Voltage Control in a Smart Distribution Network Using Demand Response

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Abstract—**Increasing demand on the conventional grid coupled with the unwillingness to add new transmission facilities, constitute a potential threat that can ultimately sprawl to jeopardize the grid's reliability. Demand response (DR) is a potent smart grid technology that can take care of that perceived threat, instead of constructing more power plants to meet the increasing demand. DR provides electricity consumers with opportunities to manage their electricity usage for the purpose of reducing their electricity bills and alleviating the power peak-average-ratio. A Genetic Algorithm (GA) based-optimization approach is developed in this paper to consider the optimum scheduling of energy utilization for consumers, participating in the DR program, to reduce voltage deviations and feeder losses. The IEEE 123 test feeder is considered as the test system. Effectiveness of the proposed method is validated through a time sequence analysis over a 24-hourly simulation period. The corresponding voltage profile is analyzed under different operating conditions, with a high penetration level of wind energy. Test results show that the DR tool causes reduction in system losses and enhances system capability to maintain voltages within the permissible limits.**

Keywords— Demand response, genetic algorithm, renewable generation, smart grid, voltage control.

I. INTRODUCTION

This Smart grid has some fundamental roles to play in transforming today's power grids. Its roles are to address growing demand; renewable generation intermittency, distributed generation and environmental concerns. The recent advancement in smart grid technologies such as advanced metering infrastructure (AMI) has made it possible for both utility and consumers to interact through bi-directional digital communications. Electricity users receive regular updated information about the electricity price on hourly basis, and can respond by adjusting their energy usage for that hour.

Demand response (DR) is one of smart grid tools that empowers customers and provides them with opportunity to interact with utilities. It has the potential to postpone the need for network upgrades and reduce overall plant and capital cost investments [1, 2]. More specifically, DR is the consumer's reaction to effectively manage their own electricity usage in response to changes in energy price overtime. It can also be realized through incentive payment provided by the utility company to consumers. Users participating in the DR program can defer their demand (shift the load to off-peak period). Alternatively, they can reduce their energy usage when the energy price is high during peak period to another period when the energy price is low at off-peak [3]. DR facilitates the integration of renewable generations and alleviates supply pressure on utility company [4].

One of the techniques in load reduction is direct load control (DLC). DLC, also known as incentive based DR, program is an agreement between a utility and consumers that empowers the utility to remotely reduce the energy consumed by such participating customers, when generation is low or at peak load period. In this case, a monetary incentive is paid to those participating customers. In the DLC, some load such as heating, ventilating, pumps, plug-in hybrid electric vehicles and refrigerators are remotely controlled during peak-period. However, the major concern is customers' privacy threat, this may be a barrier in the DLC implementation [5].

Dynamic pricing as one of the DR tools, is another alternative to the DLC, in which customers voluntarily manage their energy consumption with respect to hourly electricity price. The popular option in dynamic pricing are real–time pricing (RTP), critical-peak pricing (CTP) and time-of-use pricing (ToUP). RTP is more flexible because its price varies on hourly basis [6]. However, RTP may cause the load demand to be deferred to hours with low electricity price, which would result in higher peak electricity demand and peak-to-average ratio during the low electricity price time [7].

Various approaches have been developed in the literature to solve the problem of voltage deviation in a smart grid (SG) using the DR. Some of the developed algorithms are linear regression methods, exponential smoothing, and stochastic procedure auto regression algorithms [8]. The effect of incentive-based DR on distribution network voltage profile was carried out in [1]. A demand-price elasticity matrix was modeled for participating customers. However, the model lacks the control option to carry out the incentive-based DR program. In [5], a power network is proposed, where customers manage their electricity usage by gaming one another in response to a distribution company/retailer 24-hour electricity price scheduling. Due to customers' participation in the dynamic pricing, there was an improvement in the voltage profile and the cost of energy was reduced while keeping customers' satisfaction at a high level. However, the proposed algorithm required customers to update their energy usage scheduling asynchronously with the assumption that each customer has full information of generation cost function. This technique is hard to realize in practice.

