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Contribution of emergency demand response programs in power system reliability

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A B S T R A C T

Nowadays, demand response has become one of the essential components of recent deregulated power systems as it can offer many distinguished features, such as availability, quickness, and applicability. DRPs (Demand response programs), announced by the federal energy regulatory commission, are among the most accepted and practical features of demand side management. DRPs not only can contribute in mitigating the intermittent effects of renewable energy resources but also can be used either to lower high energy prices, occurred in wholesale electricity markets, or when the security of power systems is at risk. In this paper, the influence of emergency demand response programs in improving reliability in case of failure of generation units is investigated. In the proposed reliability based optimization approach, the generation failure is modeled based on its forced outage rate. The proposed method can help independent system operators to schedule day-ahead generating units in a more reliable manner and can facilitate the participation of consumers to increase the total social welfare in the case of an emergency. Moreover, the mixed integer programming formulation allows implementing the proposed method by using available tractable linear solvers. Eventually, the applicability of the proposed model is tested on the IEEE 24-bus reliability test system and its effects on the value of lost load and the expected load not served are discussed.

1. Introduction

1.1. Definitions and aims

In recent deregulated power systems, utilizing any available source of energy seems crucial. DR (Demand response), enabled through communication infrastructures [1], is one of the main methods that can be taken in order to decrease consumer electrical energy consumption when contingencies, like unpredictable variations in demand or generation, or unit outages take place and can prevent the balance of supply and demand. These programs can be implemented either through coordinated [2] or non-coordinated [3] schemes. Coordinated schemes refer to decentralized control strategies, while non-coordinated schemes are utilized by central operators through some procedures such as DLC (Direct Load Control) or RTP (Real-Time Pricing). Among the recently introduced sources are DRRs (Demand Response Resources), can, indeed, mitigate some problems existing in the conventional power systems and improve the overall system reliability, considerably [4–6]. To this aim, versatile DRPs (Demand Response Programs) have been introduced by FERC (Federal Energy Regulatory Commission) to classify the many different features of the DSM (Demand Side Management) [7–9]. Previously announced classification by FERC [7,8] have been recently modified by adding many new programs along with merging some of the conventional ones [9]. EDRPs (Emergency Demand Response Programs) are among the most widely used programs mainly because the participation in these kinds of programs is voluntary and may bring economic benefits for participants.

In order to examine the functionality of the DRPs, it is worth mentioning the recent definition of DR, announced by FERC. According to the given definition, "*any change in electric use by*

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Nomenclature

$A(.)$	Incentive value.
$a(.), b(.), c(.)$	Fuel cost coefficients of a unit.
b	Index of buses
$Cost_{Inc}(.)$	Total incentive cost.
$Cost_{Gen}(.)$	Fuel cost of a unit in an hour.
$D_0(.)$	Initial load demand in an hour.
$D_{DR}(.)$	Final calculated fixed and elastic demand in an hour.
D_{min}	Minimum amount of load reduction.
$dlp(.)$	Slope of a segment in linearized demand function
$dr(.)$	Demand response in segment n in an hour.
$\Delta D(.)$	Demand change per hour.
$\Delta Pr(.)$	Price deviation per hour.
$Elast(.)$	Price elasticity of demand.
$ELNS(.)$	Expected load not served ($/h).
$ELNS^{MAX}$	Maximum amount of *ELNS*
$F(.)$	Transmission line flow per hour.
$FOR(.)$	Forced outage rate.
$F^{max}(.)$	Transmission flow limit.
i	Index for conventional unit.
j_{lin}, h_{lin}	Linear demand vs. price coefficients.
k	Index for contingency.
$LS(.)$	Load shedding of bus b during contingency k in an hour.
$LS^{max}(.)$	Maximum amount of load shedding.
L_b	Number of transmission lines connected to bus b.
MU, MD	Minimum up and down time of generators.
MU_d, MD_d	Minimum up and down time of responsive demand
N_B	Number of buses.
N_{seg}	Number of linearization segments of fuel cost functions.
N_{Gen}	Number of conventional thermal units.
$N_{Gen(b)}$	Number of generating units connected to bus b.
$p\ (.)$	Power generation of a unit.
$P^{min}(.), P^{max}(.)$	Minimum/maximum generating capacity of a unit.
$Pr_0(.)$	Initial electricity price per hour.
$\pi(.)$	Probability of a generator contingency.
$r(.)$	Binary DR status
$RU(.), RD(.)$	Ramp up/down limit of a unit.
$SC(.)$	Start up cost of unit i.
$SU(.)$	Startup cost of a unit.
$SR\ (.)$	Spinning reserve per hour.
$slp(.)$	Slope of a segment of a unit in linear function
$\delta_s(.), \delta_r(.)$	Voltage angles.
t	Index for time.
τ	Spinning reserve market lead-time.
$UT(.), TD(.)$	Number of hours a unit has been on/off at the beginning of the scheduling period.
$u(.)$	Binary indicator of a unit status.
$VOLL(.)$	Value of lost load ($/MWh).
$w(.)$	Indicator of generation unit outage; 0:outage occurred/ 1:otherwise
$X(.)$	Reactance of transmission line.
$y(.)$	Startup indicator.
$y_d(.)$	Startup indicator of DR.
$z(.)$	Shutdown indicator.
$z_d(.)$	Shutdown indicator of DR.

demand-side resources from their normal consumption patterns in response to changes in the price of electricity, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized is called DR". This definition substitutes "end-use customers", used in previous survey, with "demand-side resources" in order to follow the definition used by NERC's (North American Electric Reliability Corporation) Demand Response Data Task Force the development of a Demand Response Availability Data System to collect DRP information [9]. End-use customers also can be classified into four categories: residential, commercial, industrial, and municipal customers where residential [2]and industrial customers [10] seem to be great candidates for DR implementation so far.

