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Conservation Voltage Reduction Case Study

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ABSTRACT A Conservation Voltage Reduction (CVR) is an efficient method to manage the load demand in distribution power systems. This paper proposes the utilization of the CVR method on Washington EMC's power system and Georgia Transmission Corporation facilities. The utility's peak power consumption is reduced to determine the figures of wattage and money saved. The CVR technique is implemented within the ANSI standards and with an efficient CVR, factor to maintain the efficient performance of the system and satisfy the consumers' needs. The principle of operation, concepts of modeling, and substation CVR management are illustrated. The CVR methodology including utility circuit, smart meters' data, management, savings, and analysis is presented. Then, experimental CVR scenarios, smart meters' experimental CVR data, CVR steady-state analysis and experimental CVR management using SCADA are investigated and analyzed. After that, a CVR dynamic prediction model is established using the Neural Network (NN) and validated by means of comparisons with actual data and the Gaussian model. Power saving, power demand, yearly money-saving real data from EMC utility, and real temperature data from NOAA is used to create the CVR dynamic model with a minimum average error percentage of 0.22 % w.r.t the real-data. Finally, a SCADA system operation is discussed along with the potential future improvements and research directions.

INDEX TERMS Conservation voltage reduction, ANSI standards, consumer's meter, distribution circuit, dynamic load model, peak wattage consumption, predictive model, simulations, and voltage regulators controllability.

I. INTRODUCTION

In a power grid, it is not very efficient to run all generators at full capacity all the time. This is due to the fact that the energy being generated is not being stored. Without storage, the energy that is not simultaneously consumed is lost. Typically, generation companies choose which generators to run at specific points in time in order to meet consumer needs without grossly generating more power than what is demanded. With most peak demands being simultaneous, there are drastic spikes in the demand that must be anticipated and compensated by the generation companies. The transmission companies also have to have circuits with the capacity to carry the peak loads and actively monitor load flow. Because of the dynamic characteristic of this problem, transmission companies add a demand charge.

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Conservation Voltage Reduction (CVR) is a reduction of power consumption resulting from a reduction of voltage. When implementing CVR, voltages will be reduced to the lower end of the American National Standard Institute's standard voltage band [1]. Care must be taken to ensure that all consumers are receiving adequate voltage. Manipulating the voltage can be accomplished by controlling the voltage regulation at the substation [2]. Voltage received at the substation has some degree of variance and must be regulated by the distribution companies via voltage regulators. By optimizing the voltage during peak demands, the peak consumption can be reduced [3].

CVR has many noteworthy advantages such as the energy consumption reduction, peak load decrease, and losses' reduction of the transformer and transmission line, increase some domestic appliances' lifecycles, operating cost decrease, power factor improvement, and the reduction of the greenhouse gas emission due to the fuel consumption

decrease [4], [5]. CVR implementations could be achieved mainly in two ways. The first basic technique is to reduce the voltage by utilizing capacitors, line-drop-compensators, and load-tap-changers, which is called the open-loop technique (no-voltage-feedback). The second advanced technique to decrease the voltage is to use Supervisory-control and-data-acquisition system (SCADA) and the Advance metering-infrastructure (AMI), which is called the closed loop-voltage-feedback volt-var control [6], [7]. The voltage profile which is the difference between the minimum and maximum voltage through the feeder is desired to be as flat as possible. The voltage profile could be flattened by placing capacitors at different sites to enhance the power factor and decrease power loss. However, the recent trend to reduce the dependency on the grid is to integrate the distributed generation resources and CVR technique into the distribution power system [8], [9]. The Demand Side Management (DSM) technique is considered as one of the efficient solutions for energy consumption management. But the DSM technique may not lead to energy consumption reduction. The CVR performance assessment is paramount for its implementation. The main four assessment methods are simulation-based, comparison-based, synthesis based, and regression-based [4], [10]. Therefore, accurate load modeling is vital to produce an accurate assessment of CVR. Artificial Neural Networks (ANNs) are utilized for load modeling by mapping the input data set to the output [11], [12]. The load components are categorized into two types, static (a function of the voltage and/or frequency at a specific time), and dynamic (load with time dependent characteristics) [13]. However, a modern strategy is adopted to coordinate the operation of microgrids with distributed generation resources in the application of Volt-Var optimization and CVR using a bi-level optimization strategy [14].

Recently, the usefulness of voltage reduction regulation as a degree to exploit utilities' revenues is illustrated utilizing a new approach of private environment and various regulation studies [1]. A robust time-varying load modeling method is proposed to precisely detect load-to-voltage (LTV) dependency, using an enhanced CVR assessment scheme with a robust iteratively re-weighted recursive least squares (RLS) method [2]. Another smart CVR estimation approach for energy savings in distribution systems has been utilized. This approach has utilized deeper CVR PV system while limiting the node voltages within adequate bounds and reactive power control [3]. Conservation voltage reduction (CVR) technique is investigated to identify real-time monitoring requirements for distribution system grid with innovative volt-var control, and sensitivity analyses [4].

A modern upgrade plan for a microgrid associated with distributed generation sources with CVR technique and capacitors placing is investigated. The CVR is used to minimize the loss cost and has been examined on the IEEE 69 bus system [5]. CVR is implemented to reduce peak demand and save energy using a real 1666-bus real data for mesh network [6]. However, a CVR approach with distributed

generation and a droop-control are projected to coordinate the process in an autonomous microgrid. A modern centralized AC optimal power flow (OPF)-based CVR device has been implemented to minimize energy consumption by managing the voltage. The proposed method is assessed using unbalanced U.K. residential MV-LV network and load models (2,400+ customers) [8]. CVR with a droop control method is utilized again for a PV standalone system and storage devices. The used technique has reduced the number of charging/discharging processes of storage devices and improve energy consumption with more savings [9]. Two load models ZIP and exponential are compared to evaluate the CVR in a comprehensive way utilizing real data from a 22.86 kV distribution system [10].

In this paper, the use of CVR is investigated to reduce peak power consumption for a utility and estimate the cost savings while maintaining an efficient system. This is accomplished first by finding the ad-equate utility circuits that met the criteria for applying CVR, and then: a) performing an analysis of the circuit to ensure that each consumer's meter voltage would remain within the ANSI standards, b) testing the circuit's voltage regulators controllability, c) performing simulations and calculations, and d) creating a dynamic prediction model for the system. The rest of the paper is organized as follows. In section II, the CVR concepts are introduced. In section III, the proposed approach is presented. In section IV, the CVR load management modeling along with the results are discussed. Model validation, and SCADA operation are illustrated in sections V, and VI. The future directions and conclusion are presented in sections VII, and VIII respectively.

II. CONSERVATION VOLTAGE REDUCTION

A. PRINCIPLE OF OPERATION

CVR is considered as one of the efficient conservations of energy methods by using voltage management to enhance the power grid's efficiency. Even though it was partially employed in California in 1977, CVR has not been utilized to its fullest potential. However, modern technologies of smart grids and integrated volt-var control enable CVR to be utilized efficiently. Conventionally, the substation voltage is set to the maximum permitted voltage to ensure that each customer has a base voltage level provided by the distribution network. In future power systems, it will be conceivable to control the voltage level along the transmission lines so as to supply all customers with similar voltage level, to such an extent that low-voltage substations can work near the base voltage level. In the US, the substation distribution voltage levels are regulated through American National Standards Institute (ANSI). ANSI C84.1 standard sets the range for voltages ages at the dissemination transformer secondary terminals at 120 volts $\pm 5\%$ which results in a voltage level between 114 and 126 volts. Due to the transmission line voltage drop, power must be transmitted at a sufficiently higher voltage. Therefore, power is regularly transmitted from the

substation at 126V. US homes usually get a voltage level of 122.5V, with around 90% of homes and businesses getting more voltage than what they need. The target of CVR is to have the customer's voltage set to the least acceptable level [15].

