Short-Term State Forecasting-Based Optimal Voltage Regulation in Distribution Systems

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Short-Term State Forecasting-Based Optimal Voltage Regulation in Distribution Systems

Rui Yang, *Member, IEEE*, Huaiguang Jiang, *Member, IEEE*, and Yingchen Zhang, *Senior Member, IEEE*

***Abstract*—A novel short-term state forecasting-based optimal power flow (OPF) approach for distribution system voltage regulation is proposed in this paper. An extreme learning machine-based state forecaster is developed to accurately predict system states (voltage magnitudes and angles) in the near future. Based on the forecast system states, a dynamically weighted three-phase AC OPF problem is formulated to minimize the voltage violations with higher penalization on buses which are forecast to have higher voltage violations in the near future. By solving the proposed OPF problem, the controllable resources in the system are optimally coordinated to alleviate the potential severe voltage violations and improve the overall voltage profile. The proposed approach has been tested in a 12-bus distribution system, and the simulation results are presented to demonstrate the performance of the proposed approach.**

I. Introduction

Voltage regulation has been a critical issue in distribution system operations. The recent development and integration of distributed energy resources (DERs) and smart loads has made distribution systems increasingly flexible, active, and variable, thus presenting new opportunities while bringing new challenges to distribution system voltage control [1]–[3].

With the increased presence of DERs in distribution systems, regulating the system voltage within the acceptable range becomes more difficult, as DERs may cause more significant voltage violations in the system [4]. Furthermore, voltage violation patterns vary significantly both spatially and temporally, due to the rapid fluctuations of DER output. In order to mitigate the voltage violations which may occur in the near future, it is desired that the distribution system operator have the capability to foresee the future system states (voltage magnitudes and angles) and determine the best control actions in advance.

Although resource and demand forecasting has been well studied before [5]–[9], distribution system state forecasting presents unique challenges and has received less attention in prior research. Therefore, state forecasting approaches are in need to accurately predict the near-term system states [10].

With information on future system states, the distribution system operator is able to prioritize the control needs and better coordinate the control efforts against the potential voltage violations. Hence, a better understanding of the future grid states will help the system operator better prepare for potential voltage violations. However, there is a lack of studies on how a better voltage profile can be achieved given more information on possible system states.

In this paper, a short-term state forecasting-based optimal power flow (OPF) approach for voltage regulation is proposed. Based on the forecast system states, a dynamically weighted three-phase AC OPF problem is formulated to mitigate the potential voltage violations and improve the overall voltage profile in the near future by optimally coordinating all the controllable resources in the system. Specifically, we first build an extreme learning machine (ELM) based state forecasting model using historical data. The model is then used to predict system states in the near future. The predicted system state violations are then transformed into dynamic weights in the objective function in the voltage regulation problem. As such, buses which are more likely to have voltage violations are prioritized by being assigned higher weights, whereas less weights are assigned to buses which are less likely to have violations. The resulting dynamically weighted OPF problem is then solved to achieve a better voltage profile by optimally coordinating all the available resources in the system. Hence, the proposed approach allows the system operator to dynamically prioritize its control needs and optimally determine the control actions according to the possible system states and potential voltage violations which may occur in the near future.

The rest of the paper is organized as follows: Section II provides an overview of the proposed short-term state forecasting-based OPF approach for voltage regulation. In Section III, the state forecast model is discussed. The OPF formulation for voltage regulation and the weight assignment according to the state forecast is described in Section IV. Simulation results are presented in Section V. Section VI concludes the paper.

II. Proposed Approach

Fig. 1 gives an overview of the proposed approach. Every 5 minutes, a state forecaster is employed to predict the system voltages in the near future using historical system states. Based on the potential voltage violations in the next 5 minutes, different weights associated with the voltages across the system are dynamically chosen and fed into the OPF problem. The OPF problem to minimize the voltage violations is then solved by the system operator, which determines the optimal schedule of the controllable resources in the system. In this paper, the considered controllable resources include the utility-scale photovoltaic (PV) plants equipped with advanced inverter technologies whose active and reactive power generation could be controlled and smart loads with flexible power consumption.

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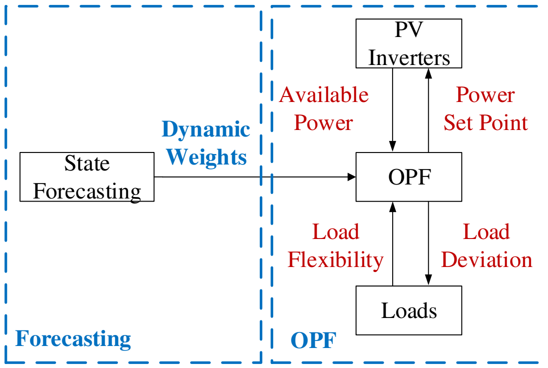

Fig. 1. Overview of the proposed approach.

