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SRTTU

Journal of Electrical and Computer Engineering Innovations

JECEI, Vol. 3, No. 2, 2015

Regular Paper

Transmission Congestion Management Considering Uncertainty of Demand Response Resources' Participation

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ARTICLE INFO

ARTICLE HISTORY:
Received 3 October 2015
Revised 23 December 2015
Accepted 3 January 2016

KEYWORDS:
Congestion management
Demand response resource
Customer's uncertainty
Multi-state model
Smart grid

ABSTRACT

Under the smart grid environment, demand response resources (DRRs) are introduced as a virtual power plant which enhance power system adequacy. DRRs often fail to reduce their load due to some external factors. In this paper, a reliability model of a DRR is constructed as multi-state conventional generation units, where the probability, frequency of occurrence, and departure rate of each state can be acquired. DRRs as consequence of demand response program implementation can be applied to transmission congestion management. Therefore, this paper presents an optimal model of congestion management (CM) by means of multi-state DRRs, namely CM_DRR. In the proposed approach, in addition to DRRs, independent system operator relieves the existing transmission line congestions using the combination of generating unit rescheduling and involuntary load shedding. The hourly historical data associated with the Connecticut region in New England is employed to achieve the DRRs' participation regime. Moreover, the impact of different capacities of DRRs on the congestion management cost and load shedding cost is evaluated. Results of applying the aforementioned model to the 24-bus Reliability Test System (RTS) indicate the efficacy of CM_DRR framework.

1. Introduction

Nowadays, in competitive electricity market environment, increased volumes of power trade happening due to the deregulation of electric power industry has led to intensive usage of transmission network, which in turn leads to more frequent congestion.

Congestion occurs on electric transmission facilities when actual or scheduled flows of electricity across a line or piece of equipment are restricted below desired levels. These restrictions may be imposed either by the physical or electrical capacity of the line, or by operational restrictions created and enforced to protect the security and reliability of the grid. Transmission congestion may prevent the existence of new contracts, lead to additional outages, increase the electricity prices in some regions of the electricity markets, and can threaten the system security and reliability [1,2]. Consequently, congestion management as an Independent System Operator (ISO) function is applied to take the actions or control measures in relieving the compression of transmission networks and increasing the power transfer capabilities [3].

The methods generally adopted to manage congestion include rescheduling generator outputs, supplying reactive power support, physically transactions curtailment, even or involuntary load shedding.

System operators generally prefer the first option to supply demand as much as possible by existing mechanisms; if not possible, they use load shedding as the last resort to manage congestion and retain the system security [4].

Recently, some techniques are presented for congestion management in competitive power markets.

In [5], optimal transmission switching as a congestion management tool is utilized to change the network topology and increase the market efficiency. In [6], wind power curtailment and energy storage as transmission congestion mitigation measures are analyzed, considering power plants ramp rates. Authors proposed the congestion management in distribution networks using electric vehicles in [7] and also the vehicle-to-grid strategies are implemented for congestion management in [8].

Verma et al. proposed a simple and efficient model for location of unified power flow controller (UPFC) for congestion management [9].

References [10] and [11] described a congestion management model considering voltage security and dynamic voltage stability of the power system in which altering the generators and demands powers are used.

Under the smart grid environment, Demand response Resources (DRRs) as consequence of implementing demand response programs (DRPs) can play a significant role for congestion management. Hence, in order to model DRRs as power system resources for participating and improving performance of electric systems, DRPs should be precisely defined and investigated. Reference [12] proposed three responsive load models, namely linear, potential and exponential demand functions to evaluate variable costs of electric energy and develop the concept of spot pricing of electricity.

An approval function based on the acceptable energy costs for different clusters of customers was presented in [13].

A DRP model in order to determine the price elasticity from demand functions based on the main definition of elasticity is presented in [14]. Moreover, economic models of responsive loads based on the concept of price elasticity have been addressed in [15, 16] where determining the price elasticity of demand requires pervasive socio-economical study on customers.

In the authors' previous research, an economic model of responsive loads is derived based on the concept of customer utility function [17-19].

In this paper, a set of responsible loads such as homes, industrials, large buildings, etc., which have the potential of participating in DRPs and communicate with demand response aggregator are called DRR. A DRR is assumed similar to conventional units with derated output states. Herein, a reliability model for DRRs based upon analytic method and historical data of aggregated small loads participation in DRPs associated with Connecticut region from independent system operator of New-England (ISO-NE) is introduced so that Capacity Outage Probability Table for DRRs, named $COPT^{DRR}$, can be calculated. After that, a congestion management by considering the aforementioned model of DRRs, the so-called CM_DRR is presented in this manuscript.

In order to assess the impact of DRRs on the congestion alleviation cost, some DRRs are called to participate in congestion management problem.

According to the uncertainty of customers' participation, multifarious scenarios have been considered for CM_DRR and ISO relieves the existing transmission lines congestion by minimizing the congestion cost problem. To do so, all optimizations in this paper are carried out using the linear programming (LP) model of CONOPT solver of General Algebraic Modeling System (GAMS) 24.1.2 software package [20].

The rest of the paper is organized as follows. Section 2 provides the hierarchy of CM_DRR from ISO perspective. Section 3 describes the reliability model of a DRR.

Section 4 presents the formulation of congestion management in the presence of multiple DRRs. Section 5 conducts the numerical simulations and finally the conclusion is drawn in section 6.

2. CONGESTION MANAGEMENT CONSIDERING THE UNCERTAINTY OF DRRS

As shown in Fig. 1, the hierarchy of investigating the impact of uncertainty model of DRRs on the congestion management, as CM_DRR, from ISO perspective is depicted.

Demand response providers who aggregate many retail customers in order to participate as a DRR, receive a monthly payment in response for a mandatory obligation to reduce load when dispatched by ISO.

Since customers may break their promise in the contract, possible scenarios for uncertainty of customers' participation are considered. After ISO clears the day-ahead electricity market without considering the transmission constraint, he/she will analyze network congestion.

Eventually, ISO will collect Generation Companies (GENCOs) bids and call DRRs willing to participate in congestion management so that the electricity market gets feasible.