CVR normally presents the largest voltage reduction conceivable to achieve the most energy savings within a specific season or even the entire year. The perpetual voltage reduction can be either consistent in time or time-shifting on a closed-loop control system. The CVR device is evaluated as far as the energy decrease it brings over a given seasonally or yearly; which can likewise be communicated utilizing measurements, for example, the notable CVR factor. This is solitary esteem that relates the perpetual voltage decrease to the comparing energy variety over the given time range. CVR efficiency is contingent on the load device's categories. CVR has been executed utilizing two various methods, the first is "Line Drop Compensation", and the second is "Voltage Spread Reduction". Utility designers will, in general, be moderate and in light of changes from light burden hours to overwhelming burden hours, the voltage data transfer capacity settings on regulators are frequently made in all respects minimalistically to guarantee that the endpoint voltage never hangs underneath preset esteem. Moreover, everyday changes in temperature, day-of-the-week, and so forth can prompt burden changes that lessen the viability of CVR settings. A decent procedure is to manage the voltage at the client's meter and the utility does not have to endeavor to set controls for CVR. A disadvantage to this procedure is that it relies upon the clients to introduce equipment on their site and to pay the capital expenses. Furthermore, it doesn't have the advantage of less conveyance transformer iron loss nor does it give very as much energy investment funds for line loss. Another viable procedure is to utilize an Adaptive Voltage Control (AVC) framework to actualize CVR. This technique utilizes newly programmed control and communications tools that were inaccessible at the time of prior CVR endeavors [1], [16].

The CVR factor is a proportion of how viable voltage decrease is from energy and demand. It is essentially the proportion between the percent demand (energy) and voltage. It is the term regularly used to allude to the proportion between voltage decrease and energy load utilization for a specific piece of a power distribution framework. It tends to be changed over to figure energy investment funds or reactive power reserve funds. CVR factor is additionally every so often communicated as the adjustment in kilowatts or kVAR partitioned by the adjustment in volts to demonstrate a decrease in peak-demand. Components fluctuate broadly from substation to substation, feeder to feeder, and particularly burden to load. Commitments to the general factor for a utility incorporate customers' load blend, transformer and conductor qualities, and voltage control devices as directed by voltage controllers, line drop compensators, and exchanged capacitor banks. On account of the huge number of parts included, CVR factors for feeders and substations

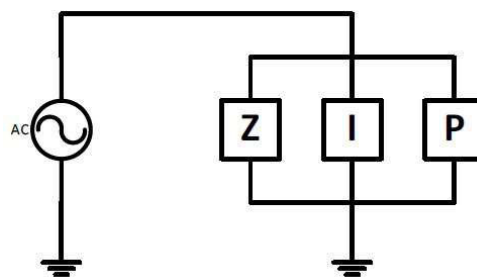


FIGURE 1. The ZIP basic load model.

normally are estimated experimentally, not hypothetically produced [1].

1) CVR LOAD MODELING

The four main loads categories are a resistive load without a feedback-loop, a resistive load with a feedback-loop, a constant-power load, and a constant-current load. To understand it more, supposing that family-unit gadgets require no reactive power, the impact of CVR on energy utilization can be clarified as pursues. By Joule's law, the power (P), voltage (V) and current (I) in a resistive circuit fulfill $P = V \times I$. It pursues from Ohm's Law $V = I \times R$ that bringing down the voltage level lessens the power when the load comprises of pure resistances with steady opposition R , in light of the fact $P = V^2/R$. This is valid if loads are constant-resistive such as fridge, incandescent lighting, oven, and hot water system, however not if loads are steady power such as TV, PC, and so on. Regarding steady power loads, dropping the voltage will imply that the current needs to increase, which prompts higher energy loss in the lines, as per the power loss equation $P_{Lines} = I^2 R_{Lines}$. Likewise, numerous constant-resistance gadgets have a feedback-loop for the most part estimating the temperature that broadens the working time, prompting consistent energy utilization. Some lighting advancements keep the current constant. The power utilization of these gadgets diminishes directly with the voltage as per $P = V \times I$. The reserve funds are in this way littler than for constant resistance gadgets, for which the power utilization is quadratic in V .

Loads' behavior can be depicted by their proportion of consistent power, impedance and current characteristics (ZIP models). ZIP models can be developed from experimental results on load response under changing voltage conditions. Because of the multifaceted nature of end-use load behavior, load models can be classified into loads with and without thermal cycles. The customary strategy for displaying a load without a thermal cycle is to utilize a ZIP model. The ZIP model is a load which is made out of time-invariant steady impedance (Z), consistent current (I), and consistent power (P) components [1], [4]. Figure 1 represents the ZIP model circuit. The ZIP load consumed active and reactive powers at a certain voltage are presented in Eqs. 1 and 2 respectively. These equations have six constants to define

the behavior of the ZIP load voltage dependent and these constants are constrained by Eq. 3.

$$P_i = \frac{V_a^2}{V_n^2} \cdot S_n Z\% \cdot \cos(Z_\theta) + \frac{V_a}{V_n} \cdot S_n \cdot I\% \cdot \cos(I_\theta) + S_n \cdot P\% \cdot \cos(P_\theta) \quad (1)$$

$$Q_i = \frac{V_a^2}{V_n^2} \cdot S_n Z\% \cdot \sin(Z_\theta) + \frac{V_a}{V_n} \cdot S_n \cdot I\% \cdot \sin(I_\theta) + S_n \cdot P\% \cdot \sin(P_\theta) \quad (2)$$

$$Z\% + I\% + P\% = 1 \quad (3)$$

where Z_θ is the phase angle of the constant impedance; I_θ is the phase angle of the constant current; P_θ is the phase angle of the constant power; P_i is the real power consumption of the i_{th} load; Q_i is the reactive power consumption of the i_{th} load; V_a is the actual terminal voltage; V_g is the nominal terminal voltage; S_g is the apparent power consumption at nominal voltage; $Z\%$ is the fraction of load that is constant impedance; $I\%$ is the fraction of load that is constant current; $P\%$ is the fraction of load that is constant power.

CVR brings down the voltage at which electrical power is conveyed and yields, all things considered, a 1% energy reserve funds for each 1% in voltage decrease down to 114V. Electrical hardware, including cooling, refrigeration, apparatuses, and lighting is designed to work most proficiently at 114V. If power is conveyed at a voltage higher than 114V, energy is squandered. The higher essential voltage additionally abbreviates the useful life of numerous kinds of equipment, since the excess of energy is dissipated as heat. Conveying voltages at the optimal stages lessen utilization, improves administration quality and expands the life of the hardware. Utilities and customers spare energy and lower working expenses by lessening the need to create extra energy at power plants. CVR likewise brings down ozone-harming substance discharges; CVR is relied upon to have extensive ecological advantages, on the grounds that the decrease of the energy utilization will prompt less CO2 emanations related to energy creation. Electrical energy is spared through decreased system losses because of the lower voltage. Customers' advantage through lower energy bills, and speedier reaction to the power outage. Utility advantage through lower losses, longer transformer life and expanded information of their system's present condition. Operating expenses are decreased amid blackouts (outages) because of a superior comprehension of the fault place. The data gave can shape the premise of a prescient support system. Utilities may control the measure of preservation and request by rapidly the modifying set focuses from the Master station [1], [4], and [16].

2) SUBSTATION CVR MANAGEMENT CONCEPT

There are two typical voltage regulation schemes in a substation. The first is bus regulated and the second is feeder regulated. Bus regulated stations have regulators on the source side of the bus work that feeds all of the circuits. Feeder regulated circuits have a set of regulators for each feeder circuit. Bus regulated stations allow the utility to save on

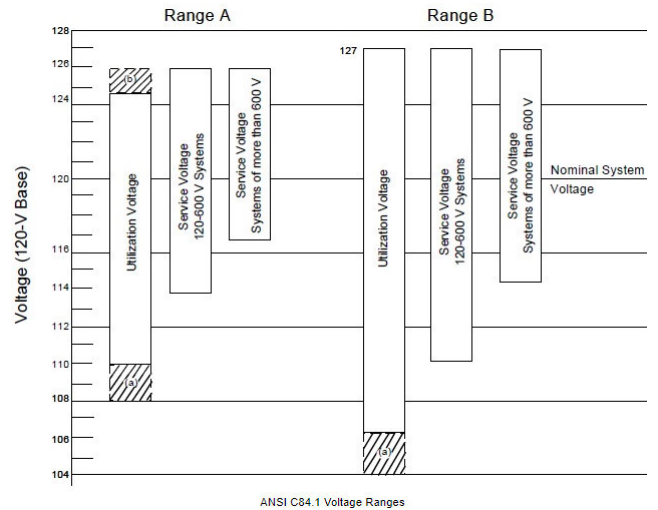


FIGURE 2. Ranges for Standard regulation and temporary conditions Parameters.

the cost of purchasing many regulators. However, feeder regulated stations allow the utility much more control over the voltage of their system due to the fact that each circuit is individually regulated [17]. The main concern with Conservation Voltage Reduction is maintaining an adequate voltage at every meter on the system [18]. This is another reason why feeder regulated circuits are ideal for CVR because they can independently contribute to the voltage demands of the circuit. The American National Standards Institute (ANSI) sets the following regulations for voltage as shown in figure 2.

