Cluster-based Volt/Var Optimization on a Utility Distribution Feeder with Forecasted EV Penetration

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***Abstract*—With significant increase in EV adoption expected in the near future and the associated impacts on power systems, the effect of volt/var optimization (VVO) as the next step to conservation voltage reduction (CVR), requires reevaluation. Implementation of a cluster-based VVO control strategy employs a novel approach with machine learning (ML) load forecasting to reduce device adjustments through k-means clustering of contiguous time steps with similar active power load in which a single adjustment would be sufficient. The cluster-based VVO method is tested on a complex real world utility distribution feeder with 2,018 nodes, 8.65MW peak load, 9 capacitor banks (CBs), and a load tap changer (LTC) at the substation transformer. Performance of the cluster-based VVO method for the circuit with high forecasted EV penetration is tested with comparison to a baseline case. Total reduction in energy consumption of 1.7% and 1.9% in the expected range of 1-4% with minimal tap changes over 24 hours was achieved by the cluster-based VVO method with and without EV charging, respectfully.**

***Index Terms*—Volt/Var Optimization (VVO), electric vehicle (EV), power distribution system (PDS)**

I. Introduction

In the United States, electricity must be delivered to consumers within the acceptable voltage range of 114-126V for normal 120V service [1]. Utilities maintain compliance through the operation of voltage-regulating devices such as capacitor banks (CBs), automatic voltage regulators (AVRs), and transformer load-tap-changers (LTCs). Improved control and management of these devices has been commonly associated with conservation voltage reduction (CVR), a traditional precursor to volt-var optimization (VVO).

As defined in [2], CVR describes the intentional operation of a power distribution system (PDS) to provide voltages at the lower end of the standard margin to reduce customer energy demand. Utilities have reported 1 to 4% reduction in energy demand from initial CVR deployment [3]. While CVR is a long-studied and well-established topic, emerging technologies such as distributed energy resources (DERs) and electric vehicles (EVs) may present new challenges for future field deployment [4], [5]. The authors of [6] claim that voltage control has more significant challenges for PDSs with high penetration of DERs (particularly solar PV) and EVs, and that many LTCs may be required.

Despite the voltage control challenges introduced, studies have found CVR to still be effective in power systems with high EV penetration. The authors of [7] achieved 3.3% energy demand reduction through implementation of model predictive CVR controls on a PDS with 20% EV penetration. In [8], coordination of CVR with EV demand control was simulated for a real PDS with reported energy savings of 4.2%. Other studies have proposed employing EV chargers and smart inverters to inject reactive power for improved VVO controls in grids with high EV and DER penetration. Energy demand reduction due to CVR was increased from 1.48% to 3.04% when dispatching EVs for reactive power injection for the simulation in [9].

The main objective of this study was to implement VVO on a real PDS with EVs using a new cluster-based method designed to optimally operate CBs and LTCs while novelly limiting the number of adjustments to prevent degradation. An optimization process with minimization objectives of active power demand and voltage buffer zone infringements was executed at the start of each cluster to select the superior combination of settings from multiple candidate designs. Application of the cluster-based VVO method for the PDS with and without EV charging was tested over a 24-hour period.

II. Power Distribution System and ZIP Load Modeling for Time Series Simulation

The circuit employed in this study, subsequently called KUs1T1, is part of a large real-world electric power distribution system and has 2,000+ nodes and a peak load greater than 8.5MW. More details are available in a different study for optimal capacitor placement by the extended group of authors [10]. The voltage-regulating devices of the circuit, i.e. nine CBs and an LTC at the substation transformer, were controlled according to a new ML clustering and optimization scheme with resulting VVO-based energy savings visualized in Fig. 1. Historical data measured at the substation and synthetically generated EV charging load profiles based on occupant travel patterns were applied to calculate community load through a series of time simulations. Equivalent load shape ratios were applied to peak active and reactive power at the main feeder.