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An optimization algorithm to find a solution to reduce the peak demand using a Genetic Algorithm (GA) is carried out in [6-8]. Chen et al [6], proposed a consumer 24-hour electricity scheduling with GA. Consumers electricity bill minimized by changing controllable loads with respect to utility 24-hour declared price and peak demand control. Zhao [7] set up a general architecture of home energy management system (HEMS) in a home area network. With the application of HEMS, GA was presented to schedule the home electricity consumption to minimize energy cost and peak-average-ratio. Consumer's energy cost was reduced by changing elastic loads in response to utility declared price where the system voltage profile is improved.

In [8], a GA approach to exert a day-ahead peak demand control for a commercial building considering central air conditioners is developed. The DLC employed on central air conditioners in the commercial building is effective in system performance improvement and energy cost reduction. However, the percentage of load reduction is small. A wider application could have been better.

This paper presents an optimization techniques that employs the GA to schedule a 24-hourly electricity consumption, in order to reduce voltage deviation and feeder losses. This is to preserve the system voltage profile against the intermittent characteristics of wind energy. A multi-period simulation is carried out on the IEEE 123 test feeder system to show the effectiveness of the proposed approach.

I. Demand Response Optimization Using Genetic Algorithm

The main objective of the DR optimization is to guide customers in their electricity consumption. The retailer supply the electricity price through the AMIs and consumers manage their electricity consumption according to the retailer declared electricity price.

With the demand sensitive to price changes, elastic load is taken as the control variable for the 24-hour consumers' electricity consumption scheduling. This is, however, limited by the available hourly elastic load.. The DR problem of optimizing the electricity consumption can be modeled as a multiperiod optimization problem, where the objective is to minimize hourly energy losses and voltage deviations across various network nodes. This can be expressed mathematically as:

$$Min\ F = w_v \sum_{t=1}^{T} \left(V_{i,t} - V_{ref}\right)^2 + w_l \sum_{t=1}^{T} P_{L,t} * \Delta t \tag{1}$$

where w_v and w_l are the weighted-coefficients of voltage minimization and loss minimization respectively. $V_{i,t}$ and V_{ref} are the voltage at bus i at time t and magnitude of voltage reference respectively, obtained from the distribution power flow. $P_{L,t}$ is the network loss at time t, Δt is 1 hour time interval. T is the total time in hours and equals 24.

The sum of the total power losses due to the DR is contemplated as [9]

$$P_{Li,t} = \sum_{j=1}^{N} \left[\alpha_{ij,t}\left(P_{i,t}P_{j,t} + Q_{i,t}Q_{j,t}\right) + \beta_{ij,t}\left(Q_{i,t}P_{j,t} + P_{i,t}Q_{j,t}\right)\right] \quad i \in N \tag{2}$$

where, $\alpha_{ij} = \dfrac{r_{ij}}{V_{i,t}V_{j,t}} \cos\left(\delta_{i,t} - \delta_{j,t}\right)$,

$$\beta_{ij} = \frac{r_{ij}}{V_{i,t}V_{j,t}} \sin\left(\delta_{i,t} - \delta_{j,t}\right)$$

$Z_{ij} = r_{ij} + x_{ij}$ is the ijth element of [$Zbus$] matrix

$P_{i,t} = P_{Gi,,t} - P_{Di,t}$; $Q_{i,t} = Q_{Gi,t} - Q_{Di,t}$.

$P_{i,t}$ and $Q_{i,t}$ are the net active and reactive power injection at bus i at time t. $P_{Gi,t}$ and $Q_{Gi,t}$ are the active and reactive powers generated from the variable renewable generation at time t. $P_{Di,t}$ and $Q_{Di,t}$ are the load active and reactive powers at bus i at time t respectively, while $P_{Li,t}$ and $Q_{Li,t}$ are the active and reactive power loss at time t respectively.