Although, three major categories of DRPs (i.e., time of use programs, voluntary programs, and mandatory programs) were previously announced by FERC, DRPs have been recently categorized as: interruptible load, direct load control, critical peak pricing with load control, load as capacity resources, spinning reserve, non-spinning reserve, emergency demand response, regulation service, demand bidding and buyback, time-of-use pricing, critical peak pricing, real time pricing, peak time rebate, system peak response transmission tariff, and other programs [4–6].

According to what is requested by Ref. [11], about examining any possible improvement in conducting DRPs, in this paper EDRPs in a SCUC (Security Constrained Unit Commitment) problem are explored.

1.2. Literature review

There is a possibility for some customers to control or schedule their demand based on the electricity prices. This idea is formulated in Ref. [12] and the concept of spot pricing of electricity is introduced. Generation scheduling and determining the price of electricity in a pool market are discussed in Ref. [12]. The model of price elasticity of electricity demand is also described in Ref. [13]. The FERC staff annual surveys since 2006 [7–9] tracked the concept of demand responsiveness. The DRPs were firstly categorized into two main groups including, incentive and time based programs [7]. In Ref. [5], this classification has been changed and detailed subclassifications of the incentive based DRPs have been introduced, i.e., voluntary and mandatory based programs and market clearing programs. The recent issue of the survey [9] declared fifteen separate versatile programs without classifying them into the above-mentioned two main groups.

In Ref. [14], an innovative method was proposed to find the customers that can contribute in I/C (interruptible/curtailable) programs while their maximum benefit is achieved. To do this, a procedure was proposed to support the regulator of the system by selecting and prioritizing DRPs by using a TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method. The most effective DPR were selected by using an AHP (Analytical Hierarchy Process) method in Ref. [15]. To propose a comprehensive model for DRPs, all possible demand vs. price functions have been combined in Ref. [16] by using a Q-learning method based on a weighting. In Ref. [17], authors tried to integrate DR programs in power systems with high renewable penetration rate through optimization of electricity price of electric storage space heating customers, in order to maximize the profit of the retailer.

In Ref. [18], a pool-based demand response exchange model has been proposed as an alternative for managing the variability of renewable energy sources. In this area, many outstanding papers have been published. In Ref. [3], a new demand response method extracted from the demand elasticity concept was presented. The realization constraints (e.g., maximum daily curtailments, up/down ramp rates and minimum up/down time) were applied to restrict the amount of curtailed load. In Ref. [19], the SCUC was considered as platform to implement DRPs. It was proposed that DRP may accumulate discrete retail customer responses and submit bid-quantity offers to the ISO (Independent System Operator). MILP (Mixed Integer Linear Programming) for UC (unit commitment) has been explored in Ref. [20] as one of the prominent works for linearized UC.

A real time demand response model considering price uncertainty was proposed in Ref. [21]. To include the price uncertainty to the problem, a robust optimization technique was adopted in Ref. [21]. In Ref. [22], DRP is considered for the smart grids with high penetration of renewable generation system. Authors recommended that, a significant balance between renewable generation and real time pricing instead of compulsory load curtailment in case of low penetration of renewable generation, can grant flexibility for the customers. Concerned with mitigating the undesirable impacts of renewable integration in power systems, the role of demand response programs both in wholesale energy market scales and micro-grid scales are also investigated in some recent papers [23] and [24]. In Ref. [23], DR management has been studies when a wind farm is connected to a smart grid. Total social welfare is maximized while the probability of power deficit due to the uncertainty in renewable production is limited by an upper bound. Similarly, in Ref. [24], authors tried to overcome the high renewable penetration rate impacts through micro-grids equipped with both distributed generation and DRPs.

Bulk demand reduction, however, can be possible through implementing incentive based DRPs. In Ref. [25], optimal incentive payments to the curtailable load as the incentive based program have been allocated using UC while considering economic and environmental issues, simultaneously. An MILP was proposed to solve a DRUC (Demand Response Unit Commitment) problem. EDRPs problem formulation is presented using a fixed elasticity factor.

