



# Residential Demand Response model and impact on voltage profile and losses of an electric distribution network

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## ARTICLE INFO

### Article history:

Received 29 June 2011

Received in revised form 26 September 2011

Accepted 25 December 2011

Available online 30 January 2012

### Keywords:

Demand Response  
Price elasticity matrix  
Demand side management  
Volt/Var control  
OpenDSS  
Smart grids

## ABSTRACT

This paper develops a model for Demand Response (DR) by utilizing consumer behavior modeling considering different scenarios and levels of consumer rationality. Consumer behavior modeling has been done by developing extensive demand-price elasticity matrices for different types of consumers. These price elasticity matrices (PEMs) are utilized to calculate the level of Demand Response for a given consumer considering a day-ahead real time pricing scenario. DR models are applied to the IEEE 8500-node test feeder which is a real world large radial distribution network. A comprehensive analysis has been performed on the effects of demand reduction and redistribution on system voltages and losses. Results show that considerable DR can boost in system voltage due for further demand curtailment through demand side management techniques like Volt/Var Control (VVC).

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## 1. Introduction

The evolution of the deregulation trend in power market has led to the division of integrated power system into individual fields: generation, transmission and distribution. The deregulation has created a healthy competition in the distribution market among distribution companies (Discos). In this process Discos are in need of innovative Smart Grid strategies to realize cost efficiency. Some of these as described by Smart Grid requirements [1] are as follows:

1. Deployment and integration of DR, demand side resources and energy efficiency resources.
2. Deployment of smart technologies for metering, communications concerning grid operations/status and distribution automation.
3. Adoption of Demand Side Management (DSM) techniques like Volt/Var control, voltage reduction, etc.

Both DR and distribution voltage reduction are crucial DSM events that have the common objective of peak demand reduction. Effective peak load shaving is possible by the combined effect of bus voltage reduction, demand reduction and demand re-distribution over time. This paper aims at exploring the possible role of DR

as a parameter for Volt/Var Control (VVC) for best possible results of load reduction to achieve energy efficiency and mutual profit for utility and consumers. Residential DR has an equally good potential as industrial DR in mitigating congestion in the network during peak hours. However, establishing DR contracts with residential consumers requires proper modeling of consumption patterns which is far more complicated and random as compared to that of industrial consumers. This could be achieved by load serving entities (LSEs) or DR aggregators (these entities are also being named as DR contractors or simply aggregators). LSEs can represent residential consumers and sign DR contracts with the utility for volume of DR that can be achieved. For the successful implementation of such residential DR contracts, LSEs need comprehensive DR models and thus a study of consumer behavioral patterns. This paper uses elaborate demand-price elasticity matrices (PEMs) to model consumer behavior.

Many previous works have focused on developing different kinds of DR models. Ref. [2] provides substantial literature on fundamental principles on spot pricing of electricity and economic analysis of spot pricing. Significant contribution towards consumer behavior modeling in the form of price elasticity matrices (PEMs) has been done in [3–5]. Other papers in literature are focused on the application of DR from a Smart Grid perspective. A generation scheduling program was developed using elasticity of DR to compute the real time market clearing price of electricity in [6]. Optimal Power Flow for nodal reliability of a system was performed using DR application in [7]. A wholesale bidding mechanism

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involving ISO, utility and the consumer was proposed in [8] that uses consumer modeling through PEMs. Load models were developed in [9] using customer benefit function and PEMs and the resultant models were used in a real world distribution system to show results of load reduction. All these papers make standard assumptions of demand-price elasticity with respect to consumer behavior modeling. However, these assumptions need vital refinement for a better understanding of electricity consumption patterns. A considerable work has been done on Volt/Var control [10] that provides basic guidelines required for optimal voltage control in the low voltage distribution side. Ref. [11] proposes a novel concept of considering DR as a parameter for applying Volt/Var control on a real time basis to realize the maximum potential of both these DSM measures. In this work, PEMs have been developed to accurately model consumer behavior. DR patterns for different consumer types have been derived from these PEMs and integrated into distribution power flow to study the resulting system voltages and losses. Further, a path has been laid to coordinate DR with Volt/Var control that would yield better results of demand curtailment, especially during peak hours.

This paper is organized into seven sections. Section 2 briefly describes DR and its types. Section 3 gives an insight on PEMs and describes the modeling of DR using PEMs. In Section 4 PEM prototypes have been developed assuming different rationality levels of consumers. Section 5 briefly describes the test distribution system and various test scenarios built. Section 6 discusses the voltage and loss analyses performed on the test system. Section 7 draws conclusions and provides the scope for future work.