The constraints include the power balance equality constraints which can be represented as:

$$P_{i,t} = V_{i,t} \sum_{j}^{N} \left[V_{i,j} G_{i,j} \cos\left(\delta_{i,t} - \delta_{j,t}\right) + B_{i,j} \sin\left(\delta_{i,t} - \delta_{j,t}\right)\right] \quad i \in N \tag{3}$$

$$Q_{i,t} = V_{i,t} \sum_{j}^{N} \left[V_{i,j} G_{i,j} \sin\left(\delta_{i,t} - \delta_{j,t}\right) - B_{i,j} \cos\left(\delta_{i,t} - \delta_{j,t}\right)\right] \quad i \in N \tag{4}$$

where $V_{i,t}$ is the voltage at bus i at time t, $G_{i,j}$ and $B_{i,j}$ are the conductance and susceptance of the line between buses i and j respectively, while $\delta_{i,t}$ is the voltage at bus i at time t.

Voltage limits:

$$V_{\min,\ t} \le V_{i,j,t} \le V_{\max,\ t} \qquad i \in N \tag{5}$$

where V_{min} and V_{max} are minimum and maximum voltage limits at bus i respectively.

Demand response operating limits:

$$P_{i,t} = P_{G_{i,t}} - P_{D_{i,t}} \qquad \forall t \in T \tag{6}$$

$$P_{D_{i,t}} = P_{U_t} + P_{E_t} \qquad \forall t \in T \tag{7}$$

$P_{D_{i,t}}$ is a process that satisfies

$$P_{D_{i,t}}^{\min} \le P_{D_{i,t}} \le P_{D_{i,t}}^{\max} \quad \forall t \in T \tag{8}$$

where $P_{D_{i,t}}$ is total power usage, P_{U_t} and P_{E_t} are the inelastic and elastic load at time t respectively.

The elastic loads are divided into controllable (P_c) and shiftable (P_s) loads. Controllable loads are thermostatically controlled loads such as heating and ventilating loads, whereas shifted loads are load that can be shifted to another time such as electric vehicles, washing machines etc. Inelastic loads are loads that can neither be shifted nor controlled such as lighting loads.

$$P_{E_t} = P_{C_t} + P_{S_t} \qquad \forall t \in T \tag{9}$$

Each customer operates a set of A_b appliances. For each appliance $a \in A_b$, the power drawn at time $t \in T$ is denoted as P_{a_t}. The summation of the power drawn by each appliance represents the total power for the day.

$$P_{C_t} = \sum_a P_{a_t} \qquad \forall t \leq\in T \tag{10}$$

$$P_{S_t} = \sum_a \sum_{t'} P_{S^a_{t't}} - \sum_a \sum_{t'} P_{S^a_{tt'}} \quad \forall t \leq\in T \tag{11}$$

$$0 \leq \sum_a P_{S^a_{tt'}} \leq k \times P_{a_t} \qquad \forall a \in A_k,\ \forall t \in T \tag{12}$$

$$P_{S^a_{tt'}} = 0, \forall a \in A_k,\ \forall t' \in T \tag{13}$$

where $P_{S^a_{tt'}}$ is power of appliance *a,* that is shifted from time *t* to time *t'* and *k* is number of customers participating in the DR program.

The optimal scheduled consumption using dynamic pricing depends on the declared retailer price $\lambda_t := (\lambda_t, t \in T)$. The total payment received by utility is:

$$Y_i(t) = \tilde{\lambda}_t(P_{U_t}) + \hat{\lambda}_t(P_{E_t}) \quad \forall t \in T \tag{14}$$

$$\hat{\lambda}_t < \tilde{\lambda}_t, \quad \forall t \in T \tag{15}$$

where $Y_i(t)$, $\hat{\lambda}_t$ and $\tilde{\lambda}_t$ are the total payment for electricity consumption, dynamic price and flat rate price at time t respectively.

