the market so they usually submit different load curve to the ISO and submitting just one load curve will jeopardize their profit in the presence of other competitors. The ISO will receive NN load curve from the DR providers, who should consider all of them so that the proposed model can be as close as possible to real world experiences.

$$L^{DA}{}_{drp,t} = \sum_{n=1}^{NN} L^{initial}_{drp,n,t} x_{drp,n} \tag{1}$$

$$\sum_{n=1}^{NN} x_{drp,n} = 1 \tag{2}$$

$$DisU_{drp,t} = \sum_{n=1}^{NN} \frac{1}{NN} \left[\lambda_{drp,n} L^{initial}_{drp,n,t} x_{drp,n} \right] \tag{3}$$

$$\lambda_{drp,n} = \begin{bmatrix} 0 & 1 & 2 & \ldots & NN-1 & NN \\ 0 & 1 & 2 & \ldots & NN-1 & NN \\ 0 & 1 & 2 & \ldots & NN-1 & NN \\ \ldots & \ldots & \ldots & \ldots & \ldots & \ldots \\ 0 & 1 & 2 & \ldots & NN-1 & NN \end{bmatrix}_{NDRP\times(NN+1)} \tag{4}$$

3. Multi-Objective Decision-Making Framework

In an attempt to consider both the system operation cost and customer disutility as a result of changing their typical consumption, it will be interesting to consolidate the suggested disutility function into the day-ahead reserve and energy market clearing procedure, especially in systems with high penetration of renewable energies.

3.1. Objective Functions

To this end, two objective functions are taken into account in the proposed multi-objective framework. The first objective function is the total operation cost of the system in energy and reserve markets which is formulated through a two-stage stochastic programming approach in order to embrace the uncertainty of wind power generation as shown in (5) [30]. The first-stage is designated for energy and up/down capacity reserve market clearing, while the second-stage pertains to the real-time corrective actions as a result of uncertainties. The conceptual schematic of the two-stage stochastic market clearing process in the presence of both supply-side and demand-side resources is illustrated in Figure 1. The ISO may serve as an information hub which gathers different types of information from both the demand and supplier side. When developing power electricity markets, there are many different sectors on each side. On the demand side, the DR providers and other agencies have an active role in providing the total demand of the power grid. First, DR providers and conventional units submit the required data with the aim of clearing the market price through the ISO. In the next stage, the feedback of the final day-ahead scheduling will be sent back to key players.

$$\begin{aligned} &Objective\,Function\,1 = OPC = \\ &\sum_{t=1}^{NT}\left[\sum_{i=1}^{NG}\left(SUC_{i,t} + MPC_i U_{i,t} + \sum_{i=1}^{NG}\sum_{m=1}^{NM} P^{e}_{i,t,m}\, C^{G\_Eng}_{i,t,m} \right.\right. \\ &\qquad \left.\left. + C^{G\_UC}_{i,t} R^{G\_UC}_{i,t} + C^{G\_DC}_{i,t} R^{G\_DC}_{i,t}\right)\right] \\ &\qquad + \sum_{t=1}^{NT}\sum_{w=1}^{NW} \pi_w \left(\sum_{i=1}^{NG} C^{G\_UE}_{i,t} r^{G\_up}_{i,t,w} - C^{G\_DE}_{i,t} r^{G\_dn}_{i,t,w} \right. \\ &\qquad \left. + \sum_{j=1}^{NJ} Voll_{j,t} LS_{j,w,t} + \sum_{wf=1}^{NWF} C^{WP\_spill}_{wf} P^{WP\_spill}_{wf,w,t} \right) \end{aligned} \tag{5}$$