In the following sections, more explanations about CM_DRR are elaborated.

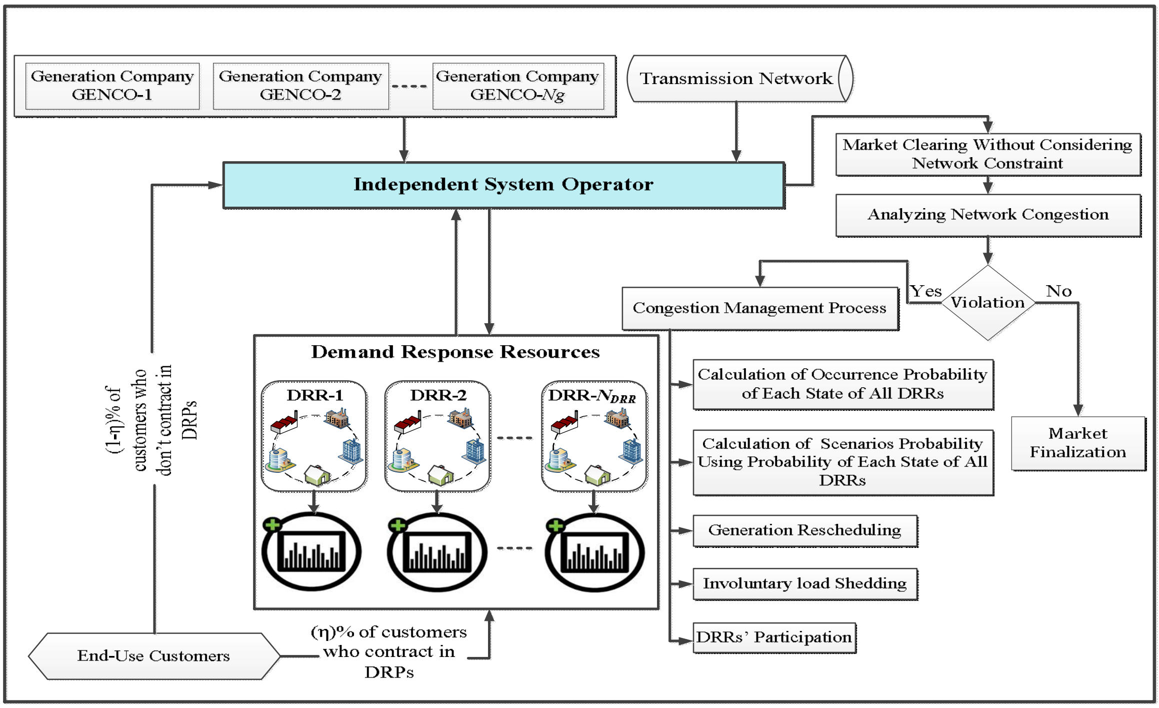

Figure 1: Hierarchy of the proposed congestion management associated with DRRs.

3. Multi-state Modeling of Demand Response Resources

A set of aggregated small loads such as homes, industrials, large buildings, etc., willing to participate and enroll in reduction programs of the system operator constitute a DRR.

The aforementioned customers enrolling in demand response programs receive the payment to curtail their consumption, whenever they are asked by the system operator. The historical data of customer's participation denotes that the customers fail to keep their promise of what they have enrolled in real-time demand response programs [21]. As mentioned in [22], conventional generating units have two states or three states model comprising one derated state. However, a DRR can usually comprise several derated states since one DRR is made up of several curtailable load resources, such as smart homes appliances, manufactures, etc.

Therefore, comparing the real demand reduction with enrollment of customers, the time series of customers' participation can be obtained from historical data. In power system reliability studies, Markov chain model is suggested for stochastic process [23]. A Markov chain is a type of Markov process which may be utilized to model the variations of a stochastic process as each transition represents a discrete value.

Hence, the Markov chain can be used for modeling uncertainty of DRRs' power reduction.

In order to determine the probabilistic model of customer's participation, it is required to split participation percentage into finite states. It should be emphasized that the number of states is arbitrary which depends on required accuracy of the probabilistic model of DRRs.

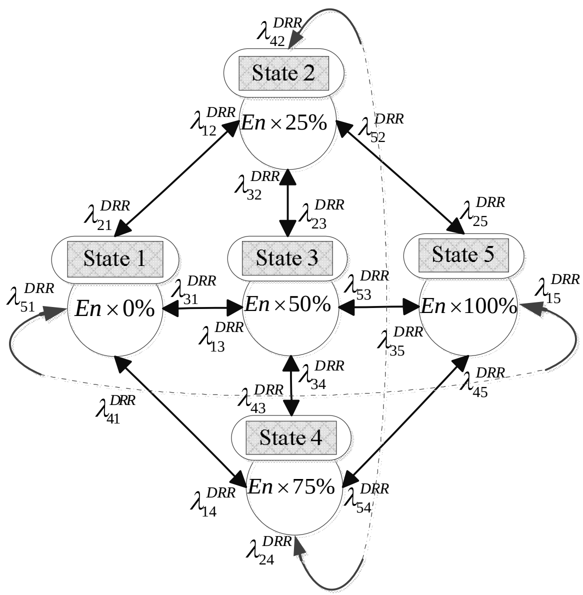

Figure 2: Markov model for DRR's participation in DRPs.

When the customers' participation time series are split into finite states, Markov model analysis can be carried out as described before.

For instance, the participation level of a DRR in a specific DRP with EN MW enrollment can be split into the five states as EN×0%, EN×25%, EN×50%, EN×75% and EN×100%. Therefore, the Markov model of the aforementioned DRR is shown in Fig. 2.