The price of the same power may change at different hours of the day. The following assumptions are taken:

- The cost functions are increasing in the supply power capacity. That is, the following inequality holds for each $t \in T$.

$$C_t(\hat{P}_t) < C_t(\tilde{P}_t), \ \forall \hat{P}_t < \tilde{P}_t \tag{16}$$

where $\hat{P}_t$ and $\tilde{P}_t$ are the dynamic power demand and flat power demand respectively at time *t*.

- The cost function is convex increasing in P for time t. For each $t \in T$, any real number $\hat{P}_t, \tilde{P}_t \geq 0$, and any real number $0 < \xi < 1$, we have:

$$C_t(\xi \hat{P}_t + (1-\xi)\tilde{P}_t) < \xi C_t(\hat{P}_t) + (1-)C_t(\tilde{P}_t) \tag{17}$$

One of the utility functions that can satisfy the assumptions above, is the quadratic function [5]. The total power usage as a function of energy cost is:

$$C_t(P_i) = b_1^t(P_i^2) + b_2^t(P_i) + b_3^t, \tag{18}$$

where $b_1^t > 0,\ b_2^t \geq 0,\ and\ b_3^t \geq 0 \quad t \in T$.

The price function used in the paper is a representation of the actual unit cost. Publicly available wholesale market data are used to estimate the system-level costs incurred by the retailer. This makes the total payment received by utility for electricity consumption is greater than cost of producing P unit of power.

$$Y_i(t) > C_t(P_D) \tag{19}$$

Power loss constraint:

$$P_{Li,t}^{with\,DR} \leq P_{Li,t}^{without\,DR} \tag{20}$$

where $P_{Li,t}^{with\ DR}$ and $P_{Li,t}^{without\ DR}$ are the power loss with and without demand response.

Eq. (7) denotes new hourly load profile as a result of elastic load and (10) describes total available controllable load. The net load shifted to hour *t* is expressed in (11). Eq. (12) caps the total shifted elastic load at the respective time, whereas (13) insures that the operation time of elastic loads is not displaced to an earlier time.

The formulation from (1) to (20) gives a complete description for the modeling of the DR necessary to counterbalance the impact of the variable renewable generation on system losses and voltage profile. To avoid multiobjective programming and generate an equivalent single-objective optimization problem, a non-inferior-solution method is developed to assign weights to the various objective functions [11]. Each objective function is multiplied by scalar coefficients called weighting factors. The weighting factors are usually normalized as:

$$\sum_{k=1}^{K} W_k = 1 \tag{21}$$

Therefore, $w_v + w_l = 1$.

II. Genetic Algorithm (GA) Implementation

Traditional optimization techniques start with a single candidate solution, then proceeds iteratively, through the search space, to the optimal solution by applying static heuristics. GA belongs to the class of Metaheuristics which operate on a population based solutions, rather than single ones. The main advantage of using GA is that it can be used for a wide variety of optimization problems, explore complex search spaces efficiently and is capable to avoid getting trapped in local optima [12]. GA-based solutions usually have good engineering accuracy and are amenable to parallel implementation that can be useful to reduce computational requirements.