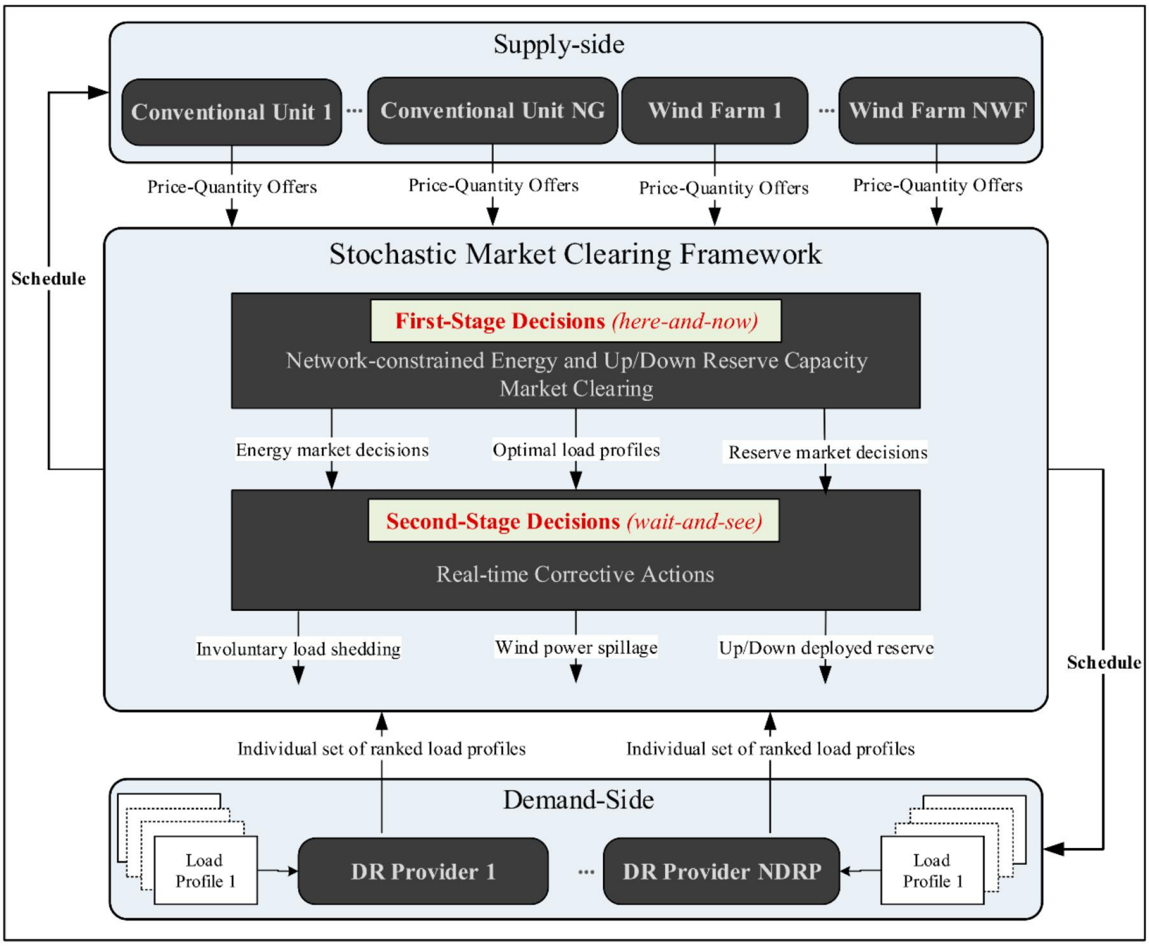

Figure 1. Conceptual schematic of two-stage stochastic market clearing in the presence of an autonomous demand response (ADR).

The first and second lines of Equation (5) represent the startup cost, minimum production cost, piecewise linear fuel consumption and up/down capacity reserve cost of conventional generation units, respectively. The second part of costs in (5) is associated with the corrective actions therefore different wind power scenario realization at the real-time operation. Accordingly, the cost terms are subsequently related to up/down implemented reserves of conventional units, load shedding and wind spillage as presented in the last part of (5). DR or load shedding measures could be a way to face increasingly fluctuating power generation concerns about supply. A monetarily quantify the consequences of power short and long interruptions is presented in [32].

The second objective function is customer disutility resulting from changing their typical power consumption as formulated in (6). It should be noted that in (6), $DisU_{drp,t}$ denotes the disutility of DR provider drp at hour t as shown in (3).

$$Objective\ Function\ 2 = Disutility = \sum_{t=1}^{NT} \sum_{drp=1}^{NDRP} \frac{1}{NT} DisU_{drp,t} \tag{6}$$

In the current paper, the operation cost (i.e., OPC) is minimized while customer disutility (i.e., Disutility) is limited by the parameter ε, as defined in (7).

$$Objective\ Function\ = \ Min(OPC); \qquad Subject\ to:\ Disutility \leq \varepsilon \tag{7}$$

3.2. Solution Methodology

To solve the proposed multi-objective problem, the ε-constraint method [33,34] is adopted to convert the problem into a single objective one. Using this technique, one of the objective functions is optimized while the others are assumed as new constraints that limit the amount of objectives by considering the parameter ε.