Generally, discrete steps are considered for one DRR with maximum capacity of power reduction C_{DRR}^{Max} MW that real demand curtailments must be split into finite demand power curtailment steps [24] as:

$$C^{\Lambda} = (\Lambda - 1)\frac{C_{DRR}^{Max}}{N_{step} - 1} \qquad \forall \Lambda \in \{1, 2, ..., N_{step}\} \tag{1}$$

Afterwards, in order to cluster all real demand curtailments into finite steps which were calculated from(1), equation (2) can be used.

$$\begin{aligned} &if \;\; C^{\Lambda} - (\frac{1}{2})\frac{C_{DRR}^{Max}}{N_{step}-1} \le C_{real} \le C^{\Lambda} + (\frac{1}{2})\frac{C_{DRR}^{Max}}{N_{step}-1} \\ &then \;\; C_{real} \rightarrow C^{\Lambda} \end{aligned} \tag{2}$$

The time ratio spent in each state when the number of returns to that state tends to infinity, approaches the bilateral of the mean residence time [25]. This residence time of each state follows the exponential distribution. The transition rate between two states of DRR's participation can be presented as:

$$\lambda_{\alpha\beta}^{DRR} = \begin{cases} \dfrac{N_{\alpha\beta}}{T_{\alpha}} & when \;\; \alpha \ne \beta \\ 0 & otherwise \end{cases} \tag{3}$$

The occurrence probability of state α for a DRR can be determined as:

$$p_{\alpha}^{DRR} = \frac{\text{Duration of state } \alpha}{\text{Entire priod of observation}} = \frac{T_{\alpha}}{\sum_{\rho=1}^{N} T_{\rho}} = \frac{T_{\alpha}}{T} \tag{4}$$

where,T_{ρ} and N correspond to period of observation in state ρ and the total number of DRR states, respectively. Here, the departure rates from state α to the lower and upper states can be denoted as:

$$\lambda_{-\alpha}^{DRR} = \sum_{\alpha \le \beta}^{N} \lambda_{\alpha\beta}^{DRR} \tag{5}$$

$$\lambda_{+\alpha}^{DRR} = \sum_{\alpha \ge \beta}^{N} \lambda_{\alpha\beta}^{DRR} \tag{6}$$

The occurrence frequency of state α for a DRR can be also computed as:

$$f_{\alpha}^{DRR} = p_{\alpha}^{DRR}(\lambda_{-\alpha}^{DRR} + \lambda_{+\alpha}^{DRR}) \tag{7}$$

It should be mentioned that this model of demand response resources can be utilized in different motivations including congestion management, power system reliability enhancement, decreasing energy cost, and etc. Hence, depending on the demand of power system operation issue, the specific parameter of the reliability model of multi-state demand response resources such as transition rates, occurrence probability and frequency of each demand response resource's state would be utilized. Herein, the proposed issue is congestion management which only the parameter of occurrence probability of each uncertain demand response resource's state is needed and brought out to calculate the probability of different scenarios for congestion management. More explanations about the proposed congestion management issue are provided in section 4.

4. Formulation of Congestion Management Using DRRs (CM_DRR)

After ISO clears day-ahead electricity market without taking the network constraints into account, he/she should analyze the electricity network congestion and relieve the existing transmission congestion. In order to mitigate the transmission congestion, the proposed model of DRRs enrolling to participate in congestion management is called by ISO. Here, it should be noted that DRRs may participate with different percentage of their Maximum Achievable Potential (MAP). For this reason, ISO should determine the best value of DRRs' MAP and the optimal power reduction for each DRR. In order to model these uncertain DRRs, different scenarios should be generated. Thus, after computing the probability of aforementioned DRRs states, scenarios must be generated such that probability of each scenario can be obtained as:

$$Prob^{\zeta} = \Pi_{S1}^{1} \times \Pi_{S2}^{2} \times ... \times \Pi_{Sd}^{d} \times ... \times \Pi_{SN_{DRR}}^{N_{DRR}} \tag{8}$$

where Π_{Sd}^{d} denotes the probability of each DRR state and *Sd* is the set of states for DRRs in alleviating congestion step. As the number of DRRs increases, the number of scenarios becomes larger and computational time of solving the problem increases so that an effective scenario reduction technique is required. The final number of scenarios should be selected by considering a trade-off between solutions accuracy and tractability but generating proper scenarios and scenario reduction are beyond the scope of this paper. More details about the scenario reduction can be obtained in[26].After generating all possible scenarios for DRRs states and computing their probability, the rescheduling of generation units and load shedding are used together for each scenario with the purpose of minimizing expected congestion cost.

$$Min\left\{\begin{array}{l}\sum_{\zeta=1}^{Ns} prob^{\zeta}.\left\{\sum_{j\in G}(B_{G,j}^{Up}.\Delta p_{G,j}^{\zeta,Up}+B_{G,j}^{Down}.\Delta p_{G,j}^{\zeta,Down})\right.\\ \left.+\sum_{d=1}^{N_{DRR}}(\pi_d^{DRR}.\Delta p_d^{DRR}.\Phi_{DRR,d}^{\zeta})+\sum_{w\in\Omega^{Load}}(VOLL_w^{LS}.\Delta p_w^{\zeta,LS})\right\}\end{array}\right\} \quad (9)$$

The objective function (9) is composed of different parts. The first part is the payment that ISO pays to generation units for altering their output as compared to the original market clearing schedule based on the percentage of DRRs' power reduction. The second part expresses the payment to DRRs because of participating in CM-DRR based on different scenarios for percentage of DRRs' MAP that they reduce their consumption, and the third part is expected payment to consumers which are involuntary shed by ISO. The optimization problem of (9) is solved subject to constraints(10)-(19):

$$p_{G,j}^{Min}\le p_{G,j}^{\zeta}\le p_{G,j}^{Max} \qquad \forall j\in\{1,...,Ng\} \;\&\; \zeta\in\{1,...,Ns\} \quad (10)$$

$$0\le \Delta p_d^{DRR}\le En_d^{DRR} \qquad \forall d\in\{1,...,N_{DRR}\} \quad (11)$$

$$\begin{array}{l}p_{Gn}^{\zeta}-p_{Ln}^{\zeta}=\sum_{q\in\Omega^n}\frac{1}{x_{nq}}\left(\delta_n^{\zeta}-\delta_q^{\zeta}\right)\\ \qquad \forall n\in\left\{\Omega^{Node}\right\} \;\&\; \zeta\in\{1,2,...,Ns\}\end{array} \quad (12)$$