1.3. Contributions

According to the previous section, many papers investigate DR in short-term operation planning of the power system. However, a predetermined fixed price elasticities of demand are majorly considered which are independent of demand functions. This independency it is not consistent with the main definition of price elasticity which implies differentiating the demand vs. price function. In addition, an incentive based DR program is investigated in a standard probabilistic SCUC problem to find optimal incentives the ISO can pay to demand side participants while considering possible contingencies in short-term operation of power system. The current paper is implemented based on enhanced models presented in Refs. [20,25] where not only an incentive based DR program is investigated but also dynamic price elasticity of demand is considered to add the flexibility of demand response programs in a probabilistic day-ahead operational scheduling. Accordingly, the current paper makes following three contributions:

- Unlike existing literature where a predetermined fixed price elasticities of demand is used to describe the dependency of demand and price, in this paper, a dynamic price elasticity is proposed to be applied in an incentive based demand response program. Dynamic price elasticity vs. a static form shows more scheduling flexibility with both lower generation and incentive charge costs.
- In the current paper, an incentive based demand response program, EDRP, is applied in a common SCUC problem to evaluate a tradeoff between additional incentive payments to the demand side customers and the value of supplying loads in case of generation units' failure;
- Stochastic programming to model uncertain nature of optimization parameters is a promising method, however, this comes at the expense of high computational burden. In this paper, a probabilistic counterpart of a stochastic SCUC is applied on predetermined set of generation unit contingencies. This method, prevent computational intractability while consider uncertain nature of generation unit failures.

1.4. Paper organization

The rest of paper is arranged as follows: Section 2 is dedicated to the problem formulation. In Section 3, the case studies and discussion about the simulation results are presented. Finally, conclusion is presented in Section 4.

2. Problem formulation

2.1. Quantifying EDRP

EDRPs formulation is presented in Ref. [25]on the basis of a fixed elasticity factor. In order to formulate the price elasticity of demand, we can define the price sensitivity of demand related to electricity price changes as:

$$Elast(t) = \frac{\Pr_0(t)\Delta D(t)}{D_0(t)\Delta \Pr(t)} \tag{1}$$

By manipulating (1), demand changes can be obtained as follows:

$$\Delta D(t) = \frac{D_0(t)\Delta \Pr(t) Elast(t)}{\Pr_0(t)} \tag{2}$$

As opposed to the fixed elasticity definition adopted in Ref. [25], dynamic elasticity [16] is employed in the this paper. Dynamic elasticity is appropriate feature to assess consumer response to various kinds of DRPs according to the consumer's load pattern, the offered prices, its demand model incentives and penalties corresponding to the DR contract and dynamic price elasticities of demand. Even though different functions of demand vs. price (i.e., linear, quadratic, exponential, and logarithmic) can be used, a linear function is used here [14–16]:

$$D_{DR}(t) = j_{lin} + h_{lin}\Pr(t) \tag{3}$$

where, $D(t) = h_{lin}\Pr(t)$ represents the elastic part of a demand. It is noted that linear demand vs. price function is chosen for two reasons. Firstly, it has been shown that the best fitted mathematical function to the historical demand and price data with the greatest absolute values of price elasticity for high rates of electricity price is linear function among others like potential, logarithmic, and exponential functions. Second is that the proposed model is an MILP so that utilizing any other forms of potential, logarithmic, and exponential functions made our problem MINLP (Mixed Integer Non-Linear Programming) which not only its optimal solution could not be guaranteed, but also the non-linearity could increase computational burden significantly.

Replacing eq. (3) into (1) and with some simple mathematical calculations the linear dynamic elasticity can be calculated as:

$$Elast(t) = h_{lin}\frac{\Pr_0(t)}{j_{lin} + h_{lin}\Pr_0(t)} \tag{4}$$

According to the results presented in Refs. [14–16], in order to maximize the social welfare, here means minimum generation cost while providing attractive demand reduction incentives, the elastic demand should be defined, introducing an incentive value *A(t)*, as follows:

$$D_{DR}(t) = D_0(t)\left\{1 + Elast(t)\frac{A(t)}{\mathrm{Pr}_0(t)}\right\} \tag{5}$$

More detailed information related to the procedure used to find the elastic part of the demand in order to maximize the social welfare can be found in Refs. [14–16]. From a combination of (4) and (5), the following expression can be deduced:

$$D_{DR}(t) = D_0(t)\left\{1 + h_{lin}\frac{A(t)}{j_{lin} + h_{lin}\mathrm{Pr}_0(t)}\right\} \tag{6}$$

The total incentive payment is as follows [25]:

$$Cost_{Inc}(t) = A(t)[D_0(t) - D_{DR}(t)] \tag{7}$$

By substituting (6) into (7) and simplifying, we have the following formula of the total amount of incentive that must be paid to the participant consumers:

$$Cost_{Inc}(t) = -\frac{D_0(t)h_{lin}A^2(t)}{j_{lin} + h_{lin}\mathrm{Pr}_0(t)} \tag{8}$$

where, h_{lin} is inherently a negative coefficient of linear demand versus price elasticity function. According to the [29–31], the linearized counterpart of (8) is:

$$Cost_{Inc}(t) = D_{\min}r(t) + \sum_{n=1}^{N_{seg}} dlp(n)dr(n,t) \tag{9}$$

where, the first term of the right side of (9) indicates the first block of stepwise linear incentive provision cost function and the second term represents the summation of upper blocks.