## 2. Demand Response and types

US Department of Energy (DOE) defines Demand Response as: changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized. DR is divided into two basic categories and several subgroups.

### 2.1. Incentive-based programs

1. Direct Load Control (DLC)
2. Interruptible/Curtailable service (I/C)
3. Demand Bidding/Buy Back
4. Emergency Demand Response Program (EDRP)
5. Capacity Market Program (CAP)
6. Ancillary Service Markets (A/S)

### 2.2. Time-based programs

1. Time-of-Use (TOU) program
2. Real Time Pricing (RTP) program
3. Critical Peak Pricing (CPP) Program

The incentive based DR programs are usually more suited for industrial consumers. Incentive based DR contracts normally exist between the distribution utility and a set of large consumers and most of these schemes involve curtailing the load by consumers for a specified period of time and by a specified level of energy to reduce congestion in the network. However, time based DRs are more suited for residential consumers. In these schemes the day is usually divided into a number of blocks that have different prices of electricity that reflect the true market price for generation of electricity. In case of real time pricing, the day would be usually divided into a number of time slots, for example 24- one hour slots

and each slot has a different price for electricity that reflects the real market clearing price. RTP scheme engages maximum customer participation. Communicating real time prices to consumers and expecting them to respond would be cumbersome for both consumers and utility. So recently, utilities have laid down the day-ahead real time pricing scheme wherein the next day's predicted real time prices would be sent to the customers before hand and they would be billed for their consumption based on this day-ahead price. Time of use pricing is more or less similar to real time pricing, but with a fewer number of time slots to cut down the complexity involved with real time pricing. Critical peak pricing has fixed rate tariff for most part of the day, however it imposes huge pricing for consumption of electricity during a few pre specified hours of the day. For DR to be implemented through a variable tariff scheme (such as real time pricing or time of use pricing) Advanced Metering Infrastructure (AMI) needs to be enabled at the customer side. In this work, day-ahead real time pricing scheme has been considered for developing the DR model.

## 3. Modeling of Demand Response – price elasticity matrix

By far, PEM has been the most powerful and feasible way of modeling consumer behavior for DR. Considerable literature is already available on the economic principles of DR and basics of PEM. As a prologue to the next section, some aspects of PEM have been described here. Considering electricity as any other commodity, electricity demand does change with price. The demand price elasticity can be defined by the following equation:

$$E = \frac{\Delta d/d_0}{\Delta p/p_0} \quad (1)$$

where  $\Delta d$  and  $\Delta p$  are the changes in demand and price respectively and  $d_0$  and  $p_0$  are the base demand and price respectively.

The whole concept of PEM revolves around the above equation. Elasticity is composed of two different coefficients namely self elasticity (or own-price elasticity) and cross elasticity. Self elasticity (Eq. (2)) is defined as the change in demand at a time instant ' $t_i$ ' due to change in price at the same time instant ' $t_i$ '. Since change in price will have an inverse effect on change in demand, self elasticity takes a negative value. Also there is a cross-time effect involved in the time varying demand-price elasticity. Cross elasticity (Eq. (3)) is defined as the change in demand at time instant ' $t_i$ ' due to change in price at some other time instant ' $t_j$ '. Cross elasticity will be either positive or zero depending on whether the customer is willing to shift the load or not.

$$E(i, i) = \frac{\Delta d(t_i)/d_0}{\Delta p(t_i)/p_0} \quad (2)$$

$$E(i, j) = \frac{\Delta d(t_i)/d_0}{\Delta p(t_j)/p_0} \quad (3)$$

Self elasticity is a measure of load curtailment by the consumer where as cross elasticity is a measure of load shifting. Both these constituents put together make the concept of DR.

For a RTP scenario that has hourly varying rates, PEM will be of the order  $24 \times 24$ . The diagonal elements of the PEM represent self elasticity coefficients and the off-diagonal elements represent cross elasticity coefficients. Each column of a PEM represents the scheduling of loads throughout the day, owing to the change in price at the time instant corresponding to the column number. The overall change in load at time ' $t_i$ ' due to change in price throughout the day can be obtained by summing up the entire row corresponding to ' $t_i$ ' as shown in the following equation:

$$\Delta d(t_i) = \sum_{j=1}^{24} E(i, j) * (\Delta p_j/p_0) * d_0 \quad (4)$$

**Table 1**  
Hourly day Ahead RTP with self elasticity coefficients.

Hour of day	Price (¢/kWh)	Self elasticity
1	2	-.01
2	2	-.01
3	2	-.01
4	2	-.01
5	2	-.01
6	2	-.01
7	3	-.01
8	4	-.02
9	6	-.02
10	8	-.02
11	10	-.03
12	10	-.03
13	11	-.04
14	12	-.16
15	13	-.20
16	14	-.25
17	15	-.45
18	12	-.16
19	12	-.16
20	10	-.20
21	13	-.22
22	9	-.10
23	7	-.05
24	5	-.05

The optimum model of PEM is the key to determine the level of DR and load reduction or redistribution per customer. With the availability of AMI and other Distribution Automation (DA) features, the real time distribution operation model with DR data could be utilized for identifying the exact set points for Volt/Var control.