$$\begin{array}{l}-F_{nq}^{Max}\le\frac{1}{x_{nq}}\left(\delta_n^{\zeta}-\delta_q^{\zeta}\right)\le F_{nq}^{Max}\\ \forall q\in\left\{\Omega^n\right\},\; n\in\left\{\Omega^{Node}\right\} \;\&\; \zeta\in\{1,2,...,Ns\}\end{array} \quad (13)$$

$$\begin{array}{l}p_{G,j}^{\zeta}=p_{G,j}^{MC}+\Delta p_{G,j}^{\zeta,Up}-\Delta p_{G,j}^{\zeta,Down}\\ \qquad \forall j\in\{1,...,Ng\} \;\&\; \zeta\in\{1,2,...,Ns\}\end{array} \quad (14)$$

$$p_{Gn}^{\zeta}=\sum_{j\in SGn}p_{G,j}^{\zeta} \qquad \forall n\in\left\{\Omega^{Node}\right\} \;\&\; \zeta\in\{1,...,Ns\} \quad (15)$$

$$\begin{array}{l}p_{Ln}^{\zeta}=p_{Ln}^{MC}-\Delta p_{DRn}^{DRR}.\Phi_{DRn}^{\zeta}-\Delta p_{wn}^{\zeta,LS}\\ \qquad \zeta\in\{1,...,Ns\} \;\&\; n\in\left\{\Omega^{Node}\right\}\end{array} \quad (16)$$

$$\begin{array}{l}\Delta p_{DRn}^{DRR}.\Phi_{DRn}^{\zeta}=\Delta p_d^{DRR}.\Phi_{DRR,d}^{\zeta}\\ \qquad \forall d\in\{DRn\} \;\&\; \zeta\in\{1,...,Ns\}\end{array} \quad (17)$$

$$\Delta p_{wn}^{\zeta,LS}=\Delta p_w^{\zeta,LS} \qquad \forall w\in\{wn\} \;\&\; \zeta\in\{1,...,Ns\} \quad (18)$$

$$\begin{array}{l}\Delta p_{G,j}^{\zeta,Up}\ge 0,\; \Delta p_{G,j}^{\zeta,Down}\ge 0,\; \Delta p_w^{\zeta,LS}\ge 0\\ \forall j\in\{1,...,Ng\} \;\&\; w\in\left\{\Omega^{Load}\right\} \;\&\; \zeta\in\{1,...,Ns\}\end{array} \quad (19)$$

Constraint (10) ensures that each generating unit runs between its maximum and minimum power outputs. The constraint (11) specifies the size of maximum power reduction for each DRR enrolling in relieving congestion procedure. DC power flow equation is presented in equation (12). The constraint (13) enforces transmission lines capacity limit for DC power flow. Equation (14) shows final rescheduled power generation of each unit and $P_{G,j}^{MC}$ is power generation of each unit determined in market clearing procedure. Equations (15) and (16) represent the total power generation at bus *n* as the sum over generation units when multiple units are connected to bus *n* and equivalent demand at bus *n*, respectively. Equation (17) determines the power reduction of each DRR placed at bus *n*. Similarly, equation (18) shows involuntary load shedding at bus *n* and equation (19) confines all up and down power changes to positive values.

5. CASE STUDY: IMPLEMENTATION OF CM_DRR ON RELIABILITY TEST SYSTEM

The congestion management in the presence of multi-state DRRs, i.e. CM_DRR, is examined on the 24-bus IEEE Reliability Test System (RTS).

This standard system comprises 32 generators, 33 lines, 5 transformers and 17 loads. The generators and load data including their power results of market clearing procedure, lower and upper limits of output power, and generating units bid are given in appendix A. The other required system characteristics can be obtained from[27, 28]. In Fig. 3, the single diagram of 24-bus RTS with some DRRs is depicted.

The historical data of consumers' participation is needed to model multi-state DRRs. Herein, the hourly historical information of customers participating in DRPs from Connecticut region by Independent System Operator of New England (ISO-NE), is employed for reliability model of a DRR [21].

As shown in Fig.4, the interval of measurements is one hour with registration of nearly seven years (2006-2013).

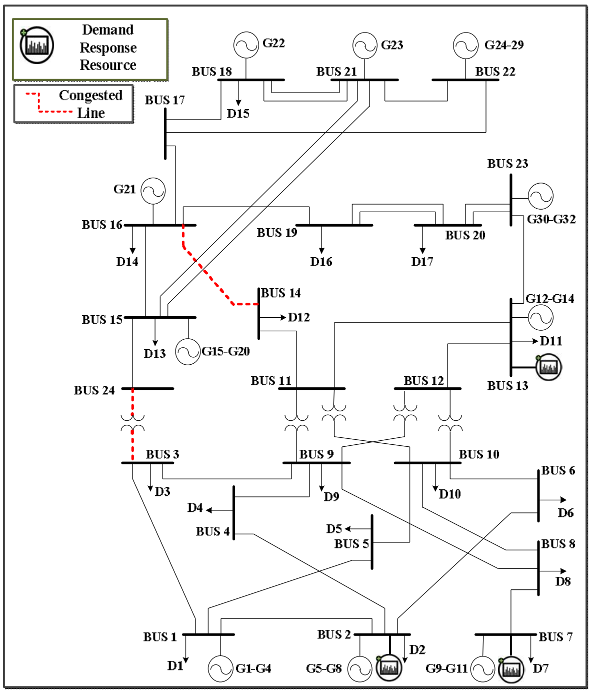

Figure 3: Single line diagram of RTS with DRRs.

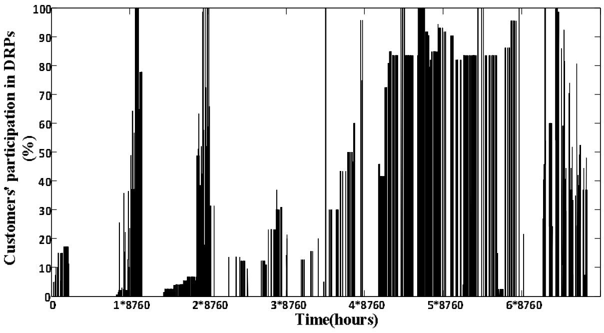

Figure 4: DRR's participation time series for state of Connecticut.