Range A is the standard regulation parameters, and range B is for temporary conditions, which CVR falls under. This window of additional range allows CVR to be much more capable of application during these times. The two main types of consumer loads are resistive loads, and inductive loads, and for these types of loads, load management based CVR is an important approach [19], [20].

Resistive loads include anything with a resistive element, such as light bulbs or heating elements. Inductive loads which constitute most of the residential loads. They are often referred to as power loads because inductive loads consume a constant amount of power. These loads are typically from devices or appliances that include some type of electrical motor. Applying the power equation ($P = V I$) is obvious that reducing the voltage will raise the current. With resistive loads, the constant variable is the resistance. Applying the principles of Ohms Law ($V = IR$), reducing the voltage reduces the current. This fact is key to conservation voltage reduction.

Washington EMC is billed according to its contribution to the peak load during the peak of five hours of the load management calling days. The peak load season usually falls in the window of June to September, but occasionally is in the winter months. When their provider (Georgia Transmission Corporation) calls for load management, the usage is monitored for the given window of time. The instantaneous

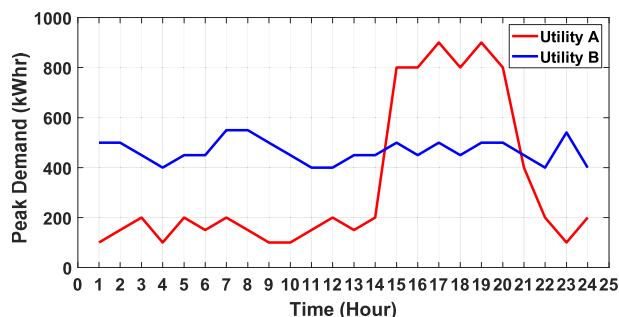


FIGURE 3. Example of two distribution utilities with different load profiles.

TABLE 1. Peak load during the peak of 5 hours.

| | 4 p.m. | 5 p.m. | 6 p.m. | 7 p.m. | 8 p.m. | Average |
|------------------|--------|--------|--------|--------|--------|---------|
| Utility A max kW | 800 | 900 | 800 | 900 | 800 | 840 kW |
| Utility B max kW | 450 | 500 | 450 | 400 | 400 | 440 kW |

TABLE 2. Monthly charge.

| | Average | Cost per KW | Monthly Charge |
|-----------|---------|-------------|----------------|
| Utility A | 840 | \$1.95 | \$1638 |
| Utility B | 440 | \$1.95 | \$858 |

peaks of each hour are recorded. The average of these peaks is multiplied by a predetermined dollar amount. The resulting dollar amount is charged to EMC every month until the next load management is called. Reducing the load during the yearly peak would save money for the rest of the year by lowering the monthly demand charge. These savings would also be translated to the consumers because the cost of their power reflects what the utility pays. To illustrate the potential magnitude of the effects of the demand charge, consider the following example shown in figure 3, and tables 1 and 2.

A power transmission company charges \$1.95 per kW for their demand charge and \$0.061 per kWh for their supply charge. There are two distribution utilities adjacent to each other with very different load profiles. Utility A has very high peaks during the peak demand times but uses very little during the rest of the day. Utility B has a very stable demand, regardless of time. Their peak consumption can be viewed in figure 3, with Utility B represented in the blue line, while Utility A is represented with the red line, kWh is shown on the Y-axis, and time (1 am to midnight) on the X-axis. If load management is called from 3 to 8 pm, the area boxed in black, their corresponding peaks would be as follows: Utility B uses more power over the course of the day in comparison to Utility A. This would equate to Utility B having a higher supply cost, but a much lower demand charge.

In some cases, it can be to the extent of the demand charge making up the majority of the bill. The fact that the demand charges are only relative to this short window of time is the reason that it is important to monitor and manage peak consumption. Table 1 shows a comparison of peak load demand over the peak of five hours between the two utilities A and B. However, table 2 introduces the monthly charge comparison between the two utilities.

III. PROPOSED CVR APPLICATION

A. EXPERIMENTAL CVR SCENARIO

There have been numerous studies of CVR deployed on systems, and there are many vendors that offer CVR based systems. The concept has been applied in various locations, but it is always case specific. Regarding this work, multiple substations have been investigated to elect a suitable system for testing with the required technologies. Then, some experiments have been done with the control systems of the distribution circuit to determine the effectiveness of remotely manipulating the voltage. Historical data from the circuit chosen was thoroughly investigated and a predictive model of the demand was created. The temperature data of the previous year was also analyzed to compare it with the consumption data. These two data sources, along with data on the power factor of the circuit with respect to time were used to develop a set of parameters that when applied to the circuit will give an estimate of power consumption. A valid measurable outcome is the determinant of success, as well as the proven accuracy of the methods to estimate power consumption. It is a very subjective application, in that it varies in effectiveness and is only feasible on particular utility circuits. Washington EMC has a 14.4/24.9 kV, system with 14 substations, and it is the main subject of this study.

The first step is to identify substations that are feeder regulated. The next step is to analyze the consumer loads to identify the circuits with the lowest resistive to inductive load ratio. A utility circuit with about 480 meters has been selected. The power factor of this circuit typically remains within 0.9. The circuit is residential in a rural location, with the distribution of the meters being relatively scattered. The entire distribution map is too large to accurately display it on this paper, and scaling it down to fit would result in the lines becoming too small to see. The best representation of the circuit that was obtained for the paper is shown in figure 4, and came from the outage system software of the utility.

The screenshot of this process is illustrated in figure 5. This information was used as the first step to identify the lowest meter’s voltages. Washington EMC has recently installed smart meters on their system, which allowed to obtain the information needed. Data from the smart meters at these locations were analyzed to identify locations with the lowest voltages. The purpose of this was to make adjustments to these particular locations to raise their voltage closer to the norm, which would allow a further reduction in voltage before any meters began to approach the lower end of the ANSI voltage standards.

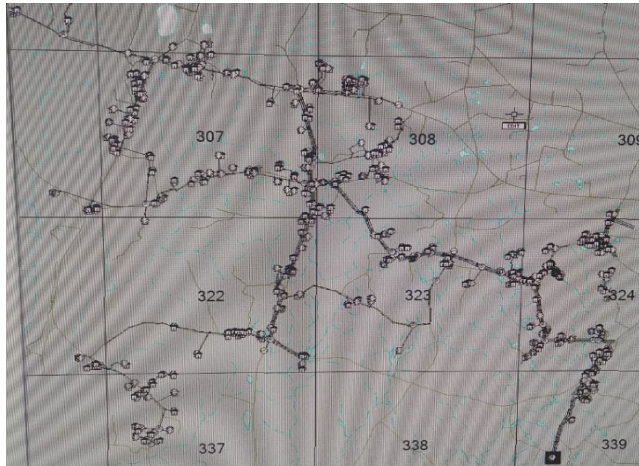


FIGURE 4. Image of the utility circuit used in this research.

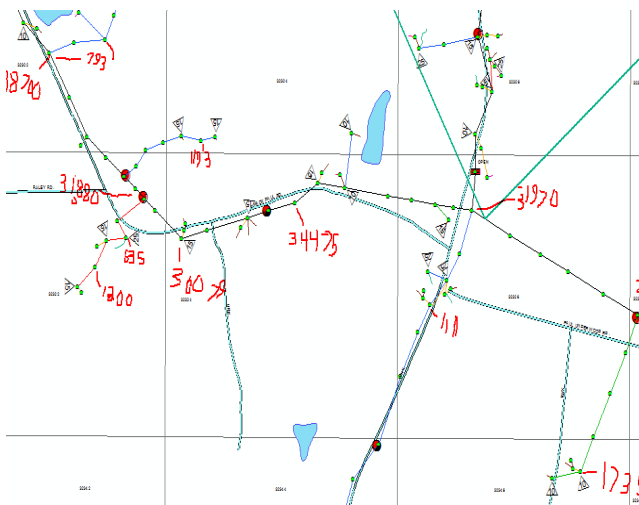


FIGURE 5. Screenshot of the process from the GIS Mapping Software.

B. EXPERIMENTAL CVR DATA

The smart meters produced a sufficient amount of information. The graphs of low voltage readings over the past 2 months were reviewed to identify instantaneous low voltages. The voltages from the previous two months of each meter were averaged together and the lowest 5 averages were selected. Next, the maps were revisited to analyze the circuits leading up to these meters. Some of the meters had very long services, one was on a potentially overloaded transformer, and some were at locations very far from the substations.