Earlier works involving PEMs have assumed constant values of self and cross elasticity coefficients which may not be applied in a real world scenario. With a constant self elasticity coefficient, for example, the relative effect on consumption is the same for an increase in price per kWh from \$0.01 to \$0.02 as an increase in price from \$0.05 to \$0.10 which is not the case with any rational consumer. Exploratory regression analysis was performed in [12] on year long consumer load profiles with a pilot RTP program to derive the price dependence of self elasticity coefficients. The self elasticity estimates for a typical 24 h RTP curve on a summer peak day have been listed in Table 1. Constant low values of self elasticity coefficients are assumed for extremely low price levels since, the self elasticity values as derived from the regression analysis were either positive or zero (effectively insignificant figures) during these low priced period. Beyond the threshold of 3 cents per kWh, self elasticity increases with increasing price signal. These self elasticity coefficients have been used along with varying cross elasticity coefficients that have been extrapolated from earlier works ([3], [6]) depending on the assumed consumer rationalities explained in Section 4.

#### 4. Consumer rationality assumptions

Consumer rationality assumptions indicating real world scenarios have been utilized. Consumers were grouped into five different categories such that any real world consumer should fall into one of these categories.

##### 4.1. Long Range (LR) or optimizing consumers

This category comprises optimizing consumers who can shift their consumption over a wide range of time following changes in prices. So, their PEMs will have more non-zero entries corresponding to self and cross elasticity coefficients. A part of the

24 × 24 matrix for LR consumer is shown in Fig. 1. It should be note that self elasticity coefficients are not constant. The same values of self elasticity coefficient will be used for other categories as well. Some observations to be made are as follows:

- With respect to the prices in Table 1, all elements below diagonal are zero because no consumer would shift his load from a low price period to a high price period.
- Some weight in the value of cross elasticity is given for shift within short range of time. A fading effect has been incorporated to take short range shift rationale of the consumer. For instance cross elasticity for load shift from  $t_{13}$  to  $t_6$  (0.04) is higher than the cross elasticity for load shift from  $t_{13}$  to  $t_1$  (0.02) despite the fact that price at  $t_6$  is the same as price at  $t_1$ .

##### 4.2. Real World (RW)-postponing consumer

This category comprises consumers whose perception depends on current and future prices only. This paper assumes a perception of 5 h into the future. A part of 24 × 24 matrix for RW-postponing consumer is shown in Fig. 2. The cross elasticity values are higher as compared to corresponding values in LR's PEM. This is due to the fact that unlike LR consumers who optimize their load throughout the day, RW-postponing consumers only shift their load over a short range of 5 h into the future.

##### 4.3. Real world-advancing consumers

These consumers have PEMs similar to postponing consumers except that there will be non-zero elements on and above the diagonal implying consumer perception into current and past time periods alone. A perception of 5 h into the past is assumed. On a 24 × 24 PEM, it can be seen that load is shifted around the high price period of  $t_{10}$ – $t_{21}$  about the diagonal.

