Data-Driven Preemptive Voltage Monitoring and Control Using Probabilistic Voltage Sensitivities

Preprint

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To be presented at the 2019 IEEE Power and Energy Society General Meeting (IEEE PES GM)
Atlanta, Georgia
August 4–8, 2019

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Contract No. DE-AC36-08GO28308

Conference Paper
NREL/CP-5D00-72661
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Suggested Citation

Jhala, Kumarsinh, Venkat Krishnan, Balasubramaniam Natarajan, and Yingchen Zhang. 2019. *Data-Driven Preemptive Voltage Monitoring and Control Using Probabilistic Voltage Sensitivities: Preprint*. Golden, CO: National Renewable Energy Laboratory. NREL/CP-5D00-72661. https://www.nrel.gov/docs/fy19osti/72661.pdf.

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This work was authored in part by the National Renewable Energy Laboratory, operated by Alliance for Sustainable Energy, LLC, for the U.S. Department of Energy (DOE) under Contract No. DE-AC36-08GO28308. Funding provided by U.S. Department of Energy Grid Modernization Laboratory Consortium. The views expressed herein do not necessarily represent the views of the DOE or the U.S. Government. The U.S. Government retains and the publisher, by accepting the article for publication, acknowledges that the U.S. Government retains a nonexclusive, paid-up, irrevocable, worldwide license to publish or reproduce the published form of this work, or allow others to do so, for U.S. Government purposes.

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Data-Driven Preemptive Voltage Monitoring and Control Using Probabilistic Voltage Sensitivities

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***Abstract*—Increased penetration levels of distributed variable renewable generation can cause random voltage fluctuations and violations at multiple nodes. Traditional methods of voltage control typically involve reactionary responses of capacitor banks, tap changers, and recently even smart inverters. But because of the lack of foresight in voltage violations, these controls are ineffective to completely mitigate the issue. Therefore, new methods of predicting voltage violations subject to random power injection changes in the distribution network are needed, which can be used to guide optimal and dynamic methods of voltage control. This work lays the foundation for such preemptive voltage monitoring and control by proposing an analytical and sensor data-driven voltage sensitivity analysis method. Driven by stochastic data and forecasts, the method can be used to develop probabilistic voltage sensitivities and consequently to predict system nodes with high likelihood of voltage limit violations. The effectiveness of this method is tested on IEEE 69-node distribution system integrated with distributed solar. The results demonstrate the proposed method's ability to successfully predict nodes with high probability of voltage violations for a specific time-series simulation. The results also demonstrate the ability to guide timely power injection control actions to mitigate future voltage violations.**

***Index Terms*—Distributed Generation, Distribution System, Sensitivity, Sensor Measurement, Voltage**

I. Introduction

The power system is evolving significantly with the proliferation of new smart grid technologies. Increased penetration of renewable generation, electric vehicles and active consumers at the grid edge create new challenges as well as opportunities. More specifically, the distribution grid is anticipated to experience random fluctuations in voltages and even ANSI limit violations under higher penetrations of rooftop photovoltaics (PV) [1], [2]. Traditional methods of voltage control such as on-load tap-changing transformers, voltage regulators and capacitor banks are not designed for bi-directional current flow, and typically are controlled to provide reactive support after an event is detected [3]. Additionally, under increasing levels of variable renewable, sole dependence on the installation of more traditional voltage control devices may not be viable [4], [5]. Therefore, extensive research have looked into utilizing the reactive power capabilities of PV systems by integrating them via smart inverters under either centralized [6]–[10] or decentralized [11]–[13] control approaches. IEEE 1547 (2018) standards and utilities have also begun to look into such smart inverter options to mitigate voltage violations. Studies [14] have shown Volt-Var and Volt-Watt options provide much-needed grid support; however, these strategies also provide reactionary support post-event, and testing studies [15] have shown them to not eradicate voltage violations completely given the maximum allowable limits of reactive power provisions and/or real power curtailments.

Therefore, a computationally efficient preemptive voltage control mechanism is needed that predicts future voltage and their uncertainty bounds and guides preventive actions in power distribution systems interconnected with renewable generation. This paper considers a power distribution system with multiple active consumers with flexible load and generation participating in demand response program with third-party aggregators. Goal of this work is to develop a data-driven approach to predict nodes with high probability of voltage violation and devise a preemptive control action by modifying consumer load/generation to prevent steady-state voltage violations.