All of the meters fell within the acceptable standards, but the information was relayed to the company to see if they wanted to shorten the service lengths, increase wire sizes, or increase the transformer Kilo-Volt-Ampere (KVA) characteristics. Figure 6 shows the screenshot graphs provided by the software that receives the data from the smart meters. The purpose of monitoring and analyzing these particular meters was to allow the utility company to be aware of these locations and consider means necessary to raise the voltages in order to allow for a larger window of safe voltage reduction.

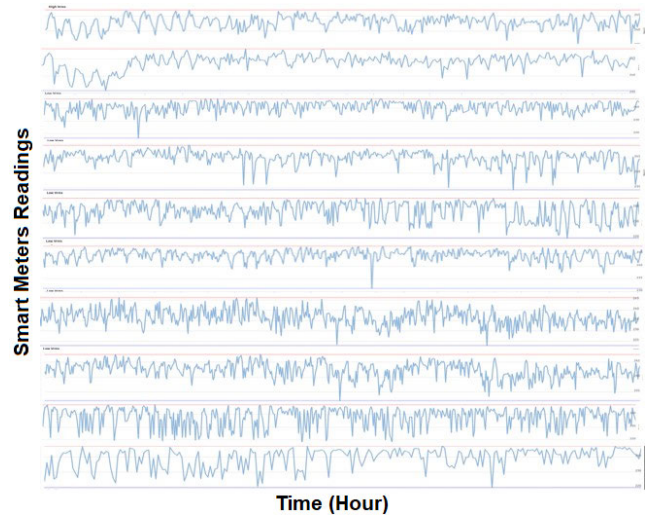


FIGURE 6. Screenshot of the smart meters data.

Depending on the particular case and cause, meter voltage could be increased by moving the transformer closer to the meter (shortening the length that the secondary voltage has to travel), installing a larger secondary service wire (reducing the resistance), and/or installing in-line regulators. The meters’ measurements’ variation was mainly interesting at their lowest voltages. It was noticed that two patterns of low fluctuations appeared and that the origin of these patterns should be determined. The reason behind that is due to the variance of weather and the difference in the customers’ appliances. The highs and lows over the past two months were observed and found that the two patterns followed the temperature extremes. One group’s low voltage fell on the high extremes and the other on the low extremes. This was a key point to consider because it showed that the critical points would vary according to the temperature.

C. EXPERIMENTAL CVR MANAGEMENT USING SCADA

To verify that consumers would all maintain adequate voltage during a CVR, a relatively cold morning was selected to examine with (visit) Washington EMC at around 5:30 am. This particular time was chosen because this is a typical high consumption period. This examination is carried out at the dispatch center, where the computer system is tied to the Supervisory Control and Data Acquisition (SCADA) system. The carried out work was to remotely use the regulators to step down the voltage one step for around a minute, then remove the remote control setting, let the voltage return to normal for around a minute, reapply remote control and step the regulator down 2 steps for around a minute and then let it settles back to normal for another minute. This process was continued until the regulators had been stepped down a total of 3 or 4 steps. To avoid stepping the regulators farther than intended, the state of the regulators was physically monitored on site during the testing period. It was verified if any low voltage alarms were received from the smart meters.

TABLE 3. Load management full data.

| Load Management #1 (9/18/17) | | | | | | | | |
|------------------------------|----------|----------|----------|----------|----------|----------|------|----------|
| | ϕ_A | ϕ_B | ϕ_C | ϕ_A | ϕ_B | ϕ_C | kW | Weighted |
| | kW | kW | kW | P.F. | P.F. | P.F. | Sum | P.F. |
| 3:50 PM | 523 | 676 | 375 | 98.2 | 97.5 | 99.8 | 1574 | 98.28 |
| 4:55 PM | 527 | 728 | 379 | 98.1 | 97.5 | 99.9 | 1634 | 98.25 |
| 6:00 PM | 543 | 721 | 385 | 98.5 | 97.7 | 99.9 | 1649 | 98.48 |
| 7:05 PM | 524 | 729 | 375 | 98.4 | 97.8 | 99.8 | 1628 | 98.45 |
| 8:10 PM | 512 | 652 | 377 | 98.4 | 97.5 | 99.8 | 1541 | 98.36 |
| Load Management #2 (1/18/18) | | | | | | | | |
| 5:35 AM | 559 | 852 | 511 | 99.9 | 100 | 99 | 1922 | 99.71 |
| 6:40 AM | 578 | 903 | 547 | 100 | 100 | 99.3 | 2028 | 99.81 |
| 7:45 AM | 611 | 868 | 603 | 100 | 100 | 99.2 | 2082 | 99.77 |
| 8:50 AM | 620 | 858 | 540 | 100 | 99.9 | 98.7 | 2018 | 99.61 |
| 9:55 AM | 544 | 784 | 444 | 100 | 100 | 98.2 | 1772 | 99.55 |

D. LOAD MANAGEMENT MODELING USING ACTUAL TEMPERATURE DATA

Accurate weather data with the highest resolution were obtained from the National Oceanic and Atmospheric Administration (NOAA). Temperature data, in twenty-minute intervals, from 1/1/2017 to 1/31/2018, was provided. After analyzing the data, outliers were removed, and interpolation was used for missing points.

Washington EMC provided the last two times load management data. The dates and times were 9/18/2017, from 4:00 pm to 8:00 pm and 1/18/2018, from 6:00 am to 10:00 am. These days fell during the summer and winter peaks respectively. These time periods were noted as points of interest for doing critical analysis. The data file includes: the time, the amperage of phase A (ϕ_A), the amperage of phase B (ϕ_B), the amperage of phase C (ϕ_C), the amperage on the neutral conductor, the volt-ampere reactive (VARs) on phase A (ϕ_A), the VARs on phase B (ϕ_B), the VARs on phase C (ϕ_C), the wattage of phase A (ϕ_A), the wattage of phase B (ϕ_B), the wattage of phase C (ϕ_C), the power factor of phase A (PF_{ϕ_A}), the power factor of phase B (PF_{ϕ_B}), and the power factor of phase C (PF_{ϕ_C}), respectively as shown in table 3.

However, the averages for kW and the power factor for each phase is illustrated in table 4. The adjusted power factor for the circuit shown in table 3, was calculated using the formula given by Eq. 4. This formula is used to calculate the weighted or the averaged power factor for the three phases.

$$PF_{Weighted} = \frac{A_{\phi kW} A_{\phi PF} + B_{\phi kW} B_{\phi PF} + C_{\phi kW} C_{\phi PF}}{Total_{kW}} \quad (4)$$

where $Total_{kW}$ is the total power in kW, $A_{\phi kW}$ is the phase ‘‘A’’ power in kW, $B_{\phi kW}$ is the phase ‘‘B’’ power in kW, $C_{\phi kW}$ is the phase ‘‘C’’ power in kW, $A_{\phi PF}$ is the phase ‘‘A’’ power factor, $B_{\phi PF}$ is the phase ‘‘B’’ power factor, and $C_{\phi PF}$ is the phase ‘‘C’’ power factor.

Next, the analysis of the data with respect to the external factors, the variance of weather, and the difference in the

TABLE 4. Load management averages.

| Phase | A | B | C |
|--------------------|-------------|-------------|-------------|
| Average Power (kW) | 313.0920934 | 359.6375597 | 229.846511 |
| Average P.F. | 99.59687863 | 99.07451309 | 88.63232297 |

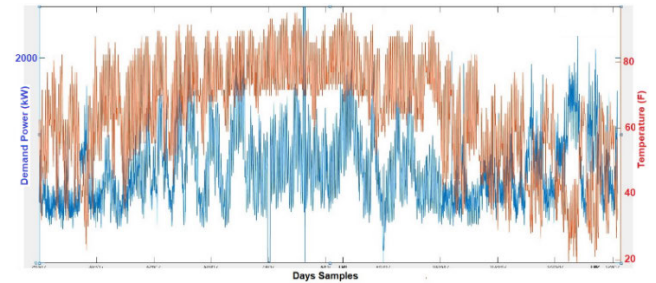


FIGURE 7. Demand power and temperature readings.

customer’s appliances, was executed. The first step of this process was finding the interconnections between the data and its contributing factors. The focus was paid first in the kW demand charge considering the temperature as a leading contributor. The data for the temperature and the kW from the SCADA system are shown in figure 7 (Temperature in Red and kW in Blue).

E. CVR APPLICATION DISCUSSION

From the analysis, it was obvious that the temperature had a large impact on the kW, but the graph contained so much data that it was still difficult to derive any more information from the graph. Next, the data was separated into two consecutive sections in order to graph the data with more detail, but it was still very difficult to extract any information from it. It was decided to investigate how much the day of the week influenced the data. The initial attempt at this analysis was to take the kW data from the SCADA and break it down into the corresponding 168 hours of each week. The average for each day of the week, for the 53 weeks of the data was calculated. Excel was used to create a matrix of this information, with 168 columns for hours and the respective kW values for the rows. Next, the readings from the past two instances of load management were added in the graph for comparison. The resulting graph is depicted in figure 8.