To model the relationship between system power and voltage with constant impedance, current, and power (ZIP) load modeling was applied [11]. Individual ZIP load active and reactive power were calculated as follows:

$$p = p_0 \left[a_p \left(\frac{|v|}{v_0} \right)^2 + b_p \left(\frac{|v|}{v_0} \right) + c_p \right], \quad (1)$$

$$q = q_0 \left[a_q \left(\frac{|v|}{v_0} \right)^2 + b_q \left(\frac{|v|}{v_0} \right) + c_q \right], \quad (2)$$

where p is the active power; a_p, b_p, c_p, the first, second, and third ZIP parameters that must sum to 1; $|v|$, the voltage

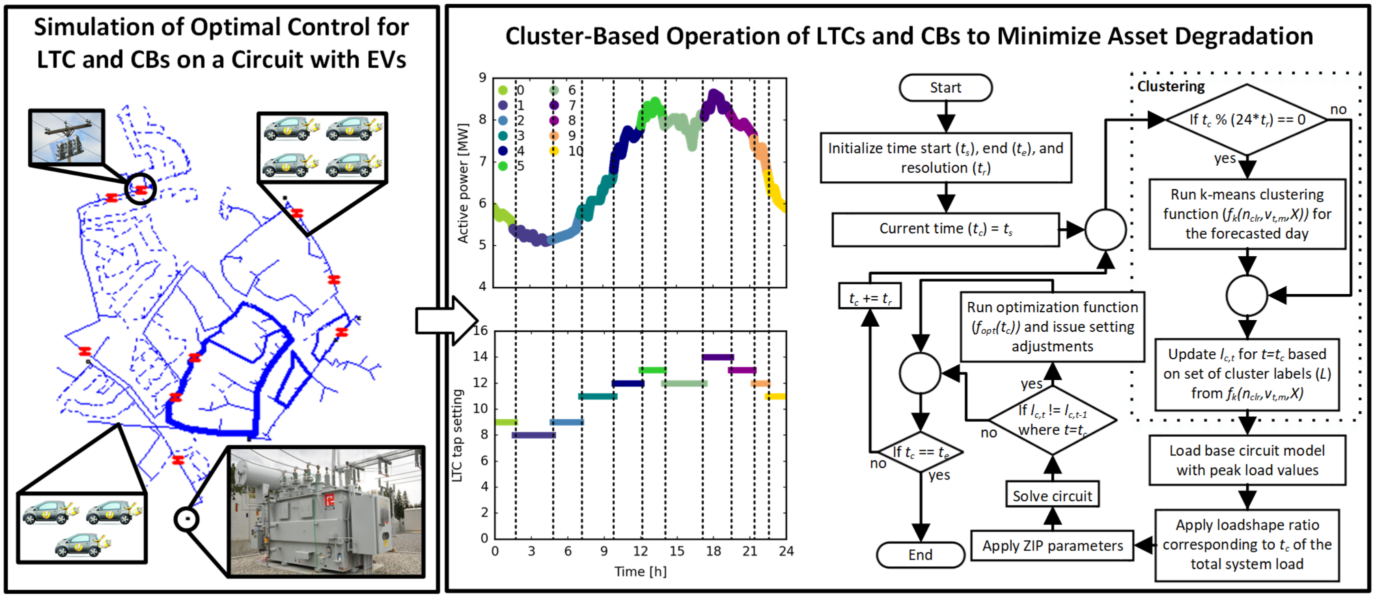

Fig. 1. A k-means clustering algorithm was employed to group timesteps of similar active power demand into clusters so that optimal CB and LTC settings remain effective as load changes over time. This novel approach requires only one adjustment per cluster and minimizes equipment degradation.

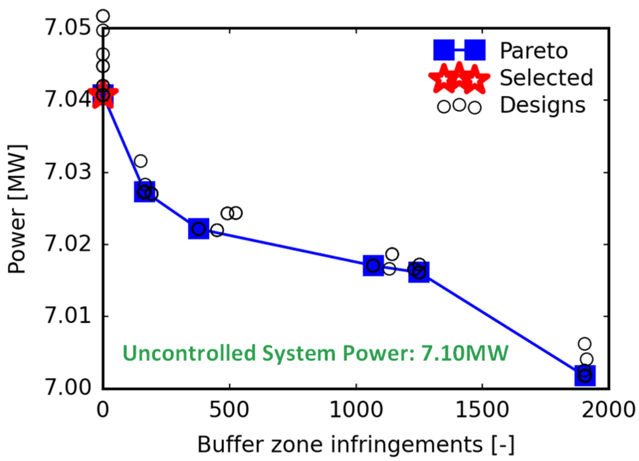

Fig. 2. Pareto front relationship between the minimization objectives of candidate designs for the first cluster of the EV charging case. For a conservative VVO case, the design with zero voltage buffer zone infringements and lowest average active power load was selected for each cluster.