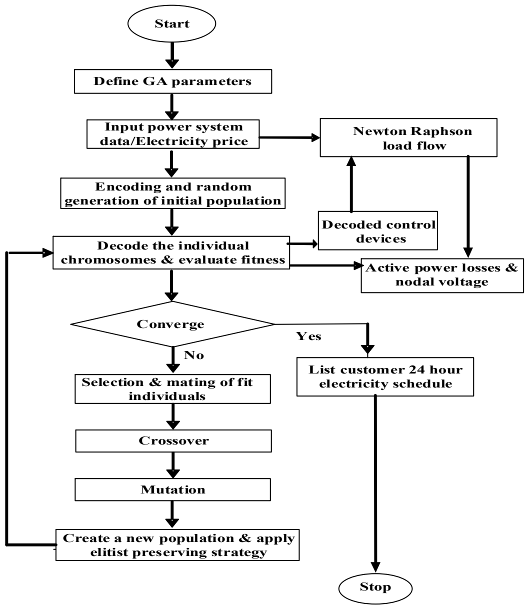

Fig. 1 GA flowchart for the optimization

The procedure for the demand response optimization problem, with GA, begins by randomly generating a population of potential solutions. Then individual's performance is analyzed through the fitness function to indicate the relative quality of each potential solution. Genetic operators are applied to the potential solution to produce the next generation from the current population and repeat the cycle again. Chromosomes which violate the constraints are discarded whilst the best fit individuals in a population are selected for the next generation. The flowchart of the basic operation of the GA is displayed in Fig. 1.

III. TEST RESULTS

The proposed method is tested on a sample circuit taken from the IEEE 123 bus feeder of an actual 115 kV/4.16 kV 50-Hz distribution network. A total load of 16MW is distributed among commercial and residential energy consumers. The IEEE 123 bus feeder, shown in Fig. 2, consists of three-phase overhead or underground primary feeders and double-phase or single-phase line sections near the end of the feeder laterals. The feeder contains one on-load tap changing transformer (OLTC) and four step voltage regulators (SVRs). The OLTC and SVRs are connected as shown in Fig. 2. The feeder also consists of a three-phase 4.16 kV, 600 kVAr shunt capacitor (SC) connected at bus 83 while each of buses 88, 90 and 92 are connected with 50 kVAr capacitor. These control devices are already ingrained in the feeder.

Loads with different types including constant current, constant impedance and constant power are modeled at the system buses. The feeder is supposed to have a unity power factor. Therefore, power injections of the wind energy systems have been represented by voltage-independent active injections with zero reactive power [13]. The voltage at bus 450, line 99 is monitored on hourly basis. That particular bus is chosen because of its high voltage sensitivity. It is a point on the feeder that responds quickly to any changes in system conditions.

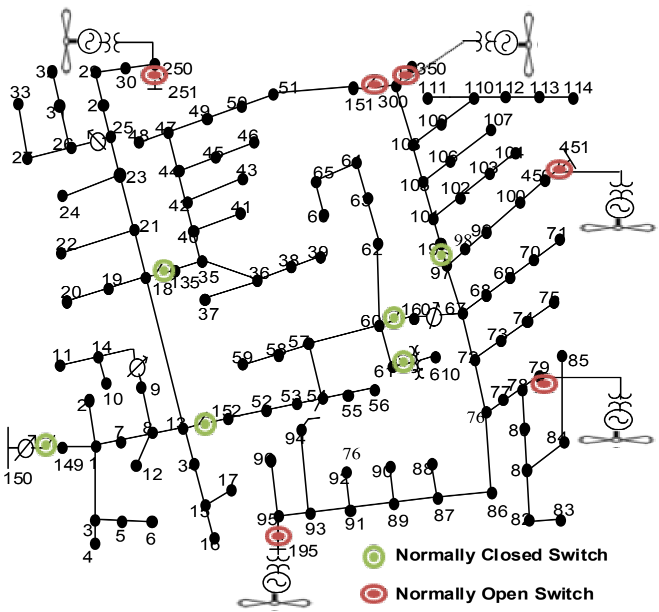

Fig. 2 IEEE 123 bus test feeder

Case I: Dynamic Pricing for Voltage Improvement in a Distribution System

Dynamic pricing is employed as a DR tool in this case study. GA is used to optimize customer electricity consumption in accordance with the changes in retailer's 24-hour electricity prices.. Flat pricing, which is commonly used, is based on long-run average cost. However, retailers depend on bilateral contracts, including wholesale spot market, to purchase the energy they supply to customers. The underlying cost structure is therefore difficult to be estimated. Hence, publicly available wholesale market data as shown in Fig. 3 [10], is used in this paper to estimate the system-level costs incurred by the retailer.

As real-time pricing is introduced, consumers will control their elastic loads based on the 24-hour electricity price released by retailer. A load limit is set, $0 \leq P \geq 385\ kW$, so that any customer that exceeds the load limit will receive a penalty. That is, making excess payment for the extra load.