The difference between the average readings and the periods of load management are very clear. The hour of day also clearly had an impact on the kW values, but the day of the week made little difference. To further investigate the external factors, another graph was generated, which shows the average kW each hour for each day of the week, the results are shown in figure 9.

The results show that the day of the week has a much greater influence on the resulting kW usage. Although there are very subtle differences, the day of the week did not seem to have near the impact that time of day had on the usage. The analysis of the data from the two periods of load management

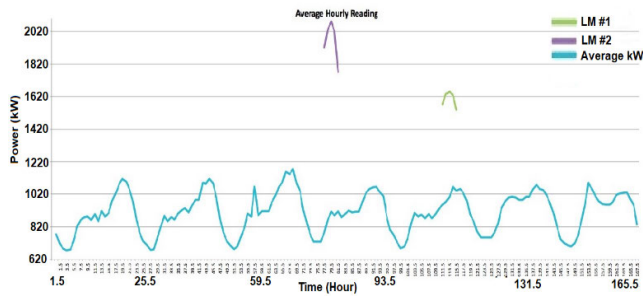


FIGURE 8. Average hourly demand power of the 53 weeks and two load management readings.

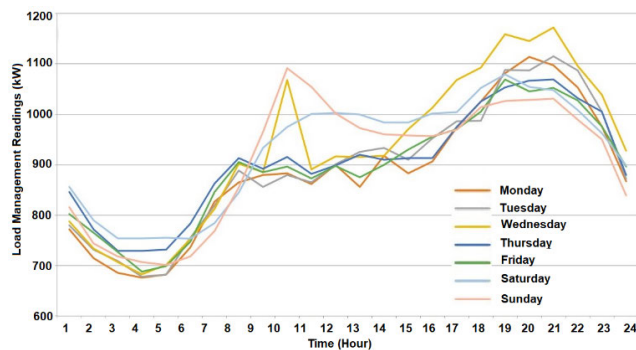


FIGURE 9. Hourly load management readings.

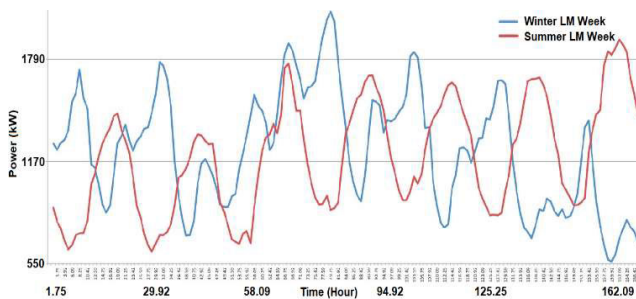


FIGURE 10. Demand power reading for the two periods of load management.

show that these periods are quite extreme in comparison to the typical readings. Then the analysis was focused on the entire week around the two instances, with the period of load management in the middle. These values can be observed in figure 10.

IV. CVR LOAD MANAGEMENT MODELING EXPERIMENTS

To benchmark the performance of the various CVR load management techniques, a steady-state model was first implemented using Multisim.

A. STEADY-STATE MODEL

To demonstrate the effect of voltage change on a circuit with constant inductive and resistive loads, a steady-state analysis was performed. Table 5 presents the effect of reducing the voltage over the power and power factor. As the voltage was

TABLE 5. Reduced voltage change effect.

| Voltage | 124 | 123 | 122 | 121 | 120 | 119 | 118 |
|------------|------|------|------|------|------|------|------|
| Power (kW) | 3.07 | 3.02 | 2.99 | 2.92 | 2.88 | 2.83 | 2.78 |
| P.F. | 0.90 | 0.90 | 0.90 | 0.90 | 0.90 | 0.90 | 0.90 |

TABLE 6. Load-voltage dependencies for common loads.

| Load Component | (% Change in I)/ (% Change in V) |
|-------------------------|----------------------------------|
| Battery Charge | 1.59 |
| Fluorescent Lamps | 1.07 |
| Constant Impedance | 1 |
| Air Conditioner | -0.5 |
| Constant Current | 0 |
| Pumps, other Motors | -0.92 |
| Small Industrial Motors | -0.9 |
| Constant Power | -1 |

reduced, the corresponding values of the power demand was also reduced, while the power factor remained unchanged regardless of the voltage.

Actual load values were utilized to improve on the initial steady-state analysis of the CVR load management. For common values of residential loads, a typical power saving of 0.4%-0.7% is attainable for every 1% reduction in the voltage. This information is used with additional common values of appliances to estimate the potential savings. Load voltage dependency relates the percentage change in current to the percentage change in voltage which is commonly used to model typical loads. Table 6 shows the typical load-voltage dependency factors of some common loads used [21].

Using the load-voltage dependency factors in table 6, the potential savings were calculated for the case if CVR has been implemented using the two load management scenarios provided in table 3. The load data used in these scenarios are seasonal which contribute to the excessive demand in certain cases due to the use of heaters to maintain a reasonable temperature within residential households.

A mixed model was created to match the average of the summer and winter load management time periods. The steady-state results are the least accurate results in this study, due to the fact that they assume a fixed state. They are useful, however, to investigate how inductive and resistive loads react to a changing voltage. Therefore, from the values the steady-state analysis provided, the estimated savings were calculated for the case if CVR has been implemented.

The amount of savings due to the CVR implementation in a substation, 1/4 of the system, and 1/2 of the system were based on the fact that this circuit accounts for approximately 1/5 of the particular substation's demand and the demand of the circuit in respect to the utility's typical peak. Table 7 presents the amount of cost savings for the two load management scenarios.

TABLE 7. Steady-State Analysis cost savings vs. voltage change.

| Load Management #1 | | | | |
|--------------------|------------|------------|-------------|-------------|
| CVR V | Circuit | Substation | 1/4 System | 1/2 System |
| 124 | \$152.48 | \$762.38 | \$1,548.03 | \$3,096.06 |
| 123 | \$305.67 | \$1,528.36 | \$3,103.31 | \$6,206.63 |
| 122 | \$459.57 | \$2,297.86 | \$4,665.86 | \$9,331.71 |
| 121 | \$614.19 | \$3,070.64 | \$6,235.66 | \$12,471.31 |
| 120 | \$769.53 | \$3,847.64 | \$7,812.71 | \$15,625.42 |
| 119 | \$925.58 | \$4,627.89 | \$9,397.02 | \$18,794.05 |
| 118 | \$1,082.34 | \$5,411.72 | \$10,988.59 | \$21,977.19 |

| Load Management #2 | | | | |
|--------------------|------------|-------------|-------------|-------------|
| CVR V | Circuit | Substation | 1/4 System | 1/2 System |
| 124 | \$435.94 | \$2,179.70 | \$3,661.67 | \$7,323.35 |
| 123 | \$869.17 | \$4,345.87 | \$7,300.64 | \$14,601.29 |
| 122 | \$1,299.71 | \$6,498.54 | \$10,916.91 | \$21,833.81 |
| 121 | \$1,727.54 | \$8,637.68 | \$14,510.46 | \$29,020.93 |
| 120 | \$2,152.66 | \$10,763.31 | \$18,081.32 | \$36,162.63 |
| 119 | \$2,575.09 | \$12,875.43 | \$21,629.46 | \$43,258.93 |
| 118 | \$2,895.41 | \$14,477.06 | \$24,320.05 | \$48,640.09 |

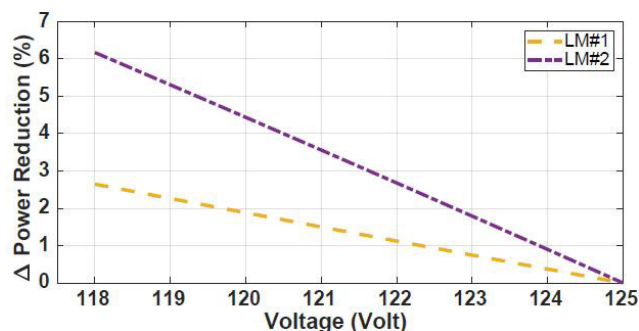


FIGURE 13. Percentage power reduction versus voltage.

B. CVR MANAGEMENT EFFICIENCY

A simple efficiency estimation as a ratio between the new value of the power in kW with the load management and the average power value in kW versus samples of voltage are proposed. It shows a high efficiency with respect to the reduced voltages with average values 98%, and 96% for the first load management, and second one respectively. However, more research will be proposed in the future to deduce new efficiency formula with all possible parasitic, economical and unrepresented characteristics.