The value of ε is raised from $Disutility^{\min}$ to $Disutility^{\max}$ so that for each value of the parameter ε, an optimal solution is obtained. The received solutions generate the Pareto front of the multi-objective problem, and then the ISO can select the best compromise solution. It is worth noting that the values of $Disutility^{\min}$ and $Disutility^{\max}$ are determined by means of a pay-off table as in [33,34].

The optimization problem must be solved with respect to several constraints associated with conventional generation units, network and wind power generation according to the load-generation balance constraint in the base case and the DC power flow equation is given in (8) and (9). The power transmission line congestion is one of the most important challenges in the operation of the wind power plant because the ISO could not schedule them so their power output usually leads to the ISO could not use the output of the other power plants. So, DC load flow is appropriate for consideration of this effect.

3.3. Constraints

The variable $P_{i,t}$ in Equation (8) shows the aggregated power output of generation unit i at hour t which was achieved from the accumulation of piecewise offered energy blocks of units as illustrated in (10). Moreover, G_b, WF_b, DRP_b, and L_b in (8) represent a set of generating units, wind farms, DR providers and transmission lines which are connected to bus b, respectively. The economic costs of power interruptions in Lebanon are calculated in [35,36], a willingness-to-pay DR mechanism based on locational area with transmission constraints is presented around income statistics and utilizes a state-space approach to analyze the possibility of altering prices by DR. The transmission thermal flow limits are taken into account in (11).

$$\sum_{i\in G_b} P_{i,t} + \sum_{wf\in WF_b} P^{WP,S}_{wf,t} - \sum_{drp\in DRP_b} {L^{DA}}_{drp,t} = \sum_{l\in L_b} F^0_{l,t} \tag{8}$$

$$F^0_{l,t} = \left(\delta^0_{b,t} - \delta^0_{b',t}\right)/X_l \tag{9}$$

$$P_{i,t} = \sum_{m=1}^{NM} P^e_{i,t,m},\ 0 \le P^e_{i,t,m} \le P^{\max}_{i,m} \tag{10}$$

$$-F^{\max}_l \le F^0_{l,t} \le F^{\max}_l \tag{11}$$

The generation unit constraints are listed in (12)–(18). Constraints (12) and (13) restrict the output power of a generating unit, also taking into account the hourly scheduled up and down reserve margins, respectively. Up and down reserve capacity limitations due to the ramp rates are formulated in (14) and (15), respectively. The minimum up and down time constraints of generating units are subsequently considered in (16) and (17). Furthermore, the startup cost of generation units is formulated in (18). The amount of scheduled wind power in the day-ahead market is limited by the forecasted wind generation in (19). Wind energy is more crucial and unpredictable for the forecasting units and thus this manuscript pays more attention to it.

$$P_{i,t} + R^{G\_UC}_{i,t} \le P^{\max}_i U_{i,t} \tag{12}$$

$$P_{i,t} - R^{G\_DC}_{i,t} \ge P^{\min}_i U_{i,t} \tag{13}$$

$$0 \le R^{G\_UC}_{i,t} \le RU_i \tag{14}$$

$$0 \leq R_{i,t}^{G\_DC} \leq RD_i \tag{15}$$

$$\sum_{t'=t+2}^{t+MUT_i} \left(1 - U_{i,t'}\right) + MUT_i \ \left(U_{i,t} - U_{i,t-1}\right) \ \leq MUT_i \tag{16}$$

$$\sum_{t'=t+2}^{t+MDT_i} U_{i,t'} + MDT_i \ \left(U_{i,t-1} - U_{i,t}\right) \ \leq MDT_i \tag{17}$$

$$SUC_{i,t} \geq SC_i(U_{i,t} - U_{i,t-1}) \tag{18}$$

$$0 \leq P_{wf,t}^{WP,S} \leq P_{wf,t}^{WP,\max} \tag{19}$$

The other set of constraints must be satisfied for each scenario. The power balance should be satisfied for each scenario realization as formulated in (20).