In order to predict voltage responses, this paper assumes the availability of voltage and power measurements from all nodes in the distribution system, and uses them to estimate probabilistic sensitivities of node voltages with respect to real and reactive power injection changes at various nodes. The probabilistic sensitivities will be used to dynamically predict nodes with high probability of voltage violations [16], [17] as well as mitigate them using a preemptive control strategy that modifies nodal injections (load/generation). Major contributions of this paper are listed below.

- Develops an analytical expression to compute the upper bound of change in voltage resulting from change in complex power at multiple nodes [16], which is computationally efficient and dynamic with use of sensor data.
- Provides a probabilistic voltage sensitivity analysis-based

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This work was authored in part by the National Renewable Energy Laboratory, operated by Alliance for Sustainable Energy, LLC, for the U.S. Department of Energy (DOE) under Contract No. DE-AC36-08GO28308. Funding provided by the U.S. Department of Energy Grid Modernization Initiative (GMI) under the project GMLC 1.2.5 Sensing and Measurement Strategy. The views expressed in the article do not necessarily represent the views of the DOE or the U.S. Government.

method that predicts probability of future voltage subject to forecasts and detects highly vulnerable nodes (sec. III).

- A simple preemptive voltage control mechanism in IEEE 69-node system where the accuracy and effectiveness of voltage prediction and control is tested. (section IV).

II. Background: Voltage Sensitivity Estimation

Voltage sensitivity analysis estimates change in complex voltage at a given node (observation node o) due to change in complex power at another node (actor node a) in a power distribution system. Traditionally, voltage sensitivity is calculated using Newton-Raphson load flow method (from the Jacobian or its eigenvectors) or perturb-and-observe method [18]. Both methods are numerical and computationally complex. This section presents an analytical upper bound for voltage change at an observation node (ΔV_o) due to change in complex power at an actor node (ΔS_a) in a radial distribution network for constant power model of loads, originally developed in [16]. When an actor node (a) changes its complex power from S_a to $S_a + \Delta S_a$, voltage at the observation node changes from V_o to $V_o + \Delta V_{oa}$, which can be calculated from Theorem 1. Here ΔV_{oa} is change in complex voltage at the observation node o due to change in complex power at the actor node a.

Theorem 1. *For a radial power distribution network, change in voltage at an observation node due to change in power of an actor node is upper bounded by*

$$\Delta V_{oa} \leq -\frac{\Delta S_a Z_{oa}}{V_a^*}, \tag{1}$$

where V_a^* is complex conjugate of voltage at the actor node; and Z_{oa} is impedance of shared line between the observation node o and the actor node a from the source node.

Proof. see [16] □

Here, inequality sign for complex number indicates the upper bound on real and imaginary values. Equation (1) provides a linear upper bound on generally non-linear power flow calculations. This notation is used throughout the paper. Effect of multiple actor nodes on the observation node voltage can be calculated using the following lemma.

Lemma 1. ***Superposition Law:*** *If $\mathcal{A}$ is a set of actor nodes in the network, effective change in complex voltage at the observation node due to the cumulative effect of all the actor nodes is bounded by (2).*

$$\Delta V_o \leq \sum_{a\in\mathcal{A}} -\frac{\Delta S_a Z_{oa}}{V_a^*}, \tag{2}$$

where $\mathcal{A}$ is set of all the actor nodes.

Proof. see [16] □

This lemma proves that the proposed analytical method represented by (2) holds the law of superposition. The analytical equation derived in Lemma 1 can be used to calculate the probability distribution of voltage change at any given node in the power distribution system. Calculating sensitivity matrix for the IEEE 69-node test system using the classical load-flow method takes 4.52 seconds, whereas using the proposed analytical method takes only 0.58 seconds [16]. This paper further advances the application of these sensitivities for dynamic prediction of future power states, by integrating phasor data from sensors and renewable forecasts. Impact of sensing errors are not considered.

III. Preemptive Analysis: Prediction and Control

The analytical sensitivity estimation method presented in Section II is used as the basis for developing data-driven probabilistic voltage sensitivity analysis for predicting the probability of voltage violation at a given node. We make an assumption that complex power and voltage measurements (or estimations) are available at each node of the balanced three phase distribution system in real time.