##### 4.4. Real world-mixed consumers

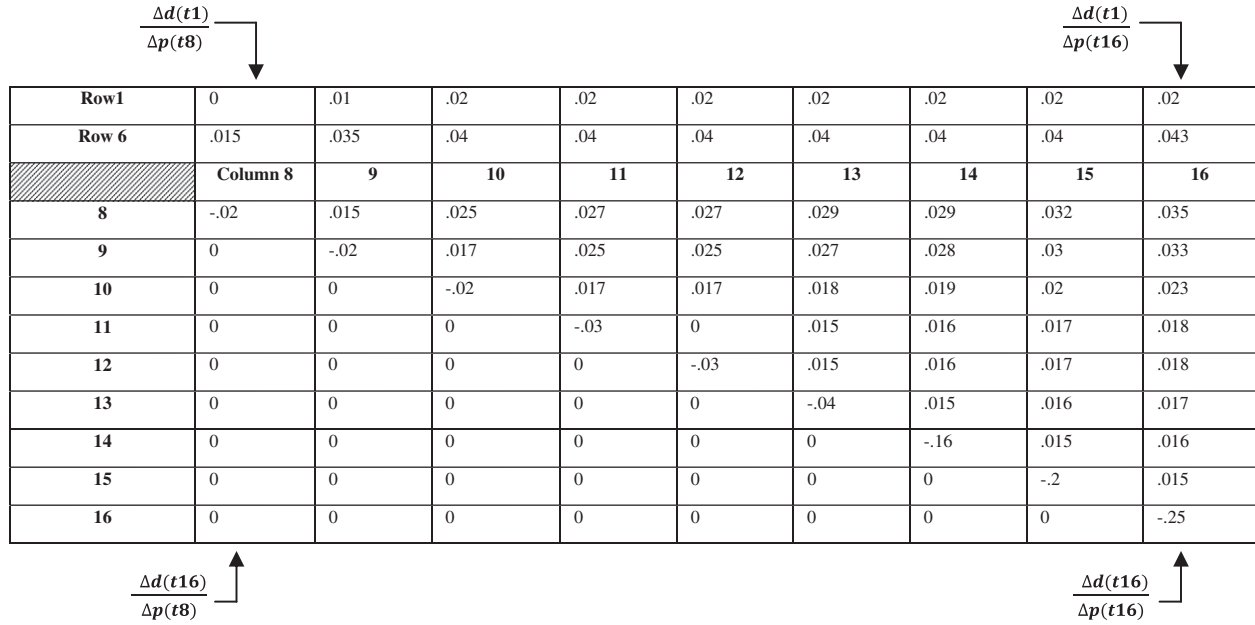
These consumers are a mix of postponing and advancing consumers. Their perception goes 5 h into the past and future which means they will have non-zero elements both above and below the diagonal. These consumers differ from LR consumers in the fact that their flexibility ranges over a period of 5 h only whereas, LR consumers are flexible throughout the 24 h period. A part of 24 × 24 matrix for RW-mixed consumer is shown in Fig. 3.

##### 4.5. Short Range (SR) consumers

These consumers do not optimize their load and are only concerned about the price at the current time instant. This PEM will only have diagonal elements implying that there is only the self elasticity component that has varying coefficients.

#### 5. Test system

The IEEE 8500 node test feeder [13] as shown in Fig. 4 represents a large radial distribution feeder and provides an excellent platform for various load shape studies and Volt/Var simulation. The test feeder consists of residential loads, each connected to a 120 V/240 V split-phase transformer. This kind of residential loading is convenient to show the impact of residential DR models on the feeder. A section of the circuit as highlighted in Fig. 4 has been chosen for analyzing the impacts of various DR models on the system. This highlighted section consists of 245 individual residential loads and contributes around 18% (around 2 MW) of the total system load (around 11 MW). Distribution simulation tool, OpenDSS



Note: The demand price ratios above indicate how to traverse the rows and columns of a PEM. Elasticity values corresponding to Rows 1, 6 and 8 through 16 for columns 8 through 16 are shown for LR consumer.

Fig. 1. A section of LR-consumer's PEM.

	13	14	15	16	17	18	19	20	21
13	-.04	0	0	0	0	0	0	0	0
14	0	-.16	0	0	0	0	0	0	0
15	0	0	-.02	0	0	.0	0	0	0
16	0	0	0	-.25	0	0	0	0	0
17	0	0	0	0	-.45	0	0	0	0
18	0	0	0.02	0	0.025	-.16	0	0	0
19	0	0	0.02	0	0.025	0	-.16	0	0
20	0	0	0.025	0.02	0.03	0.02	0	-.2	0
21	0	0	0	0	0.02	0	0.019	0	-.22

Fig. 2. A section of RW-postponing consumer's PEM.

	15	16	17	18	19	20
15	-.2	.018	.02	0	0	0
16	0	-.25	.019	0	0	0
17	0	0	-.45	0	0	0
18	.02	0	.025	-.16	0	.02
19	.02	0	.025	0	-.16	0
20	.025	.02	.03	.02	0	-.2

Fig. 3. A Section of RW-mixed consumer's PEM.

[14] has been used to perform voltage and loss analysis of the test system. OpenDSS is an open source tool for simulating utility distribution systems and performs various analyses namely power flow, harmonic and dynamics in frequency domain. OpenDSS can run annual load simulations along with daily/yearly power flow

solution modes. The simulator can also be interfaced and driven from tools like Matlab through its COM interface. In addition, OpenDSS has developed test cases for all IEEE benchmark test feeders. These features of OpenDSS have been used in this work for studying the effects of DR on IEEE 8500 node test feeder. Time series distribution power flow is run for five different scenarios as follows.