In order to utilize DRRs in CM_DRR, it is needed to obtain the information of consumers' participation corresponding to specified time. For instance, the historical data corresponding to daily consumers' participation at 6:00 PM is shown in Fig. 5.

Amongst 60072 hours in approximately seven years (2006-2013), the number of times corresponding to 6:00 PM is 2503 hours.

ISO-NE opens the eligibility period in a load zone when actual price equals or exceeds 100 $/MWh during the eligible hours [11].

Hence, amongst 2503 hours in seven years of customers' participation at 6:00 PM, the customers are called to participate in DRPs only for 619 hours with regard to the market events.

Fig. 6 demonstrates customers' participation in eligible periods at 6:00 PM.

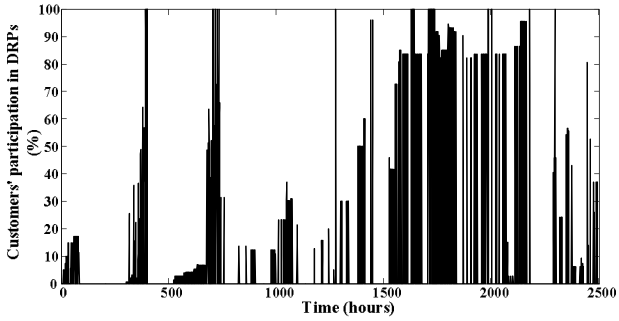

Figure 5:Daily DRRs' participation at 6:00 PM for state of Connecticut in ISO-NE's DRPs.

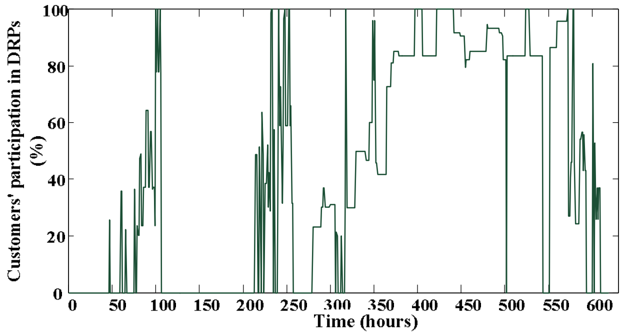

Figure 6: Approximation curve of daily customers' participation at 6:00 PM for Connecticut region in eligible periods.

As an illustration, regarding Fig. 6, DRR's participation with MAP of 2 MW for only 143 hours is captured in Fig. 7.

The DRR's participation in demand response programs can be divided into finite states. It should be noted that the number of states pertains on required accuracy of the model. Here, the participation of a DRR with MAP of 2 MW in DRP is split into {0%×2 MW, 20%×2 MW, 40%×2 MW, 60%×2 MW, 80%×2 MW and 100%×2 MW}, as shown in Fig. 7. The initial curve in Fig. 7 corresponds to the real DRR's participation for Connecticut region and the approximated curve shows the DRR's participation in finite states mentioned for sample 143 hours.

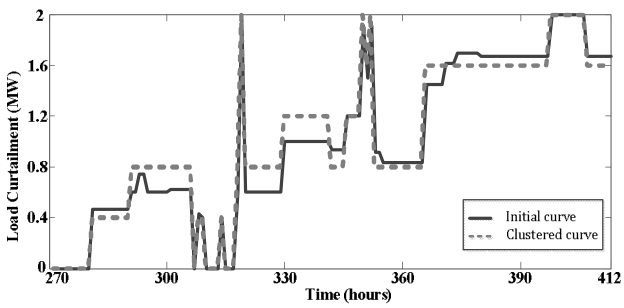

Figure 7: DRR power reduction sequence for 143 hours.

After that the DRR's reduction time series have been split into the aforementioned finite states, frequency and duration analyses are performed as described in Section 3.

Using (3), the transition matrix ($\lambda_{\alpha\beta}$) of a six-state DRR can be obtained as:

$$\lambda_{\alpha\beta}=\begin{pmatrix} 0 & 0.0245 & 0.0245 & 0.0163 & 0.0122 & 0 \\ 0.1290 & 0 & 0.1935 & 0.0323 & 0 & 0.0645 \\ 0.1098 & 0.0732 & 0 & 0.0854 & 0.0122 & 0.0366 \\ 0.0256 & 0 & 0.2821 & 0 & 0.0256 & 0.0769 \\ 0.0313 & 0 & 0 & 0.0078 & 0 & 0.0625 \\ 0.0106 & 0.0106 & 0.0319 & 0.0319 & 0.0851 & 0 \end{pmatrix}$$

As an example, according to above calculated transition matrix, transition rate from state 3, i.e. {40%×2MW}, to state 6, i.e. {100%×2MW}, is equal to 0.0366.

Moreover, Table 1 shows capacity outage probability for the aforementioned DRR named COPT^{DRR} which is calculated and brought by using frequency and duration analysis.

TABLE 1
COPT^{DRR} FOR A DEMAND RESPONSE RESOURCE

State (α)	DRR Capacity in (MW)	P_{α}^{DRR}	$\lambda_{-\alpha}^{DRR}$ (occ/hr)	$\lambda_{+\alpha}^{DRR}$ (occ/hr)	f_{α}^{DRR} (occ/hr)
1	0	0.3958	0	0.0776	0.0307
2	0.4	0.0500	0.1290	0.2903	0.0210
3	0.8	0.1325	0.1829	0.1341	0.0420
4	1.2	0.0630	0.3077	0.1026	0.0258
5	1.6	0.2068	0.0391	0.0625	0.0210
6	2	0.1519	0.1702	0	0.0258

As seen in Fig. 3, a number of DRRs located at buses #2, #7 and #13 are called to participate in the proposed congestion management and the prices of DRRs power reduction are 24, 21 and 22 $/MWh, respectively.

In addition, the value of lost load for load shedding is provided in [28]. Also, as an additional assumption in this paper, the rating of branches 3-24 and 14-16 are reduced to 200 and 300 MW, respectively.