Random changes in power drawn/injected by active consumers with renewable generation cause random voltage fluctuations, which makes voltage at any given node in the distribution system random. This work assumes normal distribution for power injection changes. Let V_o^p be current value of complex voltage at any observation node o, which is obtained from measurements or state estimation, and V_o^f represent the predicted future complex voltage at node o. Due to the variability and uncertainty introduced by renewable generation in power system, V_o^f is random and can be written as:

$$V_o^f = V_o^p + \Delta V_o, \tag{3}$$

where ΔV_o is random change in complex voltage at observation node due to random changes in net power injections. Change in real and imaginary part of voltage at an observation node due to change in complex power at an actor node can be written as:

$$\Delta V_{oa} = \Delta V_{oa}^r + i\Delta V_{oa}^i, \tag{4}$$

where

$$\begin{aligned}\Delta V_{oa}^r = -\frac{1}{|V_a|}\big(&\Delta P_a(R_{oa}\cos\theta_a - X_{oa}\sin\theta_a) \\ &-\Delta Q_a(R_{oa}\sin\theta_a + X_{oa}\cos\theta_a)\big),\end{aligned} \tag{5}$$

and

$$\begin{aligned}\Delta V_{oa}^i = -\frac{1}{|V_a|}\big(&\Delta Q_a(R_{oa}\cos\theta_a - X_{oa}\sin\theta_a) \\ &+\Delta P_a(R_{oa}\sin\theta_a + X_{oa}\cos\theta_a)\big).\end{aligned} \tag{6}$$

From superposition law (Lemma 1), change in voltage at an observation node due to cumulative effect of multiple actor nodes can be written as sum of changes in voltage at the observation node due to every actor node.

$$\Delta V_o = \sum_a \Delta V_{oa} = \sum_a \Delta V_{oa}^r + i\sum_a \Delta V_{oa}^i, \tag{7}$$

Behavior of nodal net-loads in a distribution network integrated with variable renewables can be modeled as random variables. In this work, change in real and reactive power injections at a distribution system node is modeled as Gaussian random variable. Let $\Delta S = [\Delta P_1, \cdots, \Delta P_n, \Delta Q_1, \cdots, \Delta Q_n]^T$ be a Gaussian random vector with mean μ and covariance matrix $\mathbf{\Sigma}$. Here, mean of real and reactive power reflects forecast of future net-load changes (i.e., estimated using load and renewable generation forecasts). The covariance matrix will be estimated using historical data, supplemented with probabilistic forecasts that provide variances of forecasts around the mean [19]. The cross-correlations could be estimated by generating scenarios of random forecasts for various locations, and estimating their cross-correlations. Additionally, the effect of spatial correlation of variable renewables is captured by the off-diagonal elements of the covariance matrix. Detailed modeling of variability and uncertainty in the voltage sensitivity assessment is beyond the scope of this paper, but will be undertaken for future work.

A. Computing Voltage Sensitivity Probability Distribution

Given the normal distribution assumption for power injection changes, the resultant voltage sensitivity is also expected to be normally distributed due to their linear relationship modeled by equations (5) and (6) [20]. This section further elaborates the estimation of $|\Delta V_o|$ distributions using following steps:

1) Define Σ, and compute vectors $\mathbf{C_r}$ and $\mathbf{C_i}$:

$$\mathbf{\Sigma} = \begin{bmatrix} \sigma_{p1}^2 & \cdots & \mathrm{cov}(pn, p1) & \mathrm{cov}(q1, p1) & \cdots & \mathrm{cov}(qn, p1) \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ \mathrm{cov}(p1, pn) & \cdots & \sigma_{pn}^2 & \mathrm{cov}(q1, pn) & \cdots & \mathrm{cov}(qn, qn) \\ \mathrm{cov}(p1, q1) & \cdots & \mathrm{cov}(pn, q1) & \sigma_{q1}^2 & \cdots & \mathrm{cov}(qn, p1) \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ \mathrm{cov}(p1, qn) & \cdots & \mathrm{cov}(pn, qn) & \mathrm{cov}(q1, qn) & \cdots & \sigma_{qn}^2 \end{bmatrix} \tag{8}$$

where n is number of nodes in the network. For nodes that do not have PV, values of variance can be set to zero. In this work, we assume that network topology is known. Value of complex bus voltages is gathered from measurements and values of line impedance are assumed to be known from network topology. The vectors C_r and C_i are defined and computed as follows, using equations (9) and (10). Values of C_r and C_i can be computed as following.