- Scenario 1- No Demand Response: This is the base case distribution power flow with an assumed 24 h residential load shape applied to every individual base load in the section of interest.
- Scenario 2- LR consumers: In this case, all the loads of the highlighted section are modeled as LR consumers by assigning a DR pattern derived from the PEM of LR consumer.
- Scenario 3- SR Consumers: In this case, all the loads are assigned a DR pattern derived from the PEM of SR consumer.
- Scenario 4- RW Consumers: In this case, all the loads are assigned a DR pattern derived from the PEM of RW-mixed consumer.

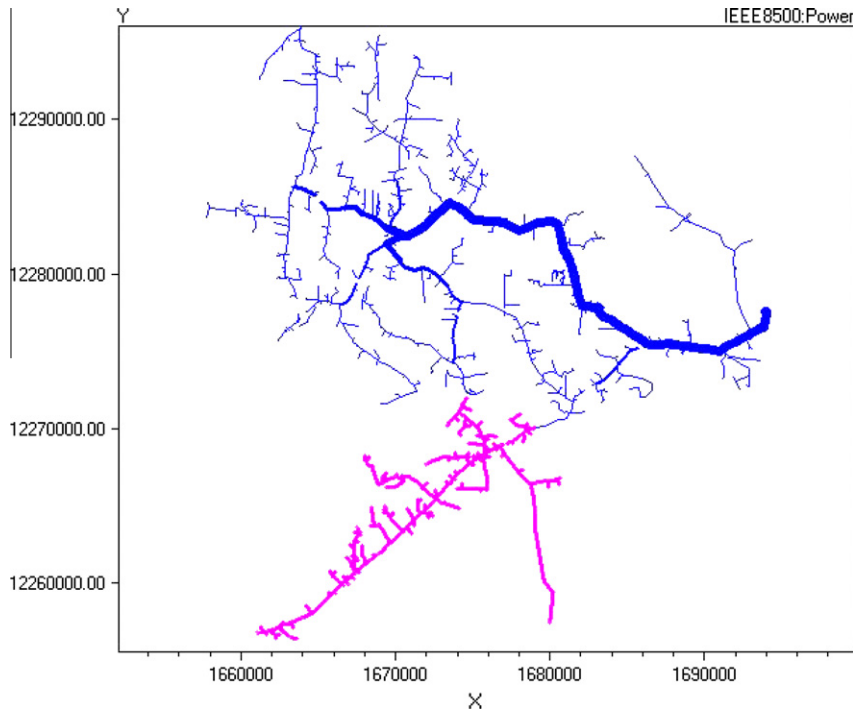


Fig. 4. IEEE 8500 node test feeder showing section with DR loads.

- Scenario 5- Mix of LR, SR and RW consumers: In this case, each consumer type (LR, SR and RW-mixed) constitutes one third of the total section load.

6. Results

6.1. Voltage analysis of DR integrated test system

Demand Response when applied to a distribution network results in a load change which in turn changes the power flows through the distribution transformers and the upstream areas of the distribution feeder [15]. In case of load reduction due to DR voltage drops across the distribution feeders reduce, causing a boost in the voltage at the far end of the feeder. This effect is even more pronounced when DR is applied at the remote nodes of the feeder. However, there is a need to explore this DR-voltage

relationship on a uniform basis throughout the day with optimum Volt/Var adjustments. Extensive deployment of AMI and availability of huge volumes of historical data and real time distribution operation models will provide for better understanding on DR-voltage relationship in the long run. In order to show the effects of DR explicitly on the system voltages, the control settings of load tap changers, regulators and capacitor banks have not been adjusted during the power flow which is taken care of by OpenDSS.

The voltage analysis of the system with DR integrated into the highlighted section yields many interesting results. As expected, all the monitored secondary nodes of the section showed improved voltage profile for scenarios 2, 3, 4 and 5 during high price periods. It was observed that DR during peak hours boosts the node voltages which would otherwise sag. Figs. 5 and 6 show voltage comparisons at one of the load end nodes of the feeder for the various test scenarios. As seen from Fig. 5, the node voltage during peak