Before applying congestion management, the power market is not feasible. In fact, there are some overloaded branches with the generations and loads determined by the market clearing process. Transmission lines 3-24 and 14-16 are overloaded to 115.9% and 120.6% of their rating, respectively.

As shown in Table A1, generation units 22-29 do not participate in relieving congestion because units 22 and 23 are nuclear power plants and also units 24-29 are hydro generators operating at their maximum output of 50 MW.

It is worthwhile to describe that the thermal generation units which were not committed in the market clearing step, cannot participate in congestion management, because the time of relieving congestion is near to operation time so that they cannot start up and also the cost of their start up is considerably high.

In this section, real power curtailment of each DRR is supposed to be clustered into six states, i.e. {0%, 20%, 40%, 60%, 80% and 100%}.

Hence, using equations (9)-(19) and considering the uncertainty of customers' participation, ISO can determine DRRs' MAP and also expect power curtailment of DRRs for mitigating the network congestion.

It should be noted that before implementation of equations (9)-(19), scenario generation is performed and the probability of each scenario is obtained from (8); effective scenario reduction is run as well. Herein, 25 probable scenarios are accepted for DRRs' power reduction.

For each accepted scenario, the proposed congestion management by means of generator rescheduling, DRRs and involuntary load shedding, is carried out.

The proposed CM_DRR problem is implemented in GAMS environment running on an Intel® Core™i7-3632QM CPU 2.20 GHz PC with 8 GB RAM. Besides, the proposed framework is a LP model which has been easily solved 0.03 sec by CONOPT solver of GAMS software.

The results of mitigating congestion for 25 accepted scenarios including probability and congestion cost and individual expected congested cost of each scenario are shown in the fifth, sixth and seventh columns of Table 2, respectively.

As presented in Tale 2, the congestion cost (38496.725 $/h) in the scenario that none of DRRs reduces its consumption, is the highest one in comparison with the other scenarios.

The MAP of DRRs along with expected load shedding is shown in Table 3, and expected change in output power of generating units is provided in Table 4. As seen in Table 3, involuntary load shedding is needed to alleviate congestion.

Table 5 denotes the impact of capacity of DRRs which are enrolling in DRP on the total expected congestion cost and the expected involuntary load shedding costs as well.

TABLE 2
RELIEVING CONGESTION SOLUTIONS FOR 25 PROBABLE SCENARIOS

Scenario No.	State of DRR at bus #2	State of DRR at bus #7	State of DRR at bus #13	Scenario probability	Congestion Cost ($/h)	Individual Expected Congestion Cost ($/h)
1	0%	0%	0%	0.0620	38496.725	2386.797
2	0%	0%	80%	0.0323	35951.609	1161.237
3	0%	80%	0%	0.0323	35401.021	1143.453
4	80%	0%	0%	0.0323	33029.102	1066.840
5	100%	0%	0%	0.0237	31667.805	750.527
6	0%	100%	0%	0.0237	34636.033	820.874
7	0%	0%	100%	0.0237	35325.063	837.204
8	0%	0%	40%	0.0207	37348.260	773.109
9	0%	40%	0%	0.0207	37072.463	767.400
10	40%	0%	0%	0.0207	35884.444	742.808
11	0%	80%	80%	0.0169	32635.680	551.543
12	80%	0%	80%	0.0169	30271.065	511.581
13	80%	80%	0%	0.0169	29722.189	502.305
14	100%	0%	80%	0.0124	13520.403	167.653
15	0%	100%	80%	0.0124	31834.435	394.747
16	100%	80%	0%	0.0124	28329.758	351.289
17	80%	100%	0%	0.0124	28920.967	358.620
18	0%	80%	100%	0.0124	31971.693	396.449
19	80%	0%	100%	0.0124	29607.096	367.128
20	0%	40%	80%	0.0108	34238.148	369.772
21	40%	0%	80%	0.0108	33055.833	357.003
22	0%	80%	40%	0.0108	33963.703	366.808
23	40%	80%	0%	0.0108	32506.944	351.075
24	80%	0%	40%	0.0108	31599.074	341.270
25	80%	40%	0%	0.0108	31324.629	338.306
Total Expected Congestion Cost ($/h)					**33559.747**	

TABLE 3
DRRS'MAPAND EXPECTED LOAD SHEDDING IN CONGESTION MANAGEMENT

DRRs' MAP		**Involuntary Load Shedding**	
Bus No.	ΔP_d^{DRR} (MW)	Bus No.	ΔP_w^{LS} (MW)
2	9.690	3	26.8444
7	12.512	14	40.9232
13	26.505		

TABLE 4
EXPECTED GENERATION CHANGE IN CONGESTION MANAGEMENT

Generator No.	$\Delta P_{G,j}^{Up}$ (MW)	$\Delta P_{G,j}^{Down}$ (MW)
1	-	-
5	-	-
6	-	-
9	-	-
10	26.7407	-
11	-	-
12	8.6307	-
13	8.6307	-
20	-	100.888
21	-	27.884

It can be obviously concluded that an increase in the capacity of DRRs decreases both the total expected congestion and load shedding costs. The main reason is that the amount of involuntary load shedding is less required when more DRRs capacity is available. Furthermore, although the expected cost of generation change increases, the expected congestion cost decreases. As presented in Table 5, when no DRR is applied, the value of congestion cost (38496.7258 $) is more than DRRs participate in relieving congestion procedure.

According to Table 5 capacity of each DRR is supposed in 6 scenarios, from 0% to 8% of relative load amount. Also, minimum expected congestion payable by ISO is 34561.5145 ($/h) corresponding to scenario 5 (i.e. 8% of relative load).

Therefore, it is worthwhile that ISO tries to make contracts such that large capacity DRRs can take part.