The CVR factor is defined as the reduction percentage of the load power with respect to the voltage reduction percentage. It is a measure of efficient conservation voltage reduction load management. It is considered as the proper independent quantitative indicator to identify how efficient the proposed voltage reduction. The active power CVR factor is shown in Eq. 5.

$$CVR_p = \frac{\% \Delta P}{\% \Delta V} \tag{5}$$

where %ΔV is the percentage of the voltage change, and %ΔP is the percentage variation of the active demand load.

The typical CVR factor values are within the range between 0.3 and 0.9 [4]. Figure 13 introduces a CVR factor’s estimation for the two load managements as percentage power reduction versus voltage. The CVR factor’ estimations are used as a measure of how efficient the proposed CVR load managements. From figure 13, the average power CVR factor for the LM# 1 equals 0.3714, and the average power CVR factor for the LM# 2 equals 0.8643. Both of them are within the perfect range from 0.3 to 0.9 [4].

C. ARTIFICIAL NEURAL NETWORK (DYNAMIC) MODEL

To improve the CVR load management modeling, a neural network (NN) model is proposed and implemented to analyze the behavior of CVR and its impact on power reduction taking into consideration time, day, and temperature to predict the nature of the utility circuit management and associated savings. An NN utilizing backpropagation with the Levenberg-Marquardt training algorithm was used to create a load management predictive model. The temperature data received from NOAA was pre-processed and interpolated to be consistent with the experimental data.

Load Management #1

| Voltage | 124.00 | 123.00 | 122.00 | 121.00 | 120.00 | 119.00 | 118.00 |
|----------------------------|---------|---------|---------|----------|----------|----------|----------|
| Average Power (kW) | 1605.20 | 1605.20 | 1605.20 | 1605.20 | 1605.20 | 1605.20 | 1605.20 |
| CVR Average Power (kW) | 1599.22 | 1593.21 | 1587.18 | 1581.11 | 1575.01 | 1568.89 | 1562.73 |
| Power savings (kW) | 5.98 | 11.99 | 18.02 | 24.09 | 30.19 | 36.31 | 42.47 |
| Monthly \$ saved (circuit) | 11.66 | 23.37 | 35.14 | 46.97 | 58.86 | 70.81 | 82.81 |
| Annual \$ saved (circuit) | 139.89 | 280.46 | 421.73 | 563.69 | 706.33 | 849.67 | 993.70 |
| Annual \$ saved (station) | 699.43 | 1402.31 | 2108.64 | 2818.43 | 3531.67 | 4248.36 | 4968.51 |
| Annual \$ saved (1/4) | 1437.89 | 2882.88 | 4334.98 | 5794.17 | 7260.47 | 8733.87 | 10214.37 |
| Annual \$ saved (1/2) | 2875.78 | 5765.77 | 8669.96 | 11588.35 | 14520.94 | 17467.73 | 20428.73 |

FIGURE 11. CVR results of load management scenario #1.

Load Management #2

| Voltage | 124.00 | 123.00 | 122.00 | 121.00 | 120.00 | 119.00 | 118.00 |
|----------------------------|---------|----------|----------|----------|----------|----------|----------|
| Average Power (kW) | 1964.40 | 1964.40 | 1964.40 | 1964.40 | 1964.40 | 1964.40 | 1964.40 |
| CVR Average Power (kW) | 1946.75 | 1929.22 | 1911.79 | 1894.48 | 1877.27 | 1860.17 | 1843.18 |
| Power savings (kW) | 17.65 | 35.18 | 52.61 | 69.92 | 87.13 | 104.23 | 121.22 |
| Monthly \$ saved (circuit) | 34.41 | 68.60 | 102.59 | 136.35 | 169.91 | 203.25 | 236.37 |
| Annual \$ saved (circuit) | 412.91 | 823.25 | 1231.03 | 1636.24 | 2038.88 | 2438.95 | 2836.46 |
| Annual \$ saved (station) | 2064.55 | 4116.26 | 6155.14 | 8181.18 | 10194.38 | 12194.75 | 14182.28 |
| Annual \$ saved (1/4) | 3468.24 | 6914.92 | 10340.03 | 13743.58 | 17125.57 | 20485.98 | 23824.84 |
| Annual \$ saved (1/2) | 6936.48 | 13829.84 | 20680.07 | 27487.16 | 34251.13 | 40971.97 | 47649.68 |

FIGURE 12. CVR results of load management scenario #2.

For comparison purposes, the proposed CVR results are tabulated in figures 11 and 12 for load management #1 and load management 2 scenarios, respectively. The results indicate a relative matching with the steady-state analysis with the proposed CVR method being more accurate in estimating the savings than the steady-state. However, the steady-state analysis is a simple approach to estimate the CVR savings to validate the initial viability of the application of CVR in a system.

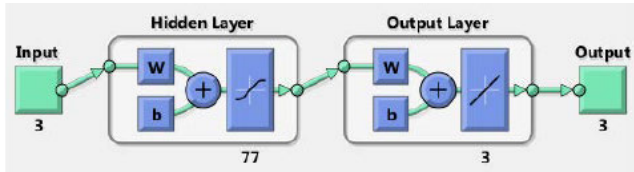


FIGURE 14. Architecture of the neural network.

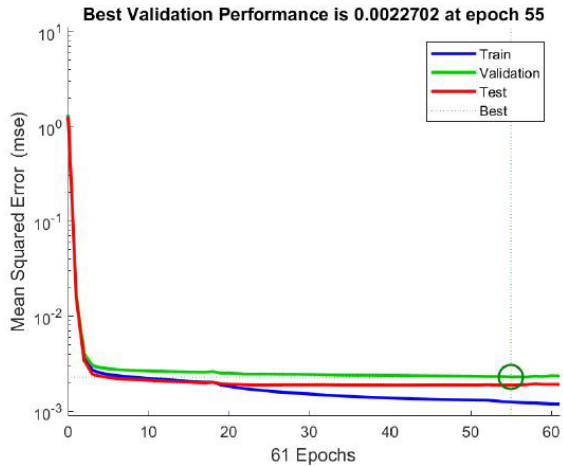


FIGURE 15. Mean Squared Error of the ANN model.

Due to the internal temperatures of houses remaining around 68° F in the winter and 70° F in the summer, a number line is created that went from 68° to 71°, and back to 68° over the course of the given data. It is notified that the peak temperatures were right at the same time frame as the summer load management. Also, the temperature data is used on a weighted scale by taking the data from the current temperature to 2 hours and twenty minutes prior to the current time with a twenty-minute interval. Then, temperature classification is adopted by selecting three different temperature ranges in terms of Fahrenheit that are equal to $T > 80^{\circ}\text{F}$, $60^{\circ}\text{F} < T < 80^{\circ}\text{F}$, and $T < 60^{\circ}\text{F}$. It is noticed that the accuracy went up for the bottom two ranges and down for the top one. Then the ranges were adjusted to $T > 85^{\circ}\text{F}$, $60^{\circ}\text{F} < T < 80^{\circ}\text{F}$, and $T < 60^{\circ}\text{F}$. It was noticed that the accuracy went up for lower temperatures $T < 92^{\circ}\text{F}$, and down for higher temperatures $T > 92^{\circ}\text{F}$. This trend is continued of adjustment with the consolidation of the data from the previous trial to maintain better accuracy. After selecting the NN architecture, the NN was trained using the Levenberg-Marquardt algorithm with randomly selected data set to use 70% for training, 15% for validation, and 15% for testing.

In figures 14 and 15, the NN architecture and one of the best error values plots that were obtained from training the neural network are shown as a sample of many trials to get the average.

The input vector has three variables: the day of the week (Monday to Sunday), the time (0-24 Hr.), and temperature (°F). However, the output vector contains the power savings (kW), power load demand (kW), and yearly money

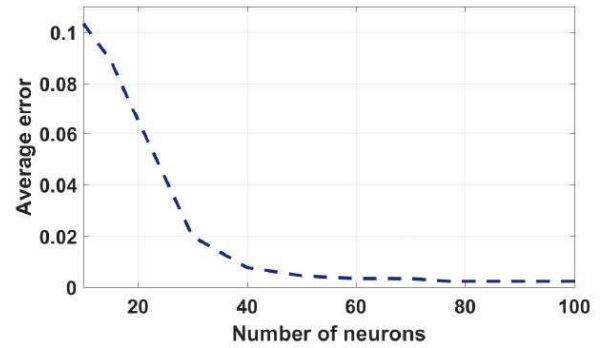


FIGURE 16. Average error values vs number of neurons.

savings (\$). ANN architectures with a range from 10 to 100 neurons in the hidden layer were tested when doing the evaluation. There were no significant differences in the results between 77 up to 100 neurons. So, for the sake of consistency the 77 neurons configuration was finally selected. The neural network has been run many times at each number of neurons in the hidden layer to get the average of each case. The number of network running at each time is 100.