magnitude; v_0, the base voltage; q, the reactive power demand of the load; a_q, b_q, c_q, the fourth, fifth, and sixth ZIP parameters that must also sum to 1. Following the method proposed by the authors in [12], ZIP models were applied for each individual load on the circuit. At each timestep, total system active and reactive power were calculated as the summation of the individual ZIP loads.

III. Cluster-Based Optimized Control Method

The proposed cluster-based optimal control method was designed to implement VVO while also considering equipment degradation by limiting the number of device adjustments. A k-means clustering algorithm was used to disperse setting adjustments over time by dividing contiguous time steps with

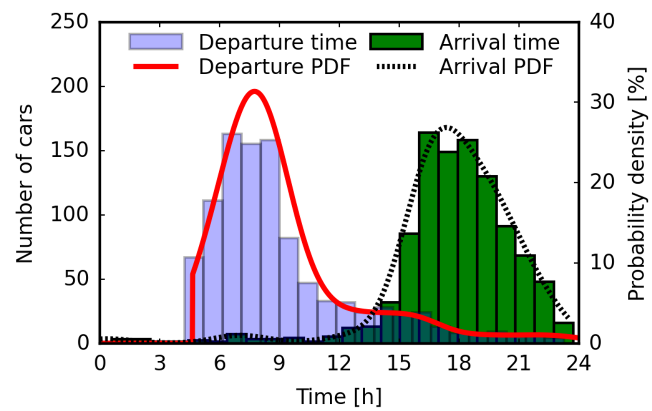

Fig. 3. Distribution of residential EV departure and arrival times from the 2017 NHTS dataset employed on KUs1T1s. Majority of vehicles likely unplug between 6 AM and 9 AM to depart and return for possible charging between 4 PM to 8 PM.

similar power demand into clusters. Forecasting was employed to select the optimal LTC and CB settings from multiple candidate designs within each cluster to minimize average active power demand and voltage buffer zone (0.95-0.975p.u.) infringements. These objectives were calculated as follows:

$$\min \left[n_{vio} = \sum_{t=1}^{n_{t,c}} \left\{ \sum_{b=1}^{n_b} (n_{vio,t,b}) \right\} \right], \tag{3}$$

$$\min \left[p_{\mu,c} = \frac{\sum_{t=1}^{n_{t,c}} (p_t + p_{ev})}{n_{t,c}} \right], \tag{4}$$

where $n_{t,c}$ is the total number of time steps within cluster c, $n_{vio,t,b}$, the total number of voltage buffer zone infringements for time t at bus b, n_b the total number of buses, p_t the total distribution system active power without EV charging