$$\mathbf{C_r} = \begin{bmatrix} -\frac{R_{o1}\cos\theta_1 - X_{o1}\sin\theta_1}{|V_1|} \\ \vdots \\ -\frac{R_{on}\cos\theta_n - X_{on}\sin\theta_n}{|V_n|} \\ \frac{R_{o1}\sin\theta_1 + X_{o1}\cos\theta_1}{|V_1|} \\ \vdots \\ \frac{R_{on}\sin\theta_n + X_{on}\cos\theta_n}{|V_n|} \end{bmatrix}, \tag{9}$$

$$\mathbf{C_i} = \begin{bmatrix} -\frac{R_{o1}\sin\theta_1 + X_{o1}\cos\theta_1}{|V_1|} \\ \vdots \\ -\frac{R_{on}\sin\theta_n + X_{on}\cos\theta_n}{|V_n|} \\ -\frac{R_{o1}\cos\theta_1 - X_{o1}\sin\theta_1}{|V_1|} \\ \vdots \\ -\frac{R_{on}\cos\theta_n - X_{on}\sin\theta_n}{|V_n|} \end{bmatrix}. \tag{10}$$

2) Compute distribution of ΔV_o^r and ΔV_o^i: Real and imaginary part of change in voltage at an observation node can be written as weighted sum of elements of vector ΔS as depicted by equation (11) and (12). Weighted sum of Gaussian random variables are normally distributed. Therefore, probability distribution of ΔV_o^r and ΔV_o^i can be derived as follows

$$\Delta V_o^r = \sum_a \Delta V_{oa}^r = \mathbf{C_r^T \Delta S} \sim \mathcal{N}(\mathbf{C_r^T}\mu, \mathbf{C_r^T \Sigma C_r}) \tag{11}$$

$$\Delta V_o^i = \sum_a \Delta V_{oa}^i = \mathbf{C_i^T \Delta S} \sim \mathcal{N}(\mathbf{C_i^T}\mu, \mathbf{C_i^T \Sigma C_i}) \tag{12}$$

3) Define bi-variate normal vector $\mathbf{\Delta \hat{V}_o}$: Covariance between ΔV_o^r and ΔV_o^i can be written $\mathrm{cov}\left(\Delta V_o^r, \Delta V_o^i\right) = \mathbf{C_r^T \Sigma C_i}$. Therefore, the change in real and imaginary part of voltage change will be a bi-variate normal vector, i.e.

$$\mathbf{\Delta V_o} \triangleq \begin{bmatrix} \Delta V_o^r \\ \Delta V_o^i \end{bmatrix} \sim \mathcal{N}\left(\mu_\mathbf{1}, \mathbf{\Sigma_1}\right) \tag{13}$$

where,

$$\mu_\mathbf{1} = \begin{bmatrix} \mathbf{C_r^T}\mu \\ \mathbf{C_i^T}\mu \end{bmatrix}, \mathbf{\Sigma_1} = \begin{bmatrix} \mathbf{C_r^T \Sigma C_r} & \mathbf{C_r^T \Sigma C_i} \\ \mathbf{C_r^T \Sigma C_i} & \mathbf{C_i^T \Sigma C_i} \end{bmatrix} \tag{14}$$

4) Calculate probability distribution of $\mathbf{V_o^f}$: Let $\mathbf{V_o^f}$ be vector of real and imaginary part of future voltage at node o defined as:

$$\mathbf{V_o^f} \triangleq \begin{bmatrix} V_o^{rf} \\ V_o^{if} \end{bmatrix} = \begin{bmatrix} V_o^{rp} \\ V_o^{ip} \end{bmatrix} + \begin{bmatrix} \Delta V_o^r \\ \Delta V_o^i \end{bmatrix} \tag{15}$$

Voltage at observation node in next time slot $\mathbf{V_o^f}$ can be written as Gaussian random vector as following.

$$\mathbf{V_o^f} \sim \mathcal{N}\left(\begin{bmatrix} V_o^{rf} + \mathbf{C_r^T}\mu \\ V_o^{if} + \mathbf{C_i^T}\mu \end{bmatrix}, \begin{bmatrix} \mathbf{C_r^T \Sigma C_r} & \mathbf{C_r^T \Sigma C_i} \\ \mathbf{C_r^T \Sigma C_i} & \mathbf{C_i^T \Sigma C_i} \end{bmatrix} \right) \tag{16}$$

The covariance matrix, voltage measurements and forecasted change in mean power injections will be updated as new forecasts and sensor data are available. This process will be continued for future estimations of voltage at some regular time intervals (though in this work, for a given time series simulation, such an update is not done for simplicity of illustration).