III. Short-Term State Forecasting

In this paper, an ELM-based approach is used to provide the future distribution system states. The ELM has certain advantages compared to conventional machine learning methods such as artificial neural network (ANN) and support vector machine (SVM). In the traditional neural network-based approaches, the parameters such as input weights, hidden layer biases, and output coefficients are usually trained by a back-propagation learning algorithm. This training algorithm is time-consuming and easy to fall into a local minimum [11]. In [12], [13], the least squares SVM and proximal SVM are two widely used evolution forms of the traditional SVM, which avoid quadratic programming to achieve fast speed. However, both contain many parameters and are difficult to converge into the global minimum [11]. The ELM-based distribution system state forecaster aims to achieve the best training performance and smallest norm of the output coefficients [11], [14], which is different from many existing forecasting approaches [15]–[18]. In [14], the single layer feedforward networks can reach very small errors with the input weights and the hidden layer biases arbitrarily chosen. Therefore, only the output coefficients need to be optimized in the ELM method, which dramatically reduces the computation load and time consumption.

Consider that in a distribution system M_1 observations are collected as $(\boldsymbol{\alpha}_{i_1}, \boldsymbol{\gamma}_{i_1})$, where $i_1 \in \{1, 2, \cdots, M_1\}$, $\boldsymbol{\alpha}_{i_1} = [\boldsymbol{\alpha}_{i_1}^1 \ \boldsymbol{\alpha}_{i_1}^2 \ \cdots \boldsymbol{\alpha}_{i_1}^{n_1}]^T \in \mathcal{R}^{n_1}$, $\boldsymbol{\gamma}_{i_1} = [\gamma_{i_1}^1 \ \gamma_{i_1}^2 \ \cdots \gamma_{i_1}^{m_1}]^T \in \mathcal{R}^{m_1}$. Then, a designed ELM-based forecaster with K_1 hidden neurons can be formulated as follows:

$$\sum_{k_1=1}^{K_1} \psi(\boldsymbol{\xi}_{k_1}, b_{k_1}, \boldsymbol{\alpha}_{i_1})\beta_{k_1} = \Psi_{i_1} \tag{1}$$

where ψ is an activation function, which contains many different forms, such as the sigmoidal function, sine function, or radial basis function, $\boldsymbol{\xi}_{k_1}$ is the input weight vector connecting the input $\boldsymbol{\alpha}_{i_1}$ and the k_1th hidden neuron, b_{k_1} is the bias, and the output weight coefficient vector β_{k_1} is used to connect the k_1th hidden neuron and output Ψ_{i_1}.

As discussed above, the input weight vector $\boldsymbol{\xi}_{k_1}$ and bias b_{k_1} can be arbitrarily generated in ELM. Therefore, the objective function of the ELM aims to achieve the best performance and smallest norm of the output weight coefficient vector β_{k_1}, which can be formulated as follows:

$$\min_{\boldsymbol{\beta}} \mathcal{J}_1 = ||\boldsymbol{H}\boldsymbol{\beta} - \boldsymbol{\alpha}||_{\sigma_1}^{\tau_1} + \boldsymbol{C}||\boldsymbol{\beta}||_{\sigma_2}^{\tau_2} \tag{2}$$

where the optimal variable is the output weight coefficient vector β_{k_1}, τ_1 and $\tau_2 > 0$ indicate the exponents, σ_1 and σ_2 indicate the norm, $\boldsymbol{C}$ is the coefficient to balance the performance and the norm of the output weight coefficient vector, and $\boldsymbol{H}$ is the matrix to map the input vector into the hidden layer feature space, which can be defined as:

$$\boldsymbol{H}\boldsymbol{\beta} = \Psi \tag{3}$$

where $\boldsymbol{H}(\boldsymbol{\xi}, \boldsymbol{b}, \boldsymbol{\alpha}) =$

$$\begin{bmatrix} \psi(\boldsymbol{\xi}_1, b_1, \boldsymbol{\alpha}_{i_1}) & \cdots & \psi(\boldsymbol{\xi}_{K_1}, b_{K_1}, \boldsymbol{\alpha}_{i_1}) \\ \cdots & \cdots & \cdots \\ \psi(\boldsymbol{\xi}_1, b_1, \boldsymbol{\alpha}_{M_1}) & \cdots & \psi(\boldsymbol{\xi}_{K_1}, b_{K_1}, \boldsymbol{\alpha}_{M_1}) \end{bmatrix}_{M_1 \times K_1} \tag{4}$$

$\boldsymbol{\beta} = [\beta_1 \cdots \beta_{K_1}]$, $\boldsymbol{\beta} \in \mathcal{R}^{K_1 \times m_1}$.