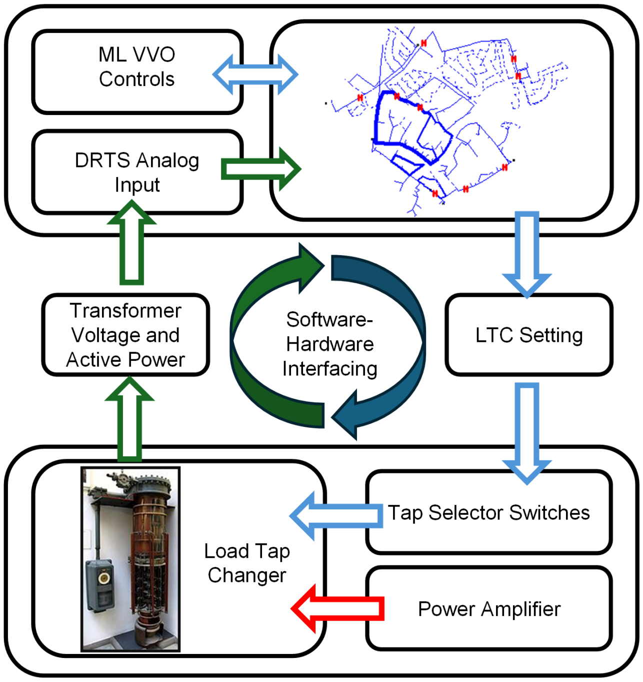

Fig. 4. Flowchart for HIL testing of the proposed cluster-based VVO method utilizing a DRTS (top) and hardware with an LTC (bottom). Blue, green, and red arrows represent control signals, measurements, and power input, respectively. Performance of CHIL may be tested by interfacing connections with a control board, while PHIL testing may be conducted with the addition of the LTC with a power amplifier.

including active power losses across lines and transformers at time t, and p_{ev} the total EV charging power demand.

Buffer zone infringements and power demand for candidate designs have an inverse relationship (Fig. 2). In this example conservative VVO case, the selected design was chosen to avoid bus voltages within the common VVO lower buffer region of 0.95-0.975p.u., while in future applications a more aggressive selection allowing infringements could lower active power demand further. The buffer zone was established to ensure voltage drop between the buses and loads does not drop below 0.95p.u. Depending on system requirements, designs with lower power demand may be selected from the Pareto if the buffer region has been reduced.

IV. Synthetic Generation of EV Charging Loads

Due to the limited availability of experimental residential EV charging data, EV power profiles for this study were synthetically generated based on human behavior. Data from the 2017 National Household Travel Survey (NHTS) was used to generate residential EV charging profiles. Home departure and arrival times with daily travel distances were randomly selected for participants from the Southeastern region of the United States to determine arrival state-of-charge (SOC) and charging start time. A charging level of 10kW, energy storage capacity of 100kWh, and 85% round-trip charging efficiency were assumed for each vehicle. These travel behaviors have been illustrated with the histogram in Fig. 3.

While the majority of residential EV charging typically occurs in the evening, smaller peaks in the morning may occur

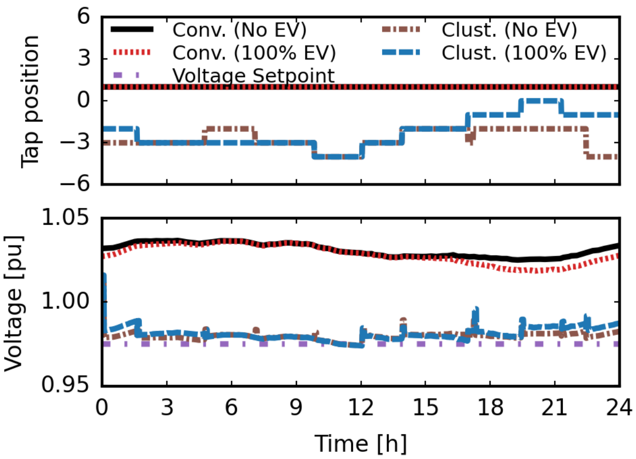

Fig. 5. Selected LTC tap positions (top) and average system bus voltage (bottom) for all simulated cases. For the EV case, higher tap positions were required to maintain the voltage setpoint in the early morning and evening due to increased EV charging demand.

due to occupants charging before their daily commute [13]. Additionally, time-of-use pricing models like those offered in California [14] increase evening electricity prices. This could result in more customers charging their EVs in the morning to avoid the higher pricing window. For the case study in Section VI, it was assumed that all EVs commuted for 7 days prior to charging; 50% of EVs charged upon home arrival the prior evening, continuing into the early morning of the simulated day; and the other 50% charged upon arrival from their daily commute on the simulated day.

V. Discussion of State-of-the-Art HIL Testing

Laboratory testing utilizing a hardware-in-the-loop (HIL) testbench may be employed to verify the application of the proposed VVO method on physical equipment. Implementation of HIL testing integrates real-time computers running simulated environments with hardware systems to analyze performance, safety, and many other test parameters for software and physical components before large-scale deployment [15].