The deployed up/down spinning reserves in different scenarios cannot surpass the earlier programmed reserve capacities discovered by the market clearing procedure (21) and (22). The sheer power output of generation units is represented by utilizing an auxiliary variable $P_{i,w,t}$ in (23), and its associated bounds are given in (24). The unit ramp down and up limits are formulated by (25) and (26). A portion of available wind power may be spilled due to the technical restrictions of system operation as enforced by (27). Moreover, the involuntary load shedding limit is declared in (28).

$$\sum_{i \in G_b} \left(r_{i,w,t}^{G\_up} - r_{i,w,t}^{G\_dn}\right) + \sum_{wf \in WF_b} \left(P_{wf,w,t}^{W} - P_{wf,t}^{WP,S} - P_{wf,w,t}^{WP\_spill}\right) + \sum_{j \in J_b} LS_{j,w,t} = \sum_{l \in L_b} F_{l,w,t} - F_{l,t}^{0} \tag{20}$$

$$0 \leq r_{i,w,t}^{G\_up} \leq R_{i,t}^{G\_UC} \tag{21}$$

$$0 \leq r_{i,w,t}^{G\_dn} \leq R_{i,t}^{G\_DC} \tag{22}$$

$$P_{i,w,t} = P_{i,t} + r_{i,w,t}^{G\_up} - r_{i,w,t}^{G\_dn} \tag{23}$$

$$P_i^{\min} U_{i,t} \leq P_{i,w,t} \leq P_i^{\max} U_{i,t} \tag{24}$$

$$P_{i,w,t} - P_{i,w,t-1} \leq RU_i \ \ U_{i,t} \ \ + SUR_i \ \left(1 - U_{i,t-1}\right) \tag{25}$$

$$P_{i,w,t-1} - P_{i,w,t} \leq RD_i \ \ U_{i,t-1} \ \ + SDR_i \ \left(1 - U_{i,t}\right) \tag{26}$$

$$0 \leq P_{wf,w,t}^{WP\_spill} \leq P_{wf,w,t}^{W} \tag{27}$$

$$0 \leq LS_{j,w,t} \leq L^{DA}{}_{drp,t} \qquad \forall drp, \forall j \in J_b \tag{28}$$

It is noteworthy that the network constraints consist of the DC power flow and thermal limits of power transmission lines have also been calculated for various scenario realizations even if their mathematical formulation is omitted.

4. Numerical Studies

The required input data including information about generation units, network, wind farms and DR resources are discussed in the first sub-section. In addition, the simulation results and discussions have been reported in the second sub-section.

4.1. Input Data Description and Specification

In order to evaluate the performance of the proposed framework and ADR scheme, several numerical case studies are exerted on the modified IEEE Reliability Test System (RTS 24-bus). There are different types of power plants in this system and their data are easily available and could easily link with other related problems in the power system such as demand response. It would also become more comparable with other future related work. So, in the current paper, this test system has been selected. It has 26 generation units including eight generation technologies with a 2850 MW daily peak load [37]. The wind production capacity in the IEEE RTS 24-bus network is 1500 MW which is generated by six 250 MW wind farms which are located at buses 1, 4, 6, 18, 21 and 22.

An autoregressive moving average (ARMA) model [38] is applied to produce wind speed scenarios according to North and South East of South Australia wind speed data.

For each wind farm using K-means clustering technique, the wind speed scenarios are then reduced to ten scenarios [39] and later applied into power scenarios using the Vestas 3 MW turbine model. The final wind power scenarios for wind farms located at bus 4 and bus 22 have been illustrated in Figure 2.