However, Figure 16 presents the average of the obtained mean-square-error (MSE) after many trials for each with respect to the change of the number of neurons in the ANN hidden layer. The best average achieved error was around 0.0022 at 77 number of neurons in the hidden layer.

The implemented ANN predictive model is not limited to predict the CVR power and money saving based on real-data, but also it is capable to predict the dynamic load behavior as shown in the next validation section.

V. MODELING VALIDATION

This section proposes a comparison between the actual CVR load management data, ANN Model, and a Gaussian model. The adopted Gaussian model from is utilized as a proof of ANN accuracy and as another alternative method for model prediction [22], [23]. However, the actual data for modeling is processed using the predefined Gaussian process regression models (kriging) inside the Matlab, [24] for the proposed real data range and ANN model. Gaussian process regression (GPR) model is a nonparametric kernel-based probabilistic models [24]. It is trained using the Matlab “fitrgp” function with the same training data set used in the neural one. The basis equations for the embedded Gaussian model in the Matlab are shown in the next formulas.

The training set is considered as $(x_i, y_i); i = 1, 2, \dots, n$, where $x_i \in \mathbb{R}^d$ and $y_i \in \mathbb{R}$. The Gaussian regression model predicts the response variable y_{new} , given the input vector x_{new} , and the training data. The Gaussian regression model is introduced as follow:

$$h(x)^T \beta + f(x) \tag{6}$$

where $f(x) \sim GP(0, k(x, x'))$, that is $f(x)$ are from a zero mean GP with covariance function, $k(x, x')$. $h(x)$ are a set of

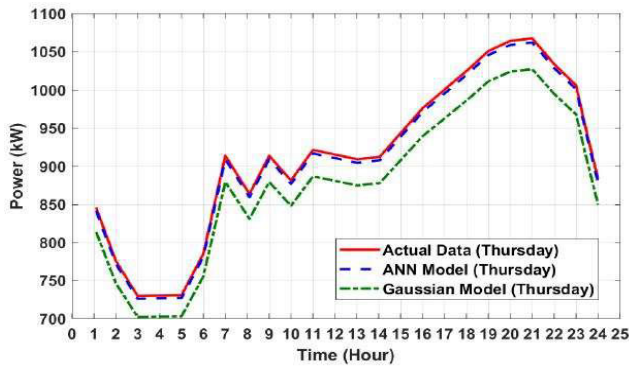


FIGURE 17. Comparison between predictive models and actual data for load demand.

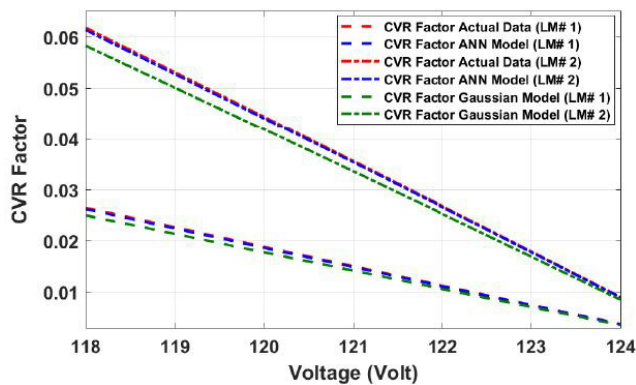


FIGURE 18. Comparison between predictive models and actual data for CVR factor.

basic functions that transform the original vector x in R^d into a new vector $h(x)$ in R^p . β is a p -by-1 vector of basis function coefficients. The instantaneous response y can be modeled as [24].

$$P(y_i | f(x_i), x_i) \sim N(y_i | h(x_i)^T \beta + f(x_i), \sigma^2) \quad (7)$$

Because, Gaussian regression model is a probabilistic model and it has a latent variable $f(x_i)$ for each observation x_i which varieties the GPR model nonparametric.

The covariance function seizes the response’s softness. However, the GR model computes the prediction interludes using the trained model.

Figure 17 shows a dynamic load performance comparison among actual data, ANN model, and Gaussian model for one day over twenty-four hours as a sample (Thursday).

From Figure 17, the ANN model has a great matching to the real actual data and then the Gaussian prediction model. However, another form of CVR prediction model’s validation is proved in Figure 18, and Figure 19 for CVR factors and annual money saving per station respectively. The ANN model is very close to the real data in both.

From the comparisons, the average Gaussian’s error and the average ANN’s error percentages are estimated as 2.145%, and 0.22% respectively w.r.t. the actual data.

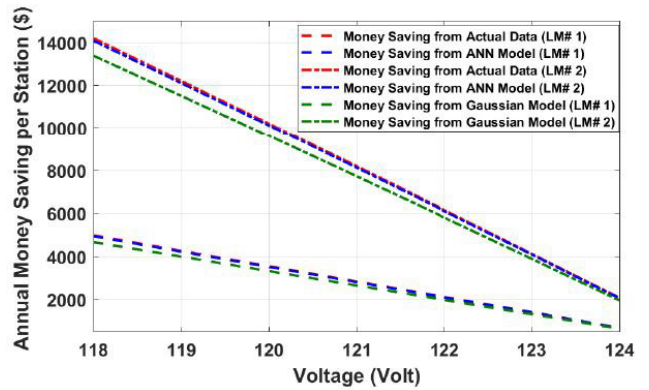


FIGURE 19. Comparison between predictive models and actual data for annual money saving per station.



FIGURE 20. SCADA system interface.



FIGURE 21. SCADA system diagram of components.

VI. SCADA SYSTEM OPERATION AND DISCUSSION

The regulators with the SCADA system are remotely operated in Washington EMC’s control center. The SCADA system has a very user-friendly interface that allows the operator to view the entire system in multiple ways. Figures 20 and 21 show the typical screen displays for the SCADA interface.

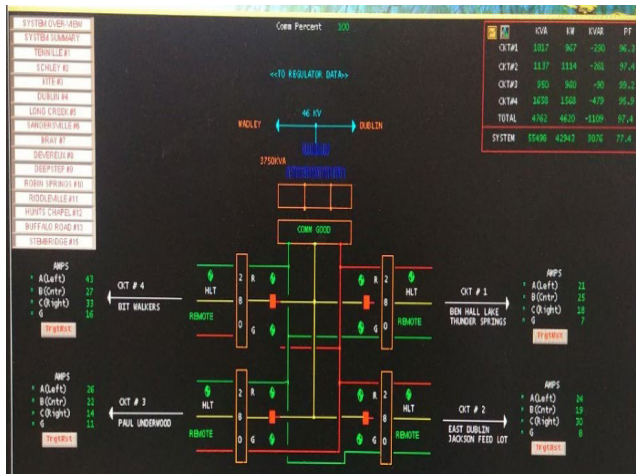


FIGURE 22. Line diagram on SCADA control.

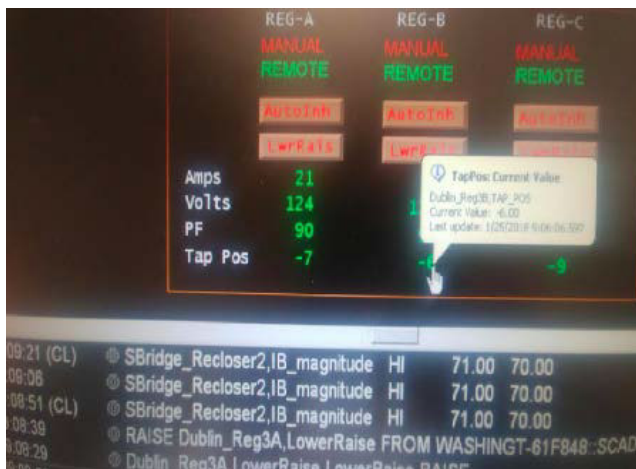


FIGURE 23. SCADA system commands to regulators.

The software allows to monitor the entire system and compare the conditions of substations and utility circuits very easy. Once a substation is chosen, a more detailed view of characteristics is shown, as seen in figure 22.