B. Detecting Vulnerable Nodes and Preemptive Control

Equation (16) shows that $|V_o^f|$ is Gaussian random variable with numerically computed mean and variance, which can be used to find probability of voltage violation. Let $\mathbb{P}_o(t)$ be the probability of voltage violation at node o at time t defined as:

$$\mathbb{P}_o(t) = 1 - P(0.95 < |V_o^f| < 1.05). \tag{17}$$

Performing this calculation for each node in the distribution system, we can identify nodes that have probability of voltage violation. After identifying nodes that are highly vulnerable to voltage violation an effective voltage control action can be taken. To test effectiveness of the proposed method, a voltage sensitivity-based heuristic voltage control approach is considered, where an upper bound on maximum power drawn/injected is enforced for nodes that are vulnerable to voltage violation. In a case where node is vulnerable to high-voltage violation, amount of power injected by the node into the grid is upper bounded by $x\%$ of current power injection for future time period. Similarly, in a case where node vulnerable to low-voltage violation, amount of power drawn from the grid is upper bounded by $x\%$ of current power for future time period. The amount of power injection change is estimated based on voltage sensitivity information. Let $\mathcal{N}(t)$ be set of nodes that are vulnerable to voltage violation at time t, and ΔV^t be voltage change required to mitigate voltage violation at node with highest/lowest voltage in case of over/under-voltage violations in the neighborhood. Eliminating highest voltage violation should result in elimination of voltage violation at most of the nodes in the neighborhood. This procedure will be undertaken iteratively until a premptive power injection control strategy for eliminating all violations is estimated. To ensure fairness between nodes, generation at all nodes is reduced by same amount. Percentage load/generation curtailment can be computed as following:

$$\Delta V^t \geq - \sum_{a \in \mathcal{N}} \frac{x S_a Z_{oa}}{V_a^*} \tag{18}$$

$$x \leq - \frac{\Delta V^t}{\sum_{a \in \mathcal{N}} \frac{S_a Z_{oa}}{V_a^*}} \tag{19}$$

Here ΔV^t is selected such that the probability of voltage violation (equation (17)) is less than the threshold used to identify nodes that have high probability of voltage violation. In ideal situation, an optimal control strategy will utilize this algorithm to estimate the time for which such power injection change has to be done. But an optimal control strategy is beyond the scope of this paper. However to show the value of having voltage violation foresight, we impose a simple 2-hour time period over which the estimated power injection changes will be implemented.

IV. Simulation and Results

To test proposed voltage violation prediction algorithm an IEEE 69 bus test system is considered [16]. Synthetic sensor data is produced using power flow solutions. A hypothetical scenario is considered from noon to 6 p.m. with voltage and power data available every 5-minute interval. MicroPMUs and other distribution level sensors are capable of providing voltage and power measurements at higher rate; however, for simplicity of demonstration 5-minute interval is considered. Roof top PVs in 20 nodes with varying generation capacity are considered. Solar generation is modeled as random process with some trend and seasonality components that reflect real world scenario as shown in equation (20) [21]–[24].

$$P_{solar}(t) = S(t) + n_s(t) \tag{20}$$

Here, $S(t)$ is PV generation mean forecast trend, and $n_s(t)$ is zero mean Gaussian random variable that models variability and uncertainties. Gaussian random noise in solar generation is correlated across different nodes to reflect spatial correlation of solar generation. In this simulation, synthetic solar generation data is generated dynamically to reflect real world scenario. Correlation coefficient of solar generation is chosen as 0.7. Load at each node is synthetically produced based on typical

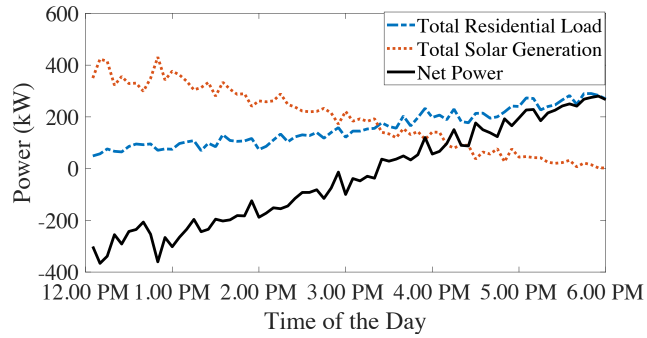

Fig. 1: Total load and generation

load profile of residential household. Figure 1 shows load, solar generation and net power of the distribution system. The figure shows that load is lowest and PV generation is highest at noon resulting in negative net power. This reverse power flow causes high-voltage violations in parts of the distribution system. For simplicity, this work considers a scenario where no low-voltage violations occur. However, the proposed preemptive voltage control algorithm is general enough to apply in case where high or low-voltage violations occur.