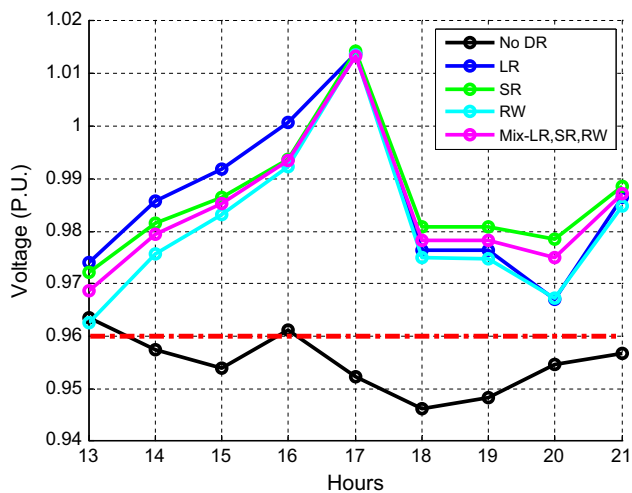


Fig. 5. Voltage profile at node SX3047289A-phase 1 during peak pricing hours.

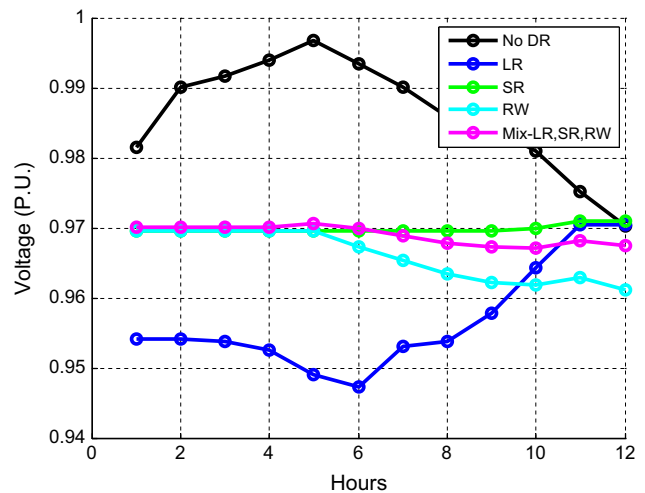


Fig. 6. Voltage profile at node SX3047289A-phase 1 during off peak hours.



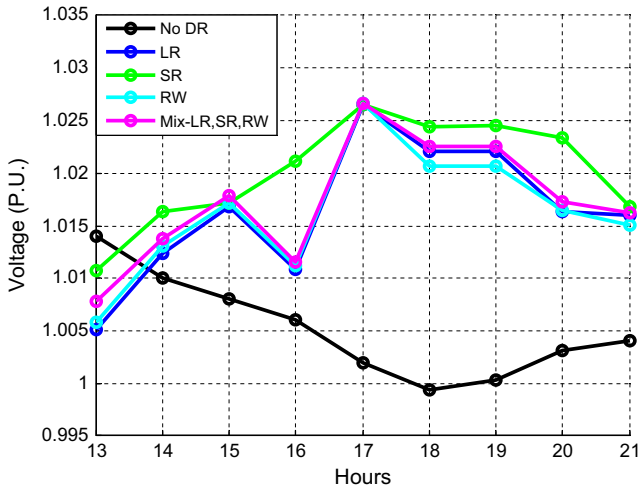


Fig. 7. Voltage profile at node SX3029498C-phase 1 during peak pricing hours.

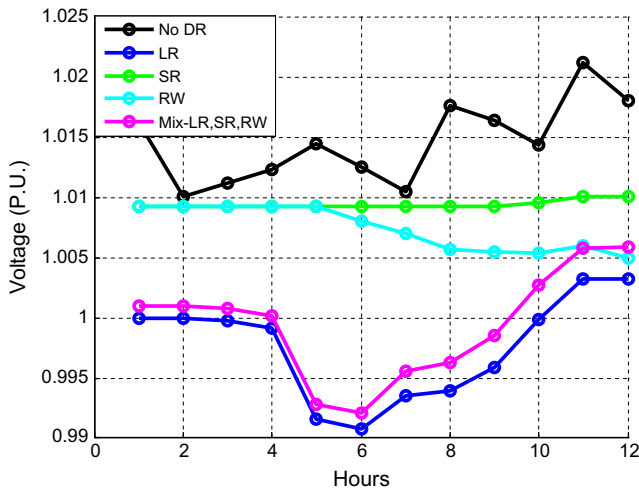


Fig. 8. Voltage profile at node SX3029498C-phase 1 during off peak hours.

pricing hours drops below 0.95 p.u. for the base case without any Demand Response. However, with DR loads in the system, a

considerable boost in voltage above 0.95 p.u. was observed for all the other scenarios.