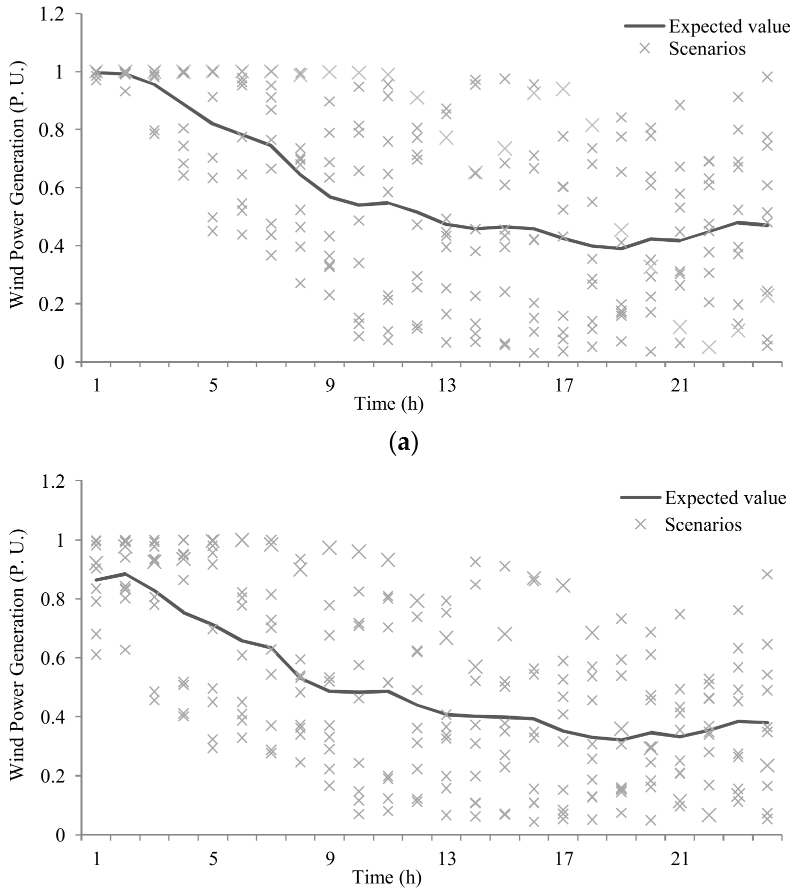

Figure 2. Wind power scenarios at two different wind farms. (**a**) Wind farm at bus 4 (downward wind farm). (**b**) Wind farm at bus 22 (upward wind farm).

The technical features of conventional units and their associated offered costs in energy and reserve markets are directly extracted from [30]. Moreover, it is assumed that there is a DR provider at each load point of the network with the aim of aggregating and managing the end-use customers. DR providers collect the end-use responses to various DR programs according to their bilateral contracts and then submit 10 individual sets of ranked load profiles in priority order to the ISO as shown in Figure 3. So, the ISO does not need any customer information because it assumes that the DR provider does it before they submitted their load curve and based on the priority of them, the ISO should exert them to its operation of the network. Note that the cost of wind spillage and the value of lost load are presumed to be 40 $/MWh and 200 $/MWh, respectively.

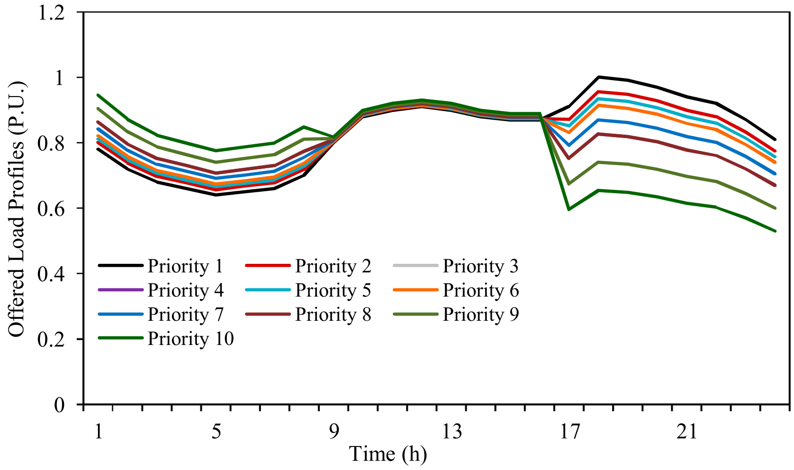

Figure 3. A typical customer's set of ranked load profiles.

4.2. Simulation Results and Discussions

The model is implemented in GAMS as a mixed integer linear program (MILP) using the CPLEX 12.5.0 solver [40]. The obtained Pareto front is illustrated in Figure 4. The Pareto front consists of ten solutions, obtained from applying ten equal steps for parameter ε. According to Figure 4, although customer participation in DR programs leads to customer disutility, it brings some cost savings. For instance, by increasing customer disutility level as a result of participation in DR programs from 0 to about 2000, the operation cost decreases by more than 12.5%. On this basis, the ISO can select each operating point on the obtained Pareto front in order to minimize the system operation cost with customer disutility.

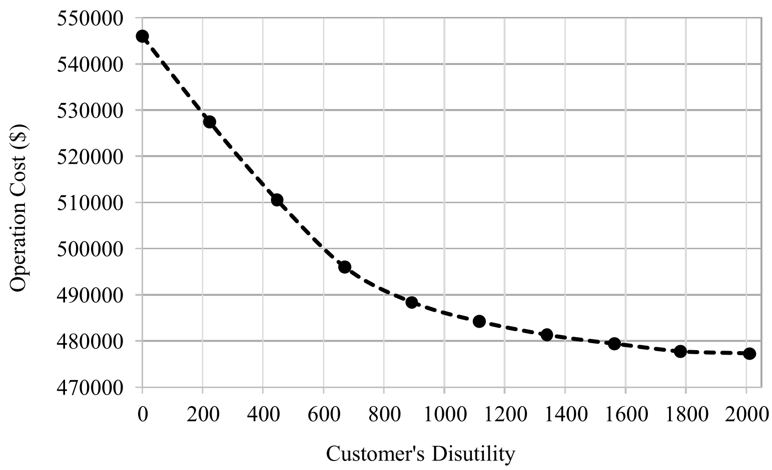

Figure 4. The obtained Pareto front.