Testing with HIL has the advantage of an isolated environment to accurately gauge the capabilities of virtual and physical systems independently of other components. This prevents interference from and damage to other systems while also providing a cost-effective and versatile experimentation method [15], [16]. Further applications of HIL, such as for power hardware-in-the-loop (PHIL) studies, include the simulation of large- and small-scale electric power distribution systems, which can be applied, for example, to analyze the impacts of EV DC fast chargers on the grid [17].

One HIL study in literature utilized a digital real-time simulator (DRTS) to test voltage regulation methods in distribution systems by interfacing with a load control system, a voltage regulation controller, and an inverter air conditioner, where active and reactive power deviation was used to measure effectiveness [18]. In another study, control hardware-in-the-loop (CHIL) simulations modeled a microgrid using a DRTS to

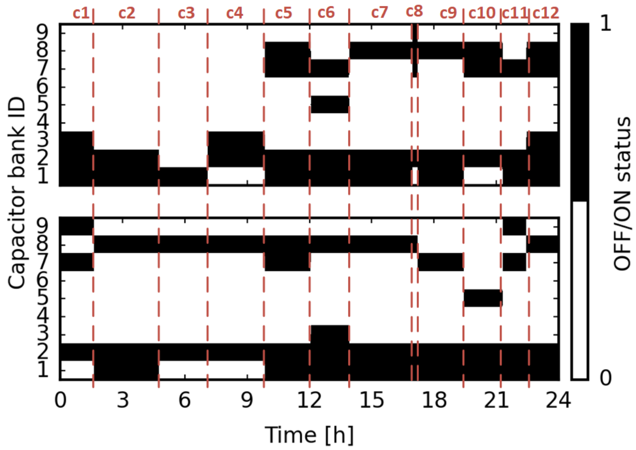

Fig. 6. Optimally-selected CB controls by the cluster-based VVO method without (top) and with (bottom) EV charging. Settings were assumed to be applicable for all timesteps within a cluster, so one adjustment per CB was permitted for each cluster.

demonstrate the difficulties faced by LTCs in automatic island operation, simulating causes for microgrid blackouts during overvoltage and undervoltage events [19].

These approaches enable the next step of performance evaluation for the cluster-based VVO method following software case studies, i.e. implementation on physical devices through PHIL testing. Fig. 4 presents the proposed software-hardware interface for a HIL testbench that utilizes a DRTS and a physical LTC unit. The DRTS would interface with the ML VVO controller and send signals to the LTC, which then may be monitored for voltage, current, and power responses. These measurements may be used to determine if the intended power control was maintained and if voltage violations would occur on the system. Both power and control HIL tests may be implemented to determine effectiveness of the proposed method when tested on physical devices, including performance during peak load conditions or the response time of the transformer's automatic switching driven by the cluster-based controls.

VI. Case Study: Cluster-Based Optimized VVO on a Distribution Circuit with High EV Penetration

Four cases were simulated for the KUs1T1 circuit modified with EV charging loads: conventional control without EV, conventional control with EV, cluster-based optimal control without EV, and cluster-based optimal control with EV. Conventional control only executed CB and LTC adjustments if voltage was outside the acceptable margin of 0.95-1.05p.u. and serves as the baseline for comparison with the cluster-based control cases. The cluster-based method discussed in Section III was employed to implement VVO while also limiting device adjustments. In the EV cases, one charging profile was assigned to each load on the circuit for 100% EV penetration.

The average system voltage and substation transformer LTC position for the simulated cases are shown in Fig. 5. In the EV cluster case, increased demand due to EV charging resulted in lower system voltage during evening hours, thus, a higher LTC tap position was selected than the non-EV cluster case from 17:00-24:00. While there were zero system voltage violations under cluster-based control in either case, the number of time steps with at least one bus voltage in the buffer zone threshold (0.95-0.975p.u.) was higher in the EV case (606) than the non-EV case (493). The CB settings were changed once per cluster following the proposed ML clustering to preserve the equipment while maintaining optimal voltage and power control objectives (Fig. 6).