TABLE 5
IMPACT OF DRRS ON CONGESTION MANAGEMENT COST

Scenario NO.	Capacity of each DRR (% of load at related bus)	Generation Shift Cost of Conventional Units ($/h)	Cost of DRRs' Participation ($/h)	Cost of Load Shedding ($/h)	Total Congestion Cost ($/h)
1	Without DRR	3315.6175	0	35181.1083	38496.7258
2	2%	3336.6639	69.1078	34161.0581	37566.8298
3	4%	3351.5207	138.2117	33075.3257	36565.0581
4	6%	3366.3776	207.3154	31989.5933	35563.2863
5	8%	3381.2344	276.4212	30903.8589	34561.5145

6. CONCLUSION

This paper has developed a methodology for transmission congestion management in which the traditional approach of using conventional generators and/or load shedding is augmented by demand response resources. Also, the historical data of customer's participation indicates that the customers are in a breach of what they have enrolled in DRPs. Hence, in this paper, a reliability model for DRRs was proposed considering the uncertainty of DRR's participation in DRPs. The frequency and duration techniques were employed here to model the DRR as a conventional unit with derated states. The present paper focused on illustrating the role of DRRs' participation in congestion management. It was concluded that employment of DRRs with high capacity can make the cost of relieving congestion lower in comparison with involuntary load shedding. Moreover, it was demonstrated that as the capacity of DRRs increases the congestion cost decreases. Herein, the results signify that DRRs are somehow efficient for reducing the cost of congestion alleviation.

NOMENCLATURE

A. Sets

Ω^{Node}	Set of nodes.
Ω^{n}	Set of buses connected to bus *n*.
Ω^{load}	Set of loads.
SGn	Set of generators connected to bus *n*.
DRn	Set of DRRs connected to bus *n*.

B. Indices

Λ	Number of approximated states in a demand response resource.
ζ	Index for power curtailment of DRRs scenarios in congestion management procedure.
j	Index for generator.
d	Index for demand response resources in congestion management.
w	Index for involuntary load shedding.
wn	Index for load shedding at bus *n*.
Gn	Index for generation units at bus *n*.
DRn	Index for DRRs at bus *n*.

C. Parameters

η	% of customers contracting in DRPs.

N_{step}	Total number of approximated states for a demand response resource.
C_{DRR}^{Max}	Capacity of a demand response resource.
C^{Λ}	Output power associated with approximated state Λ in a demand response resource.
C_{real}	Real output power of a demand response resource.
$\lambda_{\alpha\beta}^{DRR}$	Transition rate from state α to state β for a demand response resource.
$N_{\alpha\beta}$	Number of observed transition from state α to state β for a demand response resource.
T_{α}	Duration of state α in the whole period.
T	Entire period of observation.
$p_{\alpha}^{DRR}, f_{\alpha}^{DRR}$	The occurrence probability and frequency of state α for demand response resource
$\lambda_{-\alpha}^{DRR}, \lambda_{+\alpha}^{DRR}$	Departure rate from state α to the lower and higher states of demand response resource.
Ns	Total number of scenarios for power curtailment of DRRs in congestion management procedure.
$prob^{\zeta}$	Probability of scenario ζ for power curtailment of DRRs in relieving congestion procedure.
$B_{G,j}^{Up}, B_{G,j}^{Down}$	Bid price of generator *j* to increase and decrease its power.
N_{DRR}	The number of DRRs.
π_{d}^{DRR}	Price of decreasing power for DRR *d*.
$\Phi_{DRR,d}^{\zeta}$	Percentage of power curtailment of DRR *d* under scenario ζ.
$VOLL_{w}^{LS}$	Value of lost load *w* for involuntary load Shedding.
$p_{G,j}^{Min}, p_{G,j}^{Max}$	Lower and upper limit of real power generation of generator *j*.
En_{d}^{DRR}	Capacity of DRR Enrolling for participating in congestion management.
p_{Ln}^{MC}	Total demands at bus *n* obtained from market clearing procedure.
x_{nq}	Reactance of line connected to buses *n* and *q*.
F_{nq}^{Max}	Maximum line flow of the line connected to buses *n* and *q*.

D. Variables

$\Delta p_{G,j}^{\zeta,Up}, \Delta p_{G,j}^{\zeta,Down}$	Up and down generation shifts of generator *j* under scenario ζ .
Δp_{d}^{DRR}	Maximum achievable potential of DRR.
$\Delta p_{w}^{\zeta,LS}$	Amount of involuntary load shedding corresponding to load *w* under scenario ζ .
$p_{G,j}^{\zeta}$	Total generation of generator *j* under scenario ζ after rescheduling.
$p_{Gn}^{\zeta}, p_{Ln}^{\zeta}$	Total generation and load at bus *n* under scenario ζ
δ_{n}^{ζ}	Voltage angle of bus *n* under scenario ζ .
$\Delta p_{DRn}^{DRR}.\Phi_{DRn}^{\zeta}$	Amount of power curtailment of DRRs at bus *n*.
$\Delta p_{wn}^{\zeta,LS}$	Amount of involuntary load shedding at bus *n* related to load *w* under scenario ζ .

APPENDIX A

Generator and demand market data resulted from market clearing procedure are reported in Tables A1 and A2, respectively. The lower and upper limits of output power as well as generating units bid are given in Table A1. In addition, in Table A2, P_{L}^{MC} corresponds to the amount of loads attained from market clearing procedure.

TABLE A1
GENERATOR MARKET DATA

Unit	$B_{G,j}^{Down}$	$B_{G,j}^{Up}$	$P_{G,j}^{MC}$
G1	-	-	OFF
G2	-	-	OFF
G3	15.00	16.00	76
G4	15.50	16.00	76
G5	-	-	OFF
G6	-	-	OFF
G7	14.00	15.00	76
G8	14.50	15.50	76
G9	-	-	OFF
G10	21.50	20.50	73.31
G11	21.30	20.00	OFF
G12	21.80	22.00	188.39
G13	21.50	22.50	188.39
G14	-	-	OFF
G15	-	-	OFF
G16	23.5	24.50	2.4
G17	-	-	OFF
G18	-	-	OFF
G19	-	-	OFF
G20	20.00	19.00	155
G21	16.00	17.00	155
G22	-	-	400
G23	-	-	400
G24	-	-	50
G25	-	-	50
G26	-	-	50
G27	-	-	50
G28	-	-	50
G29	-	-	50
G30	25.20	24.00	155
G31	24.50	23.00	155
G32	19.00	20.00	350

TABLE A2
DEMAND MARKET DATA

Demand	P_L^{MC}	Demand	P_L^{MC}
D1	108	D10	195
D2	97	D11	265
D3	180	D12	181.83
D4	74	D13	317
D5	71	D14	100
D6	136	D15	333
D7	125	D16	169.65
D8	171	D17	128
D9	175		

REFERENCES

[1] F. D. Galiana and M. Ilic, "A mathematical framework for the analysis and management of power transactions under open access," *Power Systems, IEEE Transactions on,* vol. 13, pp. 681-687, 1998.