It is noteworthy that the generation dispatch of conventional units depends on the selected operating point by the ISO. The commitment status of generation units is compared for the first (Customer's Disutility = 0) and the last (Customer's Disutility = 2011) points as shown in Table 1.

Table 1. Unit commitment status for two customer disutility levels.

Customer's Disutility = 0																								
Unit No.	**Hours (1–24)**																							
1–9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10–13	1	1	1	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
14–16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	0
17–26	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Customer's Disutility = 2011																								
Unit No.	**Hours (1–24)**																							
1–9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10–13	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0
14–16	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17–26	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

As observed in Table 1, the generation dispatch has been changed significantly according to the customer's disutility level. In particular, the commitment status of peak-load units (Unit No. 1–9) and base-load units (Unit No. 17–26) are similar, whereas the dispatch of load following units (Unit No. 10–16) has been changed. When customer disutility is zero, the load following units must startup at the peak load period (specifically between the hours of 17:00 to 24:00). This is due to the fact that the customers have their own typical consumption in this case without any restriction as a result of DR programs. So, the Unit No. 10–16 should startup at the peak load period to meet the load demand. When customer disutility is 2011, it means that the customers adjust their typical consumption by reducing their loads at the peak-load period or shifting their consumption to low-load period. Therefore, the load following units have not committed at peak-load hours, while they must run in other periods (specifically early morning).

The aggregated system load profile is represented for three different customer disutility levels in Figure 5. As observed, although higher disutility levels are not preferable from the customer's point of view, the ISO can enjoy the DR benefits such as peak shaving as well as valley filling in this circumstance.

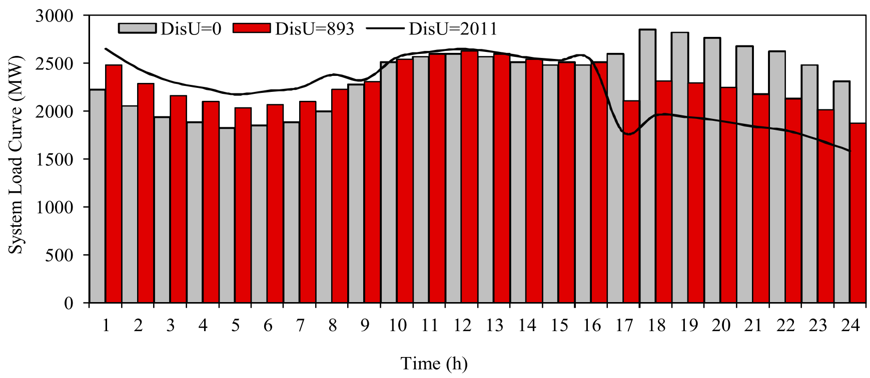

Figure 5. The aggregated load profile of the system.

It is notable that when the required disutility level is zero, the first priority ranked load profile has been selected for all the DR providers. When the ISO selects the point which has disutility equal to 893, the fourth priority ranked load profile has been scheduled for all the DR providers except those located at buses 6 and 19. Note that the tenth submitted ranked load profile has been accepted for the DR providers at the mentioned buses. Moreover, when customer satisfaction is not the preference of an ISO due to technical or economic problems (disutility equal to 2011), the tenth submitted ranked load curve is selected for all DR providers apart from those located at buses 8 and 20, where the second ranked load profile has been picked up.

Customer participation in DR programs can bring other benefits for the ISOs, especially in systems with high amounts of wind power the daily amount of wind power spillage as a function of customer disutility. As Figure 6 shows shown in Figure 6, the value of wind power spillage will be decreased when the customers adjust their typical consumption and endure some unpleasantness. For instance, the daily wind power spillage when the disutility is zero is equal to 212 MWh, while this value is diminished to 92.5 MWh when the disutility level is 893.