2.2. Objective function

In this part, the proposed model for an integrated SCUC and DR program along with considering reliability measures are explained. It is noted to say that the following assumptions are obeyed through this model;

- In the current model, optimal energy production scheduling of generation units are considered and other available products such as minimum reserve capacity allocations are not included since incorporating reserves has no additional insight to the proposed model.
- It is assumed that shut down costs are ignorable in compare with other sources of costs such as startup and normal operation fuel consuming costs.
- In the following model, except spinning reserve, other operational reserve capacity allocation services such as non-spinning, regulation and Automatic Generation Control (AGC) reserves are ignored without altering the core idea of the model.
- It is supposed that demand is forecasted without significant uncertainty, in the sense that stochastic SCUC is not included in the scopes of this paper.
- Since wholesale generation scheduling is targeted in the current paper, small individual demand response customers are not allowed to take part in the present model. Instead, DR aggregators or other market and non-market middle agents are responsible for aggregating curtailable/shiftable loads, clustering the customers to reduce their inconveniency and participate in DR programs on behalf of their clients.

According to the formulation of SCUC, the objective function can be defined as below:

$$\min \sum_{t=1}^{T}\left\{\sum_{i=1}^{N_{Gen}}(SU(i,t) + Cost_{Gen}(i,t)) + Cost_{Inc}(t) + VOLL(t)\sum_{b=1}^{N_B} \times \sum_{k=1}^{N_k} LS(b,t,k)\right\} \tag{10}$$

where, $Cost_{Gen}(i,t)$ is the conventional fuel cost of thermal generation units. The fuel cost has been linearized, as presented in the Appendix, to be applicable in an MIP (Mixed Integer Programming) problem formulation as follows:

$$Cost_{Gen}(i,t) = P_{\min}(i)u(i,t) + \sum_{n=1}^{N_{seg}} slp(n,i)p(n,i,t) \tag{11}$$

In (10), $Cost_{inc}(t)$ indicates the amount of incentive payment to the participated customers and the last terms of the objective function represents the cost of involuntary load shedding.

2.3. Generation constraints

SCUC optimization problem comprises some constraints. In order to have a unified linear model, DC power flow is used to model the power balance equation as done in Ref. [19]:

$$\sum_{i=1}^{N_{Gen(b)}} P(i,t) - D_{DR}(b,t) = \sum_{t=1}^{L_b} F(l,t) \quad \forall b, \forall t \tag{12}$$

where, the left side of (12) states the net power injection to the bus *b* at the time *t* including reduced demand through implementing DRPs and the right side shows line flow in each bus at time *t*, respectively. $D_{DR}(b,t)$ is formerly defined in (6) and $F(l,t)$ is:

$$F(l,t) = \frac{1}{X(l)}(\delta_s(l) - \delta_r(l)) \quad \forall l, t \tag{13}$$

The transmission flow limits are defined as follow:

$$F(l,t) \le |F^{\max}(l,t)| \quad \forall l, t \tag{14}$$

In addition, generating units startup cost constraint is:

$$SU(i,t) \ge SC(i)(u(i,t) - u(i,t-1)) \quad \forall i, t \tag{15}$$

Real power generation constraints are:

$$P(i,t) \le P^{\max}(i)u(i,t) \quad \forall i, t \tag{16}$$

$$P(i,t) \ge P^{\min}(i)u(i,t) \quad \forall i, t \tag{17}$$

Spinning reserve is defined over the entire system as follows:

$$\sum_{i=1}^{N_{Gen}} P^{\max}(i,t) \ge SR(t) + \sum_{b=1}^{N_B} D_{DR}(b,t) \tag{18}$$

Once the unit is committed/shut down, it has to be “on/off” for a minimum number of hours indicated in the following equations as stated in Ref. [19]:

$$\sum_{t=1}^{UT(i)}(1-u(i,t))=0 \quad \forall i\in N_{Gen} \tag{19}$$

$$y(i,t)+\sum_{m=t+1}^{\max[T,t+MU(i)-1]} z(i,m)\le 1 \quad \begin{matrix}\forall i\in N_{Gen}\\ \forall t=UT(i)+1,\dots,T\end{matrix} \tag{20}$$

where, $y(i,t)$ and $z(i,t)$ are binary variables representing the startup and shutdown status flags, respectively and $UT(i)$ is:

$$UT(i)=\max\{0,\min[T,MU(i)-TU(i,0)u(i,0)]\} \tag{21}$$

Accordingly, shutdown time constraints can be considered as given below:

$$\sum_{t=1}^{DT(i)}u(i,t)=0 \quad \forall i\in N_{Gen} \tag{22}$$

$$z(i,t)+\sum_{m=t+1}^{\max[T,t+MD(i)-1]} y(i,m)\le 1 \quad \begin{matrix}\forall i\in N_{Gen}\\ \forall t=UT(i)+1,\dots,T\end{matrix} \tag{23}$$