The distribution network (DN) is divided into four zones, representing the DR participating customers. The zones were defined by network mapping based on location [14]. The proposed method has been implemented in MATLAB, and examined on the test system for a 24-hour period. The consumer's electricity consumption scheduling is determined for the four zones using the proposed GA algorithm described in Fig.1.

The feeder consists of 20kW load, 40 kW load and 75 kW load and above. It is assumed that 20 kW and below are inelastic load, loads from 20 kW to 40 kW are assumed to be controllable loads while any load above 40 kW is assumed to be shiftable load. Loads are taken in the proportion of ratio 20%, 50% and 30% for inelastic, controllable and shiftable loads respectively. Load reduction was applied to controllable loads while the shiftable load is shifted from hour t to t', that is, from day to night.

An hourly consumer's scheduled load curve using the proposed algorithm is shown in Fig. 4 for the zones. At 15th hour, the customer's load in Zone C (solid line) is very close to the point of maximum load limit because some loads, which are essential at this hour, could not be shifted to another time. Every customer managed their load not to exceed the maximum load limits. There is load reduction in the day and some loads are shifted from day to night due to low electricity price per kWh energy consumption.

A 24-hourly simulation was carried out with a 30% wind penetration level, distributed in a modified peak load feeder of 16 MW, with the voltage of the DN monitored at each zone. The output voltage of the DN at different hours of the day is illustrated in Fig. 5 for the zones. A peak-valley leveling is observed in Fig. 5 with a better voltage profile. There is a wide gap between minimum and maximum pu voltage without the DR. However, application of the DR has reduced the voltage deviation and improved the voltage profile. The real-time pricing DR was able to alleviate the disparity of energy consumption by reducing the energy usage at peak period and increase it at off-peak period. The result of the proposed algorithm is compared to price elasticity matrices used in [1]. Both results show that the load reduction/shifting due to the implementation of the DR reduced the system line losses causing improvement in the feeder voltage profile. This shows the effectiveness of the DR in not only improving the voltage profile during peak-load period but also during off-peak period. In other words, the DR did not only mitigate voltage drop as a result of peak load but also voltage rise as a result of wind gush. It also brings further improvement to overall voltage profile.