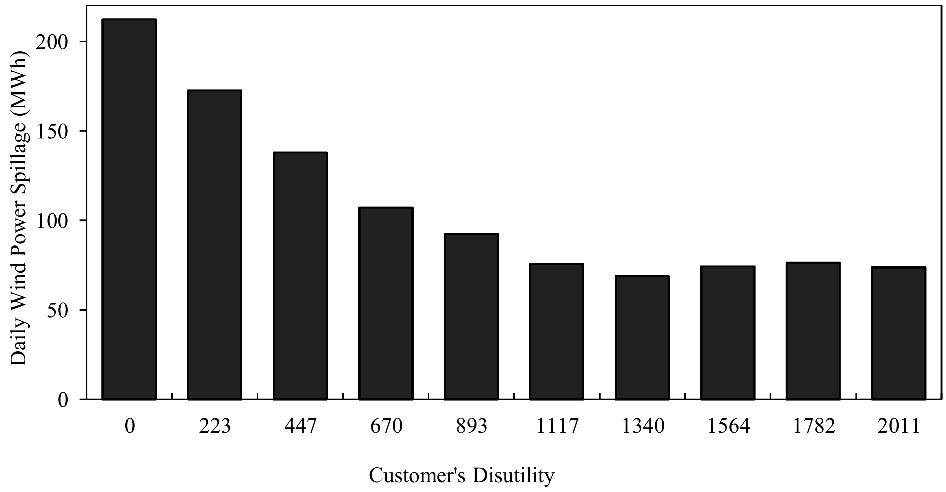

Figure 6. The daily wind power spillage vs. customer disutility.

The hourly amounts of wind power spillage for three different disutility levels are compared in Figure 7. It should be mentioned that the wind power spillage at other hours (13:00–24:00) is zero. As shown in Figure 2, the wind power generation has an approximately anti-peak feature so that the wind generation is remarkable at the low-load period and vice versa. On this basis, DR participation of customers may facilitate wind power integration by motivating the customers to shift their load from peak-load to low-load periods, when wind generation is significant.

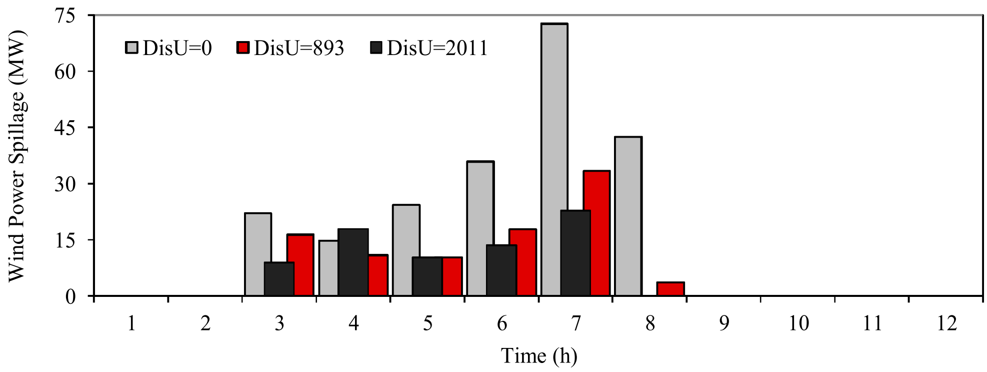

Figure 7. Hourly wind power spillage for the given case studies.

Up to now, it was assumed that there is a DR provider at all load points of the system. However, this may be an optimistic assumption. Therefore, comprehensive techno-economic analyses have been provided in Table 2 with the aim of investigating the impact of customer responsiveness; that is, the ability to not only perceive, but also swiftly respond to the changing needs. By increasing customer responsiveness from 0% to 40%, the system operation cost will be reduced by more than 8.5%. Moreover, the wind power spillage is remarkably decreased by more than 45%.

Table 2. A summary of techno-economic results of different customer responsiveness share.

Obtained Results	Customer Responsiveness Level		
	0%	20%	40%
Operation Cost ($)	545,992	520,966	499,407
Daily Wind Spillage (MWh)	212.2	163.9	116.2
Conventional Units Ramping (MW)	5079.5	4894.2	4878.9
Startup Number of Conventional Units	14	6	1

In order to evaluate the technical performance of the system at different customer responsiveness levels, two technical indices have been considered, including up/down ramping and shutdown/startup numbers of conventional units in the scheduling horizon.