Consecutively, $DT(i)$ is

$$DT(i)=\max\{0,\min[T,MD(i)-TD(i,0)(1-u(i,0))]\} \tag{24}$$

Logical relations between start up and shut down indicators should be considered as follows [19]:

$$y(i,t+1)-z(i,t+1)=u(i,t+1)-u(i,t) \tag{25}$$

$$y(i,t)+z(i,t)\le 1 \tag{26}$$

2.4. Demand response constraints

Realization constraints are considered in the following subsection. Realization here means to add constraints imposed to DRPs when it is implemented in the "real world". Just like a generation unit, minimum up/down constraints can decrease the inconvenience of implementing DRPs for consumers as follows:

$$\sum_{t=1}^{UT(i)}(1-r(t))=0 \quad \forall t=UT_d+1,\dots,T \tag{27}$$

$$y_d(t)+\sum_{m=t+1}^{\max[T,t+MU_d-1]} z_d(m)\le 1 \quad \forall t=UT_d+1,\dots,T \tag{28}$$

where, $y_d(t)$ and $z_d(t)$ are binary variables indicating the startup and shutdown states, respectively and UT_d is:

$$UT_d=\max\{0,\min[T,MU_d-r(0)]\} \tag{29}$$

Accordingly, off time constraints can be written as follow:

$$\sum_{t=1}^{DT_d}r(t)=0 \quad \forall t=UT_d+1,\dots,T \tag{30}$$

$$z_d(t)+\sum_{m=t+1}^{\max[T,t+MD_d-1]} y_d(m)\le 1 \quad \forall t=UT_d+1,\dots,T \tag{31}$$

Consecutively, DT_d is

$$DT_d=\max\{0,\min[T,MD_d-(1-r(0))]\} \tag{32}$$

The joint equation between on and off time indicators are

$$y_d(t+1)-z_d(t+1)=r(t+1)-r(t) \tag{33}$$

$$y_d(t)+z_d(t)\le 1 \tag{34}$$

The capacity shortage may lead to involuntary load shedding in order to maintain system security. Due to high loss of load costs, load shedding should not exceed from a limit as follows:

$$0\le LS(b,t,k)\le LS^{\max}(b,t) \tag{35}$$

It has to be mentioned that the upper limit of the load shedding should not exceed demand at that hour in its corresponding bus.

In order to obtain a failure probability in a contingency, we used Forced Outage Rate (FOR) of generation units to calculate the $\pi(k)$ as presented in Ref. [26]. It is worth noting that we consider just generation failure here. Thus in the proposed formulation "k" is identical to "i" that is the number of generation units.

$$\pi(k)=\frac{FOR(k)}{1-FOR(k)}\prod_{i=1}^{N_{Gen}}(1-FOR(k)) \tag{36}$$

As previously mentioned, single contingency in generation unit failure is considered. Consequently, load shedding of bus b during contingency k in an hour t is defined as follows:

$$LS(b,t,k)=D_{DR}(b,t)-\sum_{i=1}^{N_{Gen(b)}}P(i,t)w(i,k)+\sum_{l=1}^{N_b}\frac{1}{X(l)}(\delta_s(l)-\delta_r(l)) \quad \forall b\in N_B, t\in T, k\in N_k \tag{37}$$

In contingency case, different from the regular situation when the generation must satisfy the demand, demand may not be satisfied because of lack of adequate generation. Thus, the difference between hourly generation and demand imposes a penalty cost namely, load shedding parameter. When $w(i,k)$ is equal to zero $P(i,t)$ remains zero due to a contingency occurred in unit "i" during time "t".

Expected Load Not Served (ELNS) that guarantees a reliable generation scheduling is obtainable by multiplying the probability of component failure to the load shedding value for each outage in each bus in time "t" as below:

$$ELNS(t)=\sum_{b=1}^{N_B}\sum_{k=1}^{N_k}\pi(k)LS(b,t,k) \tag{38}$$

$$ELNS(t)\le ELNS^{MAX} \tag{39}$$

It is noted that in the proposed optimization problem, the objective function, i.e., (10), of the MILP problem is minimized subject to constraints, i.e., (12) to (39). Also, the decision variables of the optimization problem can be listed as: $P(i,t)$, $D_{DR}(b,t)$, $LS(b,t,k)$ and $u(i,t)$.

3. Case studies and discussion

In the current section, the advantages of utilizing DRPs are clearly illustrated by versatile case studies. To this aim, different case studies are implemented, namely:

- Case #0: UC scheduling without considering DRP and reliability measures.

- Case #1: UC scheduling considering DRP but no reliability measures are included.
- Case #2: SCUC scheduling considering both EDRP and reliability measures.

In all case studies, 24-bus IEEE-RTS [27] is considered as the base test system. All generation units' data are given in Table 1. In the proposed model, all six hydro units out of 32 other type units operate at their maximum output and do not participate in the optimization procedure. It is noted that this assumption has no impact on the main purposes of the proposed framework. MIP is modeled implementing CPLEX 11.2.0 solver powered by GAMS optimization software. The CPU (central processing unit) time required for solving all the presented cases with a personal computer powered by core i3 processor and 3 GB of RAM is less than 5 s.

3.1. Case #0: normal operation without DR and reliability measures

In this study, the goal is to determine the optimal generation scheduling in a general day-ahead UC problem. The optimal costs and generation status obtained in the current case can be counted as benchmarks for next case studies. Total cost in this case is $826,750 where the value of lost load and DR costs are ignored. In this case all of forecasted demand is supplied and the load factor is calculated 82.9%. In this case, units 23–26 and 31–32 are always on during the scheduling period, units 1–9, 14, and 16–19 are not committed at all and peak unit is 20 with 32 MW power generation from hours 9 am to 4 pm.