A utility’s circuit can be chosen if the operator desires to modify the voltage regulators from the control center. The setting has to be changed to “remote” instead of “manual”. After this is complete, the regulators are ready to receive commands. This can be viewed in figure 23. A problem was noticed related to the resolution of the results due to the precision of the data used for the analysis. The control center’s computer shows the voltage rationalized in terms of 120V, so 120 volts = 14,400 volts. This means that the 125 volts that the regulators are set to represent 15,000 volts. The wattage is read in kilowatts, and the resolution of the amperage is only available to the one thousand of the unit. In order to get a more accurate measurement of the results, a higher resolution on the original data was needed. When the data from the SCADA system was received, the resolution was the same.

There are other options that can be used to accomplish load management during peak hours. A utility could install large

generators to carry a portion of the load, set up solar panel arrays, or engage in load shedding with willing customers. Each of these has its advantages and disadvantages. The large generators are a great way to handle some of the load, but they are very expensive. The size of generators allows many substations to have generators installed inside of them. They also need to be maintained, consume fuel, and have to have special equipment to be remotely controlled and synchronized with the power system. Solar arrays are another option that allows the utility to generate power within its own system. The drawbacks of solar are the initial cost, the battery cost, and the size of the area needed to carry a significant portion of the load. Load shedding is a more common method used in utilities. A utility often sells power to certain customers at a discounted rate in exchange for the control of dropping them from the system during these peak times. This can be inconvenient for the customer, and it also reduces the money that the utility will receive for power distribution.

VII. FUTURE DIRECTIONS AND ROOM OF IMPROVEMENT

As future directions of this paper, the following research points could be addressed:

- Optimize the demand prediction at the extreme end of the temperatures with additional constraints,
- Explore stability, uncertainty and sensitivity analysis for the power network with CVR along and intelligent systems,
- Investigate time-varying ZIP plug loads, search the effect of electric vehicles and distributed generation penetration on CVR in distribution power system,
- Investigate the influence of distorted voltage at the substation on the optimal capacitor placement with their transient effect,
- Measure the practical impact on the consumer’s comfort level on implementing the CVR method.
- Propose inverter-based VAR control with the presented model,
- Explore developing online optimization platform for the customer, and
- Study the effect of various filters on the voltage magnitude.

In addition to that, there is ongoing work on two important topics for efficiency optimization and the measure of customer satisfaction. These two topics need more data from the EMC utility such as losses under different circumstances and customers’ surveys about their service along with economic characteristics investigation. The required data will be obtained to be used in the future.

The combination of the knowledge of the different types of load and the different types of voltage-regulated substations can be used to seek out opportunities to save utility money on demand charges. After making calculations and simply lowering the voltage by a small percentage during load management, a utility could cut their demand charge by a large enough degree to make an impact. The impact of this

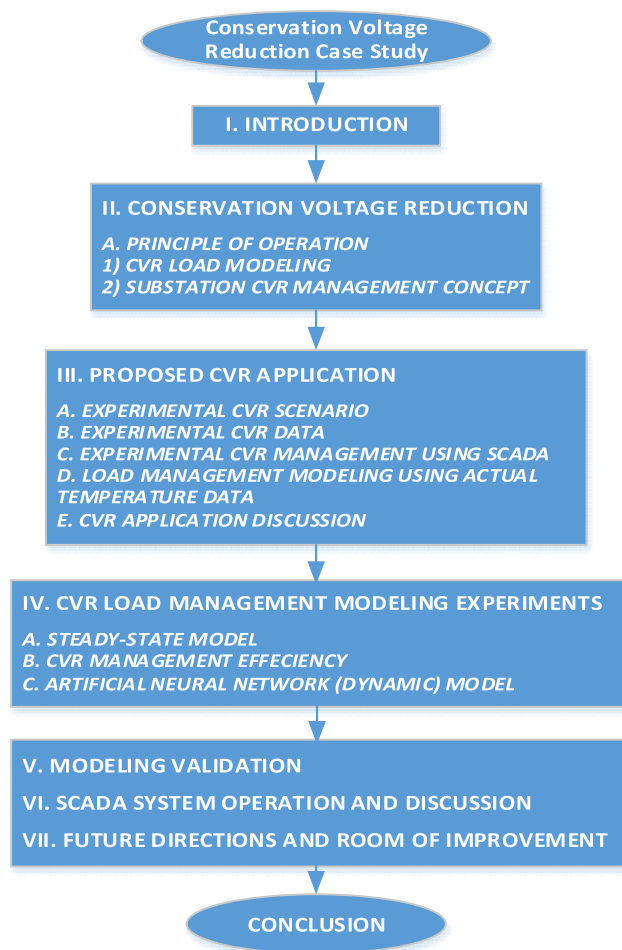


FIGURE 24. Overall paper flowchart.

goes beyond the utility. If a nonprofit provider, such as an EMC, is paying less for the power that is being distributed, then the consumers' cost will be a reflection of this as well. Optimizing the voltage will also save on consumed energy, and prolong the amount of time that infrastructures are capable of carrying the peak demands. This is a proactive way to help manage the world's limited resources that allows all parties to benefit. Figure 24 shows the overall paper's flowchart including different sections.

From this research on CVR, several messages are clear to utilities investigating the potential use and benefits of applying this concept. It would increase the validity of the results if temperature, humidity, rainfall, and sunlight are recorded. All of these would contribute to the rate of heat transfer in the building, which would contribute to the demand. The type of demands served (agricultural, residential, and industrial) should be considered. A recording device that measures amperage and voltage to a higher degree of precision would be beneficial, especially in continuous measurements. When a regulator steps, the change in the current would indicate the load voltage dependency. This would need to take place quite often and would eventually allow the modeling of the dynamic load with respect to time. Finally, the outage data

from the smart meters should be continually considered. If all of this information were accessible, then the calculations for CVR would have a high degree of accuracy.

VIII. CONCLUSION

The paper confirms the importance of the Conservation Voltage Reduction (CVR) for a reduction of power consumption by reducing the voltages to be within the lower end of the American National Standard Institute's standard voltage band. The paper illustrates the CVR management concept, philosophy, CVR dynamic modeling, and demand management of the CVR technique. The CVR concept has been applied in Washington EMC utility after multiple substations has been investigated to determine the effectiveness of remotely manipulating the voltage. Washington EMC is the main subject of this paper and it has a 14.4/24.9 kV system with 14 substations. A utility circuit with 480 meters has been selected to analyze the consumer loads and get the smart meter data. The circuit is residential in a rural location, with the distribution of the meters being relatively scattered. Two load management scenarios utilizing the CVR method are experimentally implemented for summer and winter seasons. The CVR factor' estimations for the two load management cases are used to evaluate how efficient the proposed CVR method. The average active power CVR factors for the load management one and two equal 0.3714, and 0.8643 respectively and they are within the referenced efficient range. Verification of all consumers would maintain adequate voltage during a CVR that has been done by examining with the Washington EMC center through the (SCADA) system. Step by step operation for experimental investigation, analysis, and CVR application are explained with the aid of the Futura Systems' GIS Mapping software, smart meters, and Supervisory Control and Data Acquisition (SCADA) system. This is done to ensure the effectiveness of remotely manipulating the voltage by the regulators and to verify that consumers' satisfaction with the aid of Washington EMC during a typical high consumption period. The power factor of this circuit typically remains unchanged and stays within 0.9 while the voltage changes. The steady-state characteristics and amount of savings for the CVR technique have been done based on real common loads to show the load-voltage dependencies. Then, a modern dynamic CVR load management model using neural networks (NN) is proposed. It is implemented to analyze the behavior of CVR taking into consideration time, day, and temperature to predict the nature of utility circuit management. The real training data for NN model are obtained from the utility's smart meters and SCADA system along with real temperature data from the (NOAA) over one year. This model shows the impact of the temperature and the time on power demand, power saving, and money savings. The NN model is trained for minimal error, tested many times to get the average performance, and achieved good accuracy. The number of neurons in the hidden layer is altered and tested over a range from 10 to 100 neurons until reaching the optimal number for minimal error. The best average

mean-square-error (MSE) after the neural network has been run 100 times at each number of neurons is 0.0022 and it achieved at 77 neurons in the hidden layer. The ANN predictive model is not limited to predict the CVR power and money-saving based on real data, but also it is capable to predict the dynamic load behavior. The NN model is validated in the form of comparisons with real data, and the Gaussian model for power demand, CVR factors, and money savings per station. The NN model has a great matching to the real actual data and then the Gaussian prediction model with average NN's error percentage equals 0.22% and the average Gaussian one equals 2.145%. The SCADA system operation is discussed to monitor the entire system and compare the conditions of substations and utility circuits. Finally, the shortcomings of the paper and recommendations for future work are addressed by the end of the paper.

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