As shown in Table 2, the growth of customer responsiveness decreases the startup number of the conventional fleet significantly. In addition, comparing the daily required ramping of the conventional fleet at two customer responsiveness levels (0% vs. 40%) reveals that the conventional fleet ramping has been decreased by about 3.95%.

5. Conclusions

Accurate estimation of the price–elastic demand curve is the main obstacle for widespread implementation of DR from an ISO point of view. To solve the mentioned challenge, this paper presented a novel DR scheme called ADR with the aim of providing a more accurate DR potential assessment, taking into account customer disutility. Thereafter, the day-ahead energy and reserve market clearing problem were modeled through a multi-objective decision-making approach, including the operation cost and customer disutility as a result of changing their typical consumption pattern as the objective functions. The proposed bi-objective optimization framework was solved by two-stage stochastic programming in the form of a MILP formulation to consider the wind power generation uncertainty. The proposed model made it possible for the ISO to have a favorable choice among operating points on the obtained Pareto front, so that it minimized the system operation cost with customer disutility. The simulation results revealed that although DR implementation raised customer disutility, it could significantly facilitate wind power integration. It is worth noting that customer responsiveness level was an impressive factor in this context. According to the case study results, by increasing customer responsiveness from 0% to 40%, the operation cost, wind power spillage and ramp need of conventional units decreased up to 8.5%, 45% and 3.95%, respectively. According to the obtained results, customer responsiveness could have a dominant effect on the wind power output and the operation cost. By increasing customer disutility, the general spillage of the wind power would be decreased. To present a reliable day-ahead scheduling, the problem would manage different sources of the uncertainty and would change the scheduling of the power plants, and consequently the daily cost would be increased.

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Nomenclature

Indices	
b, b'	System buses $b = 1, \ldots, NB$
i	Conventional units $i = 1, \ldots, NG$
drp	DR providers $drp = 1, \ldots, NDRP$
j	Loads $j = 1, \ldots, NJ$
l	Transmission lines $l = 1, \ldots, L$
wf	Number of wind farms $wf = 1, \ldots, NWF$
t, t'	Time periods $t = 1, \ldots, NT$
w	Number of different scenarios $w = 1, \ldots, NW$
m	Segment for linearized fuel cost $m = 1, \ldots, NM$
n	Candidate load profiles $n = 1, \ldots, NN$
Parameters	
C^{G_Eng}	Offered energy cost of conventional units
$C^{G\_UC/DC}$	Up/down capacity reserve cost of conventional units
$C^{G\_UE/DE}$	Up/down deployed reserve cost of conventional units
$C_{wf}^{WP\_spill}$	Cost of wind spillage
MPC_i	Minimum production cost of generation units
SC_i	Start-up cost of generation units
$P_i^{\max}/P_i^{\min}$	Maximum/minimum output of units
RU_i/RD_i	Ramp up/down constraints of units
MUT_i/MDT_i	Minimum up/down time of generation units
SUR_i/SDR_i	Startup/shutdown ramp rate limit for units
$P_{wf,t}^{WP,\max}$	Forecasted wind generation of wind farms
$P_{wf,w,t}^{W}$	Real-time wind generation of wind farms
$L_{drp,n,t}^{initial}$	Initial candidate load profiles submitted by DR providers
$\lambda_{drp,n}$	Load profile rank of DR providers
$Voll_{j,t}$	Value of lost load j at time t
X_l	Reactance of power transmission line l
$F_l^{\max}$	Maximum capacity of power transmission line l
π_w	Probability of occurrence of scenario w
Variables	
$U_{i,t}$	Binary on/off status indicator of units
$SUC_{i,t}$	Start-up cost of conventional units
$x_{drp,n}$	Binary indicator of selected load profile of DR providers
$R^{G\_UC/DC}$	Scheduled up/down reserve capacity of units
$L^{DA}{}_{drp,t}$	Individual final selected load profiles of DR providers
$P_{i,t,m}^{e}$	Generation of segment m in linearized fuel cost curve
$F_{l,t}^{0}/F_{l,w,t}$	Power flow through transmission line l
$LS_{j,w,t}$	Load shedding of load j
$\delta_{b,t}^{0}/\delta_{b,t,w}$	Voltage angle at bus b
$P_{wf,t}^{WP,S}$	Scheduled wind power of wind farms
$P_{wf,w,t}^{WP\_spill}$	Wind power spillage of wind farms
$P_{i,w,t}$	Real-time power generation of units
$r^{G\_up/dn}$	Deployed up/down spinning reserve of units

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