3.2. Case #1: effect of the dynamic elasticity on normal operation

In the current case study, the effect of the dynamic elasticity is investigated along with the social welfare provided by implementing DRPs. EDRP has been then implemented considering the elasticity coefficients jlin and hlin equal to 209.38 and −1.5, respectively [16]. It is noted that these parameters are not fixed for every systems and may change based on many factors such as, load groups (i.e. residential, commercial, industrial, agricultural and so on), load characteristics and market behaviors. In this paper, it is supposed that these parameters are predetermined and a modified version of [16] is applied here. Since these parameters have significant effects on our results, different values in an upward and downward range are examined and compared in upcoming cases. Moreover, buses15 and 18 are allowed to participate in EDRP. This selection is done based on Table 2 by selecting the most heavily loaded buses. This approach is based on the ideas that demand response implementation on all buses might not be practical due to high investment costs of Advanced Metering Infrastructures (AMI). It can be, however, demonstrated that significant reductions in generation costs in a day-ahead horizon can be achieved if only buses with high demand profile are selected as candidates for implementing DRP. In this case, the total generation cost and total incentive payment are equal to $826,045 and $6,564 respectively. Fig. 1 shows the curtailment in the demand profile for bus 15. Note that almost the same reduction is observed for bus 18. It is clear from Fig. 1 that demand is started to be curtailed gradually from valley hours in the morning to off peak and peak hours in the noon and afternoon, respectively. This load curtailment behavior is acceptable since there is no curtailment during valley hours and the maximum curtailment is occurred during peak hours by up to 14 MW reductions in hour 11.

3.3. Case study #2: effect of demand response on reliability

As previously mentioned, the main purpose of this paper is to investigate the effect of DR in the case of contingencies. To this aim, single contingencies in generation units are investigated in the presence of reliability indices. For the first step, SCUC is investigated without considering EDRP. *VOLL* and $ELNS^{MAX}$ are set to 1500 $/MWh and 3 MWh, respectively and the must run generators are supposed to be completely reliable. An operational cost of 888,429 $ has been obtained which is $61,298 more than the base case. This rise in the conventional operating costs is due to reliability costs.

To implement an EDRP, 10% of the two most heavily loaded buses (i.e., buses 15 and 18) are allowed to be flexible. The market-clearing price, calculated in the base case, is presented in Table 3. It is noted that nodal marginal prices are same as the value of dual variables in power balancing equality constraint. The operational cost and total incentive payments in this case are $880,484 and $6,540, respectively. It is observable that flexible loads reduced the cost up to $7945 in comparison with the no-EDRP counterpart.

Demands vs. price elasticity function coefficients are significantly depend on historical data. In addition, variation in coefficients may have noticeable effects on the quality of the optimization procedure and solutions as well. Hence, an expanded range for h_{lin} is studied to clarify the influence of the parameter which is the main parameter in all kinds of elasticity functions (i.e., logarithmic, potential, exponential, and linear). All responsive demands regarding versatile h_{lin} for the contingency based unit commitment are shown in Fig. 2. It is clear that in almost all variations, demand reduction in early hours in the morning is negligible. This behavior was expected because of accommodating electricity price in the elastic demand formulation. Meanwhile, according to the formulation section, demand compensation in off peak hours is not permitted. In addition, doubling h_{lin} is resulted to an almost double reduction in peak hours which shows the significance of the fine setting of the parameter. On the other hand, when h_{lin} is 1.05, the slightest reduction during peak hours occurs. Because of some inherent restriction in implementing EDRPs such as price alert delay in communication systems and also the low inertia attitude of some loads, sudden variations of demand can occur. In order to prevent such unrealistic events in DRPs,

Table 1
Specifications of generation units.

No.	Type	P^{max}	P^{min}	a_i	b_i	c_i
1–5	Fossil-Oil	12	2	56	0.08	38.9
6–9	Combustion Turbine	20	16	633	0.44	48.4
10–13	Fossil-Coal	76	15	145	0.01	11
14–9	Hydro	50	0	0	0	0
20–22	Fossil-Oil	100	25	615	0.07	25.4
23–26	Fossil-Coal	155	54	220	0.01	9.3
27–29	Fossil-Oil	197	69	739	0.02	28.5
30	Fossil-Coal	350	140	440	0.01	8.6
31–32	Nuclear	400	100	621	0.0	13.5

Table 2
Hourly peak load in percent of daily peak for buses.

No.	Load	% Of peak	No.	Load	% Of peak
1	108	3.8	10	195	6.8
2	97	3.4	13	265	9.3
3	180	6.3	14	194	6.8
4	74	2.6	15	317	11.1
5	71	2.5	16	100	3.5
6	136	4.8	18	333	11.7
7	125	4.4	19	181	6.4
8	171	6.0	20	128	4.5
9	175	6.1			

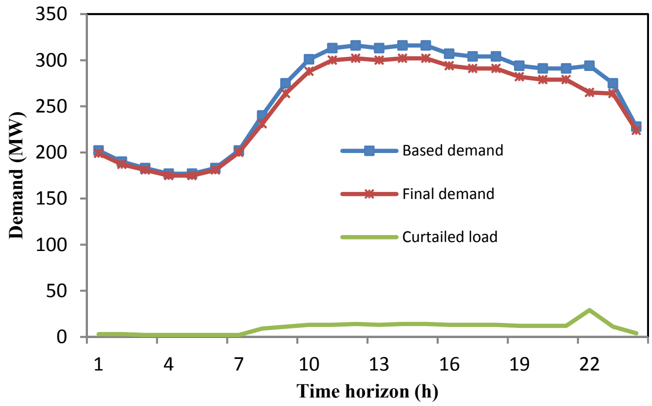

Fig. 1. Demand profile at bus 15 before and after DRP.