A closer look at Fig. 6 shows the redistribution trend with LR consumer during off peak hours. As seen from the Figure, most of LR consumer's load is shifted to these early hours of the day due to which voltage for LR load dips as compared to any other consumer type. Since a RW consumer shifts load over a range of 5 h, there is some voltage dip from hours 6–12 after which peak pricing starts. Voltages of SR consumer are constant for these hours and for scenario 5 (mix of all consumer patterns), voltages lie between voltage profiles of SR and LR consumers. Fig. 7 examines the voltage profile at another secondary node for all the consumer types. Sharp rise in the voltages is observed during peak hours as a result of vigorous DR measures by all the consumer types. At instants when voltages of No DR case are over 0.98 p.u., an additional boost of 0.1–0.25 p.u. is seen with DR enabled loads. This rise in the secondary node voltages can provide the required room for Volt/Var control program to further curtail the system demand during peak hours. Fig. 8 shows voltage analysis for the same node during off peak hours.

### 6.2. Loss analysis of DR integrated test system

The real power losses for the section of interest were analyzed as a percentage of the total feeder loss over the period of 24 h for different consumer type scenarios. For the base case snapshot power flow without any load shape assigned to the system loads, the total feeder loss recorded was 1.2 MW and the loss recorded for the analyzed section was around 160 KW. For scenarios with responsive loads, tremendous reduction in losses was observed for the peak pricing periods as shown in the surface plot of Fig. 9. The Y-axis represents customer types. For the No DR case, losses are at maximum during peak hours. However, for other customer types, the percentage losses are considerably less. At hour 17, the percentage losses for LR, SR and RW consumers dip to as low as 4% as against 15% for the case without Demand Response. Lowest percentage losses occur for SR consumer as they respond to high prices during peak hours by immediately shedding their load. However, an LR or RW consumer sheds load partially and redistributes it to lower priced periods.

A similar loss analysis of the system during early hours shows that the case with No DR has minimum loss percentage as indicated by Fig. 10. Following this, SR, RW and Mix consumers have

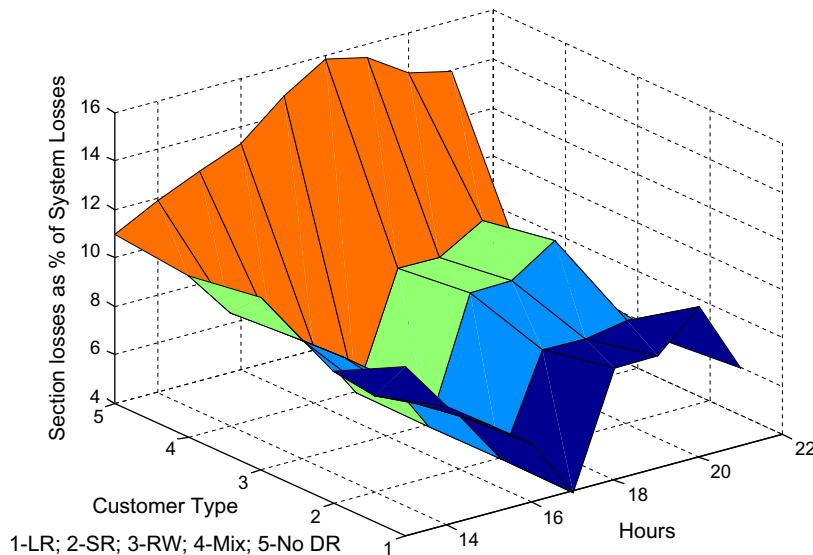


Fig. 9. Loss analysis of section during peak pricing hours.

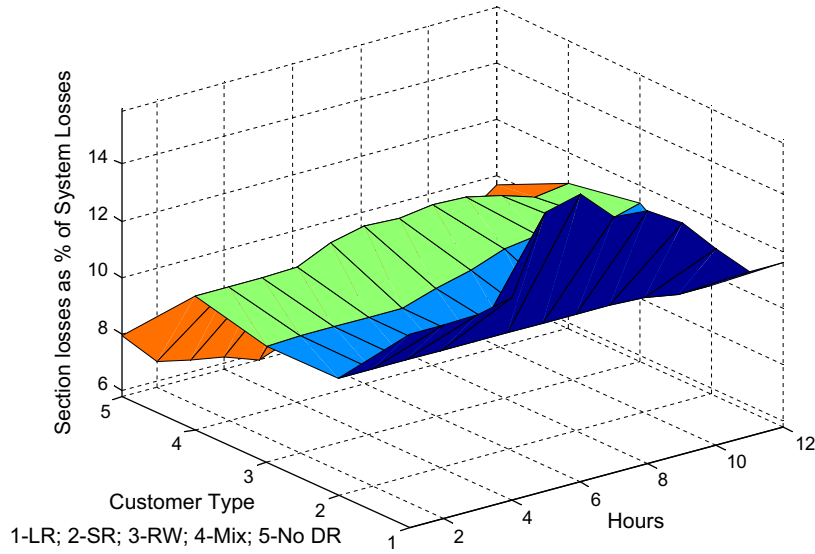


Fig. 10. Loss analysis of section during off peak hours.