The aggregator receives power injection and voltage measurements at all nodes. This information along with bus impedance data is used to compute voltage sensitivity matrix using proposed analytical method of voltage sensitivity analysis discussed in section II in a computationally efficient manner. The mean and variance of real and imaginary part of voltage change at each node is estimated analytically as shown in section III. Vectors $\mathbf{C_r}$ and $\mathbf{C_i}$ are computed based on network topology and synthetic measurement data. Covariance matrix $\mathbf{\Sigma}$ is estimated based on probabilistic variance of historical data. Based on node voltage measurements and calculated probability distribution of voltage change, the probability of high and low-voltage violation is computed numerically. Nodes that have probability of voltage violation greater than threshold are classified as highly vulnerable nodes for voltage violation perspective. In this illustration, nodes that have probability of voltage violation more than 50% are considered as highly vulnerable. Number of voltage violation in the system every time slot are shown in Figure 2 by blue bars. Red stem plot in Figure 2 shows number of voltage violations predicted by proposed method, based on nodes with probability of voltage violation greater than 50%. The proposed method predicts nodes vulnerable to voltage violation accurately, thereby giving a foresight to system operators for optimal control.

To demonstrate preemptive control, a voltage sensitivity based heuristic voltage control method is used. An upper bound on power injected into the grid is enforced for next two hours for nodes that are identified as highly vulnerable to voltage violations. Value of upper bound is calculated using equation (19), which is 65% of power injected into the grid. Figure 3 shows voltage at node 65 of IEEE 69 bus test system with and without (no foresight or prediction) preemptive voltage control. Figure 3 shows that proposed method successfully eliminates high-voltage problems.

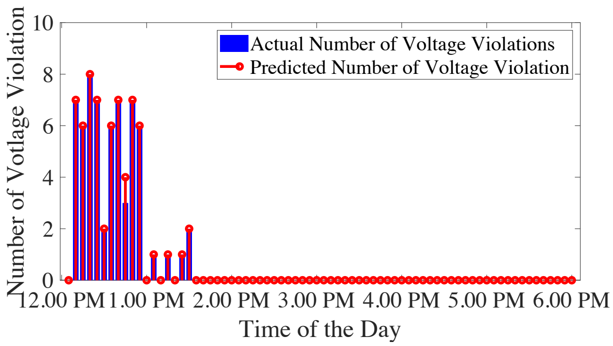

Fig. 2: Number of voltage violations

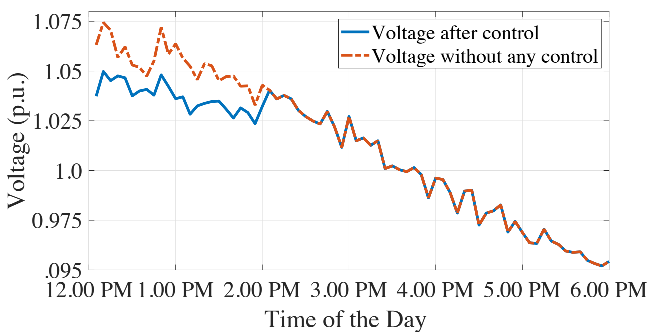

Fig. 3: Voltage at node 65 before and after control

V. Conclusion and Future-work

This paper develops a preemptive voltage control method that mitigates voltage violation in a power distribution system with renewable generation by taking a control action before actual voltage violation. This paper uses an analytical method of voltage sensitivity analysis with phasor measurements and nodal power injection forecasts to compute probability of future voltage violations. With this foresight, vulnerable nodes prone to voltage violations are detected (greater than certain probability of voltage violation), and appropriate power injection control actions can be taken. The paper illustrated a simple preemptive control approach that is capable of mitigating future voltage issues altogether, thereby laying the foundation for future investigations on real-time optimal control strategies. Related future work will also include improving voltage sensitivities prediction using empirical probabilities (rather than gaussian distributions) and developing methods to ensure complete system observability even under sparse sensor proliferation scenarios.

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