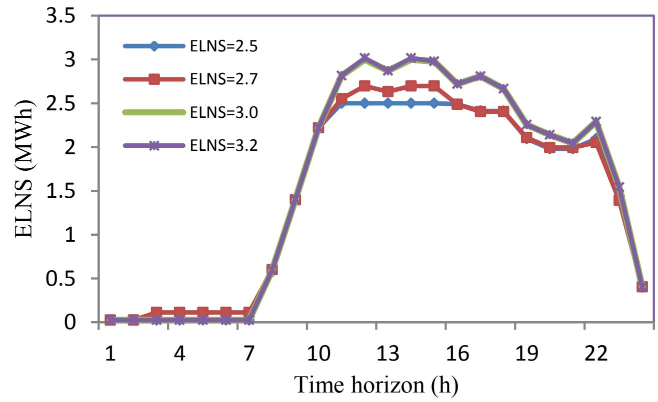

Fig. 3. Deviations in $ELNS^{MAX}$ in the last case.

Table 3
Market-clearing prices.

Bus-no.	Price ($/MWh)	Bus-no.	Price ($/MWh)
1	14.34	13	36.32
2–8,24	13.50	12,14-15	38.42
8	35.20	16–18	36.32
9,23	35.34	19,22	36.30
11	37.30	10,20-21	35.86

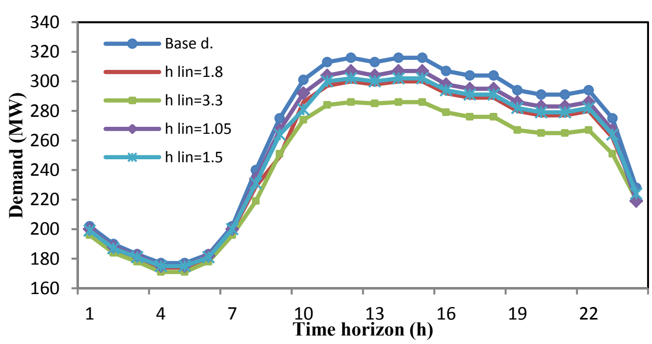

Fig. 2. Effects of h_{lin} on demand reduction.

minimum up/down and load reduction ramp rates is considered. Meanwhile, load reduction is occurred with the same pattern in all of the cases, which is expectable for non-compensated DRPs. The same patterns verify that implementing DRPs may not force customers to change their conventional consumption pattern.

3.4. $ELNS^{MAX}$ variation

In the following section, the impact of $ELNS^{MAX}$ deviation in hourly scheduling is discussed. The $ELNS^{MAX}$ for both considered contingency cases is 3 MWh and upward and downward variations from this value are examined to explicitly demonstrate the impacts of this parameter. According to what illustrated in Fig. 3, *ELNS* remained almost zero during early hours of the day. Moreover, the lowest value 2.5 MWh forced *ELNS* to remain in its maximum value from 11 am to 16 pm. In addition, when the maximum value is set to 2.7 MWh, the maximum ELNS reduced at hour 12. The upper levels of the $ELNS^{MAX}$ from 3 MWh, however, showed no significant increment during peak hours. In order to effectively interpret the recent trends, they have to be considered with their corresponding generation costs, shown in Fig. 4. It is noted that in this figure the curves for the cases 3 MWh and 3.2 MWh are almost the same.

Also, Fig. 4 indicates the generation cost and incentive payment for different $ELNS^{Max}$ values. It can be seen that generation cost shows a decreasing trend as the $ELNS^{Max}$ value increases. This trend can be proven according to the fact that increasing upper limit on inequality (39) not only enlarges optimal feasibility region but also required generation capacity to reach reliability criterion can be reduced. Incentive payment, however, has a different trend. It can be seen that for small amounts of $ELNS^{Max}$ value, the incentive payment is quiet much more than those of larger $ELNS^{Max}$ values. It can be observed that implementing DRPs can be used as suitable measures in case of high reliability requirements. Moreover, for larger amounts of $ELNS^{Max}$ values, incentive payments decrease significantly. This shows that the proposed DRP may not impose additional costs on system operator during normal situations. It should be noted that a slight increase in incentive payments for the $ELNS^{Max}$ equal to 2.7 MWh can be justified in a way that DR framework proposed in this paper follows a piecewise linear function.

Accordingly, moving to upper segments requires reaching to the maximum point of the lower segment. This might cause some extra costs in some cases, such as occurred in the case $ELNS^{Max} = 2.7$. The hourly demand is also indicated in Fig. 5. As it can be observed from Fig. 5, very tight reliability limits caused more demand reductions majorly during peak hours. As an example, for $ELNS^{Max}$ equal to 2.7 (MWh) demand is reduced up to 31 MW during hours 11, 12, 15 and 16.