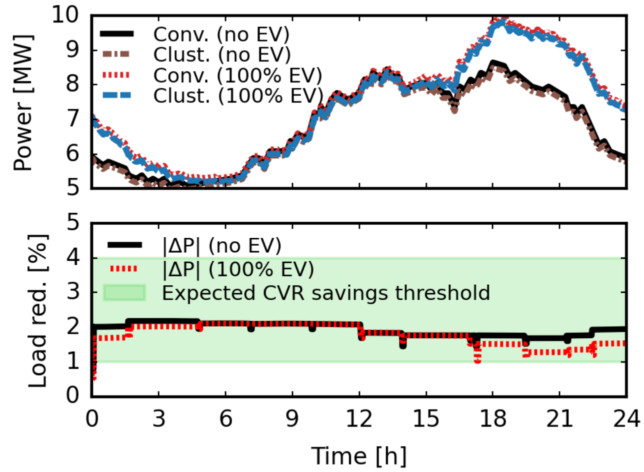

Fig. 7. System active power load for all control cases (top) and the percent load reduction of cluster-based VVO from the conventional control method with and without EV charging (bottom). While both cases maintained the expected 1-4% CVR savings threshold, performance was reduced during the early morning and evening hours when EV charging load was the highest.

In terms of percent energy reduction from conventional control, the cluster-based method performed similarly well with and without EV charging, where total energy consumption was reduced by 1.7%, and 1.9% respectively. As shown in Fig. 7, the percent active power reduction by the cluster-based method for the EV case was slightly lower during the early morning and evening hours when charging demand was high. For the EV case, total energy reduction remained within the 1-4% expected CVR savings range reported by utilities with a comparable number of device adjustments to the non-EV case. There were a total of 40 LTC and CB adjustments in the non-EV case, which was approximately equivalent to the 41 in the EV case and shows the robustness of the cluster-based control method. The count for total number of LTC and CB adjustments executed along with the total system reactive power during the simulation are visualized Fig. 8.

VII. Conclusion

Experimental historical data, synthetically generated EV charging profiles, and ZIP modeling were employed to execute time series simulation and capture individual load dependency on voltage for a real utility PDS with thousands of nodes. The proposed cluster-based method was used to implement VVO while minimizing device adjustments for the PDS with and without EV charging. Optimal device settings were selected for each cluster from a Pareto front of candidate designs for

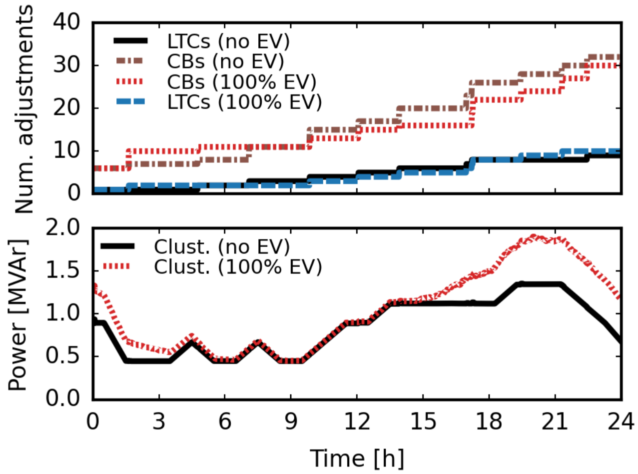

Fig. 8. Total number of LTC and CB adjustments (top) and system reactive power load (bottom) for the cluster-based method with and without EV charging. Both cases achieved VVO with a similar number of utility device adjustments, which was 40 and 41 with and without EV charging respectfully.

minimization objectives of active power load and number of bus voltage buffer zone infringements.

The proposed cluster-based VVO method was effective on the real large-scale distribution system even with high EV penetration. The total energy demand was reduced by 1.7% with zero voltage violations, which was slightly lower than the 1.9% without EV charging. The expected 1-4% savings from CVR reported by utilities was achieved while implementing 40 and 41 total utility device adjustments for the EV and non-EV cases respectfully. The energy savings realized translated to over $37,000 per year for the tested circuit when calculated using the 2023 average wholesale energy price reported by the Energy Information Administration [20]. Following this procedure and example, representative circuits may be identified and the results may be extrapolated for very large regions and nationally, indicating the major potential for large savings and improvements. These results indicated that the cluster-based VVO method was robust enough to perform well under typical and high EV penetration while also maintaining the benefit of minimal equipment degradation.

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