a slightly higher loss percentage due to increased consumption due to lower prices. LR consumer records the maximum percentage losses during early hours of the day. LR consumers, owing to their optimizing nature, shift loads throughout the day and also consume maximum possible energy during low priced periods thus consuming more energy than other type of consumers resulting in more losses than any other consumer type. Fig. 11 shows the sectional losses in kWh for various scenarios over an extended period of time that includes both peak and off peak pricing hours. It can be observed that the sectional losses for the No DR case gradually decrease as we move from peak loading (or pricing) hours to valley periods. A reverse effect is observed with DR implemented since consumption shifts to these valley periods. This increase in losses is an indication of more energy being consumed in the off peak hours giving way for valley filling.

Table 2 summarizes the loss analysis results obtained for the entire system and the section of interest.

It can be seen from Table 2 that the overall 24 h section and system losses are considerably decreased with all DR scenarios except for the case with LR consumers. Excessive losses noted with LR consumers are again attributed to their optimizing nature due to which they maximize their energy consumption. However, such

Table 2

Twenty four hour losses for the feeder and the analyzed section for different scenarios.

Scenarios	No. DR	LR	SR	RW	Mix-LR,SR,RW
24 h System losses (kWh)	29192.2	30156.1	27931.7	28662.2	28826.9
24 h Section losses (kWh)	3074.3	3526.9	2504.1	2827.9	2869.9

a case of increased number of optimizing consumers would shift the system peak to an early low priced hour of the day leading to unexpected congestion. This reasoning throws up the importance of exploring various clustering techniques to aggregate residential consumers based on their behavior. A right mix of LR, RW and SR consumers in the system can help avoid unnecessary peaks in the system demand curve.

### 7. Conclusions

This paper has developed a model for residential Demand Response by developing price elasticity matrices for different types of consumers. Comprehensive price elasticity matrices have been developed for each consumer type based on their rationality assumptions. Further, the impact of Demand Response on system voltage and losses has been evaluated on a large IEEE test feeder. Results indicate that DR impacts the distribution network in 3 positive ways:

1. Voltage profile improvement
2. Loss minimization
3. Valley filling

Voltage analysis results indicate that DR has a great potential to boost the distribution system voltage at most of the critical nodes. Until recently, DR was only viewed as a means of curtailing demand side load during peak hours. However, with advancement in smart grid technologies and advanced metering infrastructure, there is an excellent scope for integrating DR with demand side Volt/Var control. This coordination can yield huge profits to utilities and consumers if applied appropriately during peak hours.

Maximum benefits of peak demand curtailment can be achieved through integration of DR with Volt/Var control

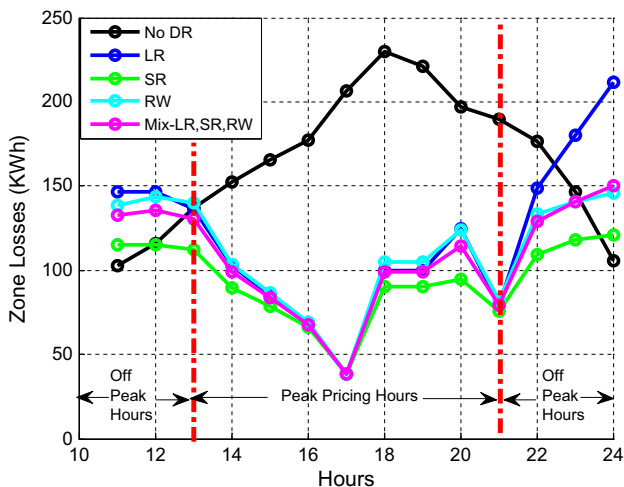


Fig. 11. kWh losses for the section for various DR scenarios.

algorithm. Future work will be directed towards implementing a Volt/Var control algorithm that utilizes DR model and distribution operation model in real time to demonstrate their combined effect on peak load shaving.

### Acknowledgment

This research work was partially supported by West Virginia University PSCoR grant. The authors gratefully acknowledge the support provided by Mr. Roger Dugan, EPRI for the extensive workshop sessions on OpenDSS.

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