3.5. VOLL effect

Another important factor which has significant role in allocating load shedding is VOLL. VOLL can be defined as the average constant

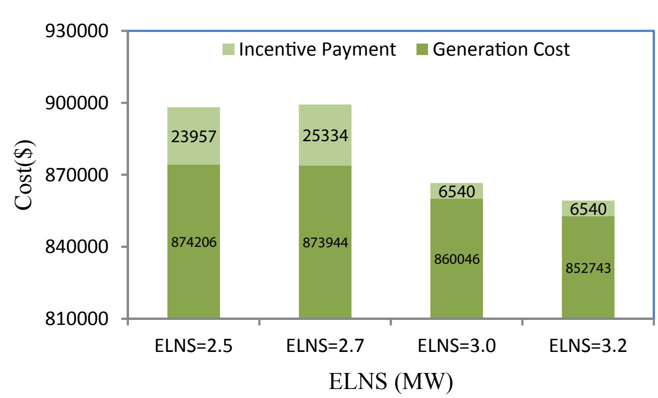

Fig. 4. Generation costs for versatile $ELNS^{MAX}$.

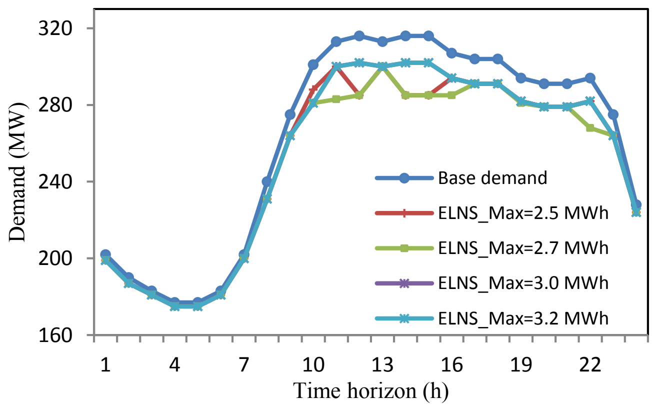

Fig. 5. Effect of ELNS on demand reduction.

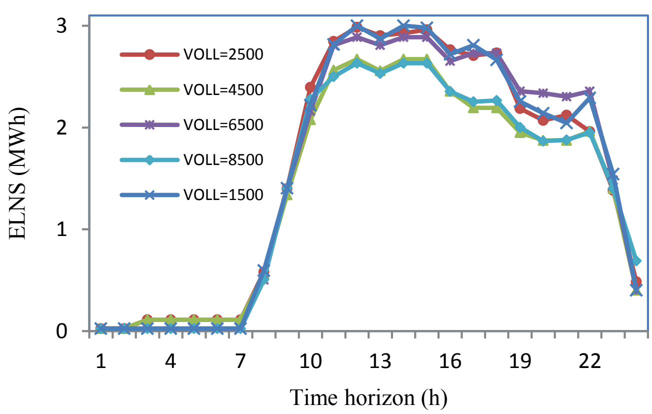

Fig. 6. Effects of different VOLL on hourly ENLS.

cost value that customers will lose due to the loss of one kWh of energy for one hour [28]. In order to clarify the applicability of the proposed method in mitigating load shedding, different values of VOLL are examined in four enhancing steps, illustrated in Fig. 6.

For almost all cases, *ELNS* remains zero during early hours of the day, as observed in reliability-based cases. It can be inferred from Fig. 6 that more *VOLL* value caused much more demand reductions during peak hours. This implies that suitable coordination of DRPs and the value of loads may lead to an optimal utilization of system resources. On the other words, high *VOLL* values during peak hours impose extreme costs on system operator, who can use demand response programs to mitigate such high costs through incentive payments.

4. Conclusions

In this paper, the efficiency of integrating DRPs to the SCUC problem to improve both social welfare and reliability indices has been investigated. Improving in social welfare is expectable since participating consumers in wholesale electric markets can not only mitigate the market power in supply side but also may provide benefits for demand side consumers by being paid in return for load reduction. Reliability also may be improved by reducing very expensive involuntary load shedding during on-peak periods. Among fifteen different programs announced by FERC, the EDRP has been selected here because of its prevalent application in today's deregulated markets. In addition, demand vs. price parameters have magnificent influence on load reduction decision making. Prior to the current paper, fixed elasticity based on historical behavior of demand vs. price was used to model elasticity of demand, which may cause misunderstanding from price elasticity. In this paper, considering dynamic elasticity factor realized the concept of price responsiveness more than previous interpretations. To demonstrate the applicability of such program, versatile case studies have been considered. It is stated that the real conflict is between demand reduction and expensive involuntary load shedding. Moreover, it is declared that, even low EDRP penetration in power systems may have magnificent influences mostly on contingency management, which was on the focus in the paper.

Although our model does not include uncertainty and intermittency of RES (renewable energy sources), an augmented version of our proposed model can mitigate these impacts as well. For further studies in this regard, RESs can be integrated both as non-dispatchable generation units or negative loads as in many similar papers. It is expected that particularly for peak hours that might not necessarily be the peak hours for generating power from RESs, EDRP, proposed in the current paper, can both prevent price spikes for specific hours, and act as additional reserve capacities to increase the overall reliability of the system for critical hours.

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