[2] A. Kumar, S. C. Srivastava, and S. N. Singh, "Congestion management in competitive power market: A bibliographical survey," *Electric Power Systems Research,* vol. 76, pp. 153-164, sept. 2005.

[3] Y. R. Sood and R. Singh, "Optimal model of congestion management in deregulated environment of power sector with promotion of renewable energy sources," *Renewable Energy*, vol. 35, pp. 1828-1836, Aug. 2010.

[4] M. Esmaili, N. Amjady, and H. A. Shayanfar, "Multi-objective congestion management by modified augmented ε-constraint method," *Applied Energy*, vol. 88, pp. 755-766, March. 2011.

[5] M. Khanabadi, H. Ghasemi, and M. Doostizadeh, "Optimal transmission switching considering voltage security and N-1 contingency analysis," *Power Systems, IEEE Transactions on*, vol. 28, pp. 542-550, 2013.

[6] L. S. Vargas, G. Bustos-Turu, and F. Larrain, "Wind power curtailment and energy storage in transmission congestion management considering power plants ramp rates," *Power Systems, IEEE Transactions on*, vol. 30, pp. 2498-2506, 2015.

[7] J. Hu, A. Saleem, S. You, L. Nordström, M. Lind, and J. Østergaard, "A multi-agent system for distribution grid congestion management with electric vehicles," *Engineering Applications of Artificial Intelligence*, vol. 38, pp. 45-58, Feb. 2015.

[8] M. A. López, S. Martín, J. A. Aguado, and S. de la Torre, "V2G strategies for congestion management in microgrids with high penetration of electric vehicles," *Electric Power Systems Research*, vol. 104, pp. 28-34, Nov. 2013.

[9] K. S. Verma, S. N. Singh, and H. O. Gupta, "Location of unified power flow controller for congestion management," *Electric Power Systems Research*, vol. 58, pp. 89-96, June. 2001.

[10] M. Esmaili, H. A. Shayanfar, and N. Amjady, "Congestion management considering voltage security of power systems," *Energy Conversion and Management*, vol. 50, pp. 2562-2569, Oct. 2009.

[11] N. Amjady and M. Hakimi, "Dynamic voltage stability constrained congestion management framework for deregulated electricity markets," *Energy Conversion and Management*, vol. 58, pp. 66-75, June. 2012.

[12] F. C. Schweppe, R. D. Tabors, R. E. Bohn, and M.C. Caramanis, "Spot pricing of electricity", 1988 edition. Boston: Springer, 1988.

[13] N. Mahmoudi-Kohan, M. P. Moghaddam, and M. K. Sheikh-El-Eslami, "An annual framework for clustering-based pricing for an electricity retailer," *Electric Power Systems Research*, vol. 80, pp. 1042-1048, Sept. 2010.

[14] S. Yousefi, M. P. Moghaddam, and V. J. Majd, "Optimal real time pricing in an agent-based retail market using a comprehensive demand response model," Energy, vol. 36, pp. 5716-5727, Sept. 2011.

[15] Z. Jun Hua, D. Zhao Yang, P. Lindsay, and W. Kit Po, "Flexible transmission expansion planning with uncertainties in an electricity market," *Power Systems, IEEE Transactions on*, vol. 24, pp. 479-488, 2009.

[16] N. Venkatesan, J. Solanki, and S. K. Solanki, "Residential demand response model and impact on voltage profile and losses of an electric distribution network," *Applied Energy*, vol. 96, pp. 84-91, Aug. 2012.

[17] A. Abdollahi, M. P. Moghaddam, M. Rashidinejad, and M. K. Sheikh-el-Eslami, "Investigation of economic and environmental-driven demand response measures incorporating UC," Smart Grid, *IEEE Transactions on*, vol. 3, pp. 12-25, 2012.

[18] M. Mollahassani-pour, A. Abdollahi, and M. Rashidinejad, "Investigation of market-based demand response impacts on security-constrained preventive maintenance scheduling," *Systems Journal, IEEE*, vol. PP, pp. 1-11, 2015.

[19] M. P. Moghaddam, A. Abdollahi, and M. Rashidinejad, "Flexible demand response programs modeling in competitive

electricity markets," *Applied Energy*, vol. 88, pp. 3257-3269, Sept. 2011.

[20] GAMS (General Algebraic Modeling System) software package. www.gams.com.

[21] "The historical data of DRR in DRPs." [Online]. Available: www.iso-ne.com.

[22] R. Billinton, Power system reliability evaluation: Taylor & Francis, 1970.

[23] M. Čepin, Assessment of Power System Reliability: Methods and Applications: Springer Science & Business Media, 2011.

[24] C. C. Aggarwal and C. K. Reddy, Data clustering: algorithms and applications: CRC Press, 2013.

[25] F. Castro Sayas and R. N. Allan, "Generation availability assessment of wind farms," *Generation, Transmission and Distribution, IEE Proceedings*, vol. 143, pp. 507-518, 1996.

[26] W. Lei, M. Shahidehpour, and L. Tao, "Cost of reliability analysis based on stochastic unit commitment," *Power Systems, IEEE Transactions on*, vol. 23, pp. 1364-1374, 2008.

[27] P. Wong, P. Albrecht, R. Allan, R. Billinton, Q. Chen, C. Fong, et al., "The IEEE reliability test system-1996. A report prepared by the reliability test system task force of the application of probability methods subcommittee," *Power Systems, IEEE Transactions on*, vol. 14, pp. 1010-1020, 1999.

[28] M. Esmaili, N. Amjady, and H. A. Shayanfar, "Stochastic congestion management in power markets using efficient scenario approaches," *Energy Conversion and Management*, vol. 51, pp. 2285-2293, Nov. 2010.

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