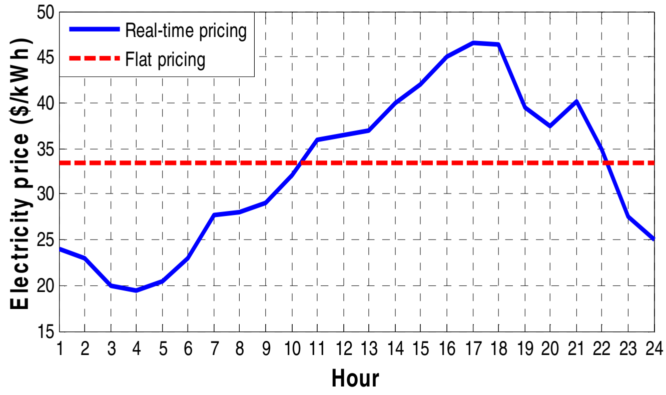

Fig. 3 24-hour electricity price released by retailer

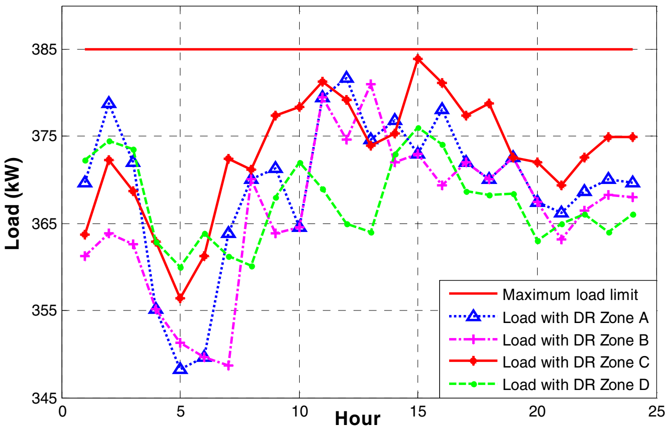

Fig. 4. 24-hour power usage (load) scheduled curve

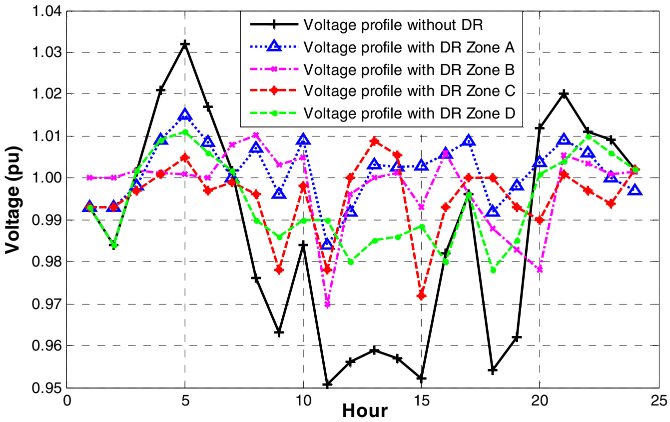

Fig. 5 Application of dynamic pricing for voltage control

Case II: Effect of Customer Participation in Demand Response on System Voltage and Energy Loss

Different levels of customer's participation in the DR program from 15% to 35% are investigated to observe their effect on voltage profile and energy loss. The feeder used is described in Fig. 2. It contains 123 nodes with 85 loads of different types. It is assumed that a node with a load represent a customer, which gives a total of 85 customers on the feeder. Not all customers participated in the DR and not all the loads are controllable. Customers respond to the real-time pricing based on the retailer's declared electricity price. However, a customer participates (if selected to be in the DR) with the same proportion of individual load with respect to total load at base case. The feeder load curve and wind energy curve integrated in the feeder is as shown in Fig. 6.

The per unit voltage of the 24-hour simulation of different customers participation level, at a peak load of 16 MW, 30% wind energy penetration is carried out. The result is as shown in Fig. 7. The more the customers participated in the DR, the more the benefits of DR, the more the voltage profile improves and the more the security of the network system. Most especially with 35% customer's penetration level, the voltage profile centered on 1.0 pu. The feeder load curve with and without DR at 35% penetration is shown in Fig. 8.

The energy loss without the DR and with the DR at different customer's participation (CP) level is shown in Fig. 9. The detail of energy loss at the 5th hour of the day with corresponding percentage energy loss reduction as the customer participation level increases is illustrated in Table 1.

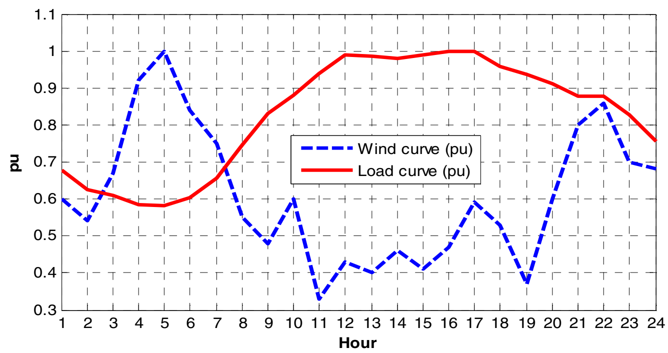

Fig. 6 IEEE 123 feeder load and wind curve

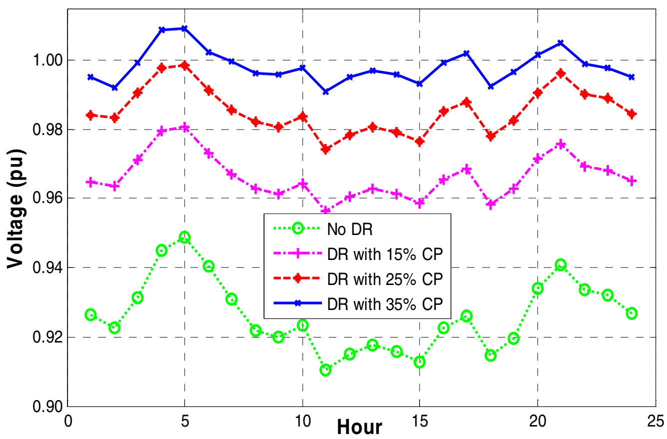

Fig. 7 Customer's participation (CP)

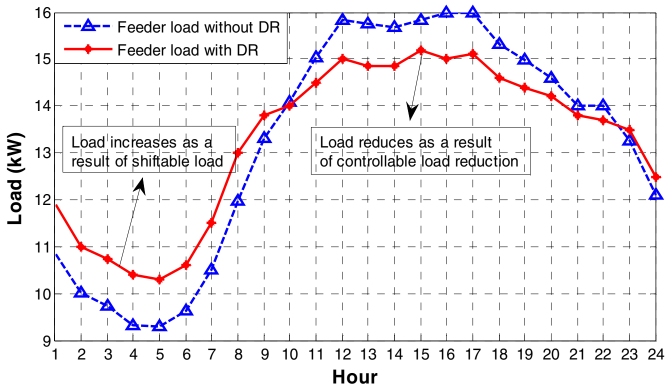

Fig. 8 The feeder load curve with and without DR

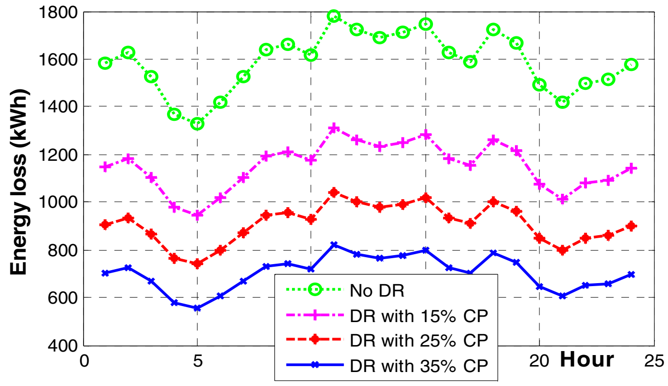

Fig. 9 Energy loss with and without demand response at bus 450

Table 1: Voltage profile, and energy losses at customer participation level

	No DR	**With DR (Customer participation level)**		
		15%	25%	40%
Min Voltage (pu)	0.9104	0.9563	0.9720	1.0036
Max Voltage (pu)	0.9486	0.9806	1.0340	1.0430
Losses (kW)	1330.11	945.68	741.17	555.26
Loss Reduction (%)	-	28.90	44.28	58.25

It is observed that as the customer participation level increases, the percentage energy loss reduction increases. This energy loss reduction leads to voltage improvement. The implementation of the DR reduces peak load demand and adapts controllable load to fluctuating variable renewable generation.

IV. Conclusions

Aggregate demand response (DR) that curtails some of the customer load could be hypothetically comparable to the provision of reserves by generators. It thus has the capability to defer future generation investment. Demand response was explored in this paper as a tool to maintain the voltage profile in a distribution system that has a deep penetration of wind energy. The problem of invoking demand response options among shiftable and curtailable load portions was modeled as a nonlinear optimization problem. A genetic algorithm (GA) was used to solve the resulting problem spanning over a 24-hour period. Test results conducted on the IEEE 123 test feeder have shown that using real-time pricing, as one of the DR techniques, enabled shifting the demand from high electricity price peak period to lower price, off-peak periods. As customer participation level in the DR increases, the steadier the voltage profile becomes and the lesser the network losses that the system has to sustain. Demand response can definitely facilitate the integration of higher proportion of renewable generation into the smart grid and alleviate supply pressure on utility companies.

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