Therefore, the designed ELM-based system state forecaster can optimize the parameter $\boldsymbol{\beta}$ with less computational burden and forecast the future system state quickly.

IV. Distribution Optimal Power Flow

With the forecast system states, the distribution system operator is aware of possible voltage violations in the near future. In order to alleviate the possible voltage violations and improve the overall system performance, a three-phase AC OPF problem is formulated and solved by the system operator to determine the optimal schedule of the controllable resources in the system. In this paper, the controllable resources include the utility-scale PV plants and smart loads. The mathematical formulation of the considered OPF problem is as follows:

$$\min_{P_{S,m}^{\phi}, Q_{S,m}^{\phi}, P_{L,k}^{\phi}} \sum_{i \in \mathcal{N}} \sum_{\phi \in \mathcal{P}_i} \omega_i^{\phi} \cdot s_i^{\phi}$$

$$+\omega_L \cdot \sum_{k \in \mathcal{N}_L} \sum_{\phi \in \mathcal{P}_{L,k}} \left(\frac{P_{L,k}^{\phi} - \widetilde{P}_{L,k}^{\phi}}{\widetilde{P}_{L,k}^{\phi}} \right)^2 \tag{5}$$

$$\text{s.t.} \quad P_{G,i}^{\phi} + P_{S,i}^{\phi} - P_{L,i}^{\phi} = \Re\{V_i^{\phi} \cdot (I_i^{\phi})^*\} \tag{6}$$

$$Q_{G,i}^{\phi} + Q_{S,i}^{\phi} - Q_{L,i}^{\phi} = \Im\{V_i^{\phi} \cdot (I_i^{\phi})^*\} \tag{7}$$

$$\underline{V}_i^{\phi} - s_i^{\phi} \le |V_i^{\phi}| \le \overline{V}_i^{\phi} + s_i^{\phi}, \ s_i^{\phi} \ge 0 \tag{8}$$

$$0 \le P_{S,m}^{\phi} \le \overline{P}_{S,m}^{\phi} \tag{9}$$

$$P_{S,m}^{\phi^2} + Q_{S,m}^{\phi^2} \le S_m^{\phi^2} \tag{10}$$

$$\underline{P}_{L,k}^{\phi} \le P_{L,k}^{\phi} \le \overline{P}_{L,k}^{\phi} \tag{11}$$

$$Q_{L,k}^{\phi} = \sqrt{\frac{1}{\eta_{L,k}^{\phi^2}} - 1} \cdot P_{L,k}^{\phi} \tag{12}$$

where $\mathcal{N}$ denotes the set of all buses and $\mathcal{P}_i \subseteq \{a_i, b_i, c_i\}$ the set of phases at bus i. V_i^{ϕ} and $|V_i^{\phi}|$ represent the complex voltage and the corresponding voltage magnitude at bus i phase ϕ with $\underline{V}_i^{\phi}$ and $\overline{V}_i^{\phi}$ as the associated lower and upper limits of the voltage magnitude. I_i^{ϕ} is the complex current flowing out of bus i in phase ϕ. $P_{G,i}$ and $Q_{G,i}$ correspond to the active and reactive power produced by the conventional generator at bus i phase ϕ, respectively.

The control variables in the considered OPF problem are the active and reactive power generation of the PV plants and the active power consumption of smart loads. For a PV plant connected to bus m, $P_{S,m}^{\phi}$ and $Q_{S,m}^{\phi}$ represent the active and reactive power generation of this PV plant in phase ϕ. As shown in constraints (9) and (10), the active power output $P_{S,m}^{\phi}$ in phase ϕ is limited by the forecast maximum active power generation $\overline{P}_{S,m}^{\phi}$, while the apparent power is constrained by the rated apparent power S_{k}^{ϕ} in phase ϕ.

For a smart load connected to bus k, $P_{L,k}^{\phi}$ and $Q_{L,k}^{\phi}$ are its active and reactive power consumption and $\eta_{L,k}^{\phi}$ is the power factor in phase ϕ. $\widetilde{P}_{L,k}^{\phi}$, $\underline{P}_{L,k}^{\phi}$, and $\overline{P}_{L,k}^{\phi}$ represent the desired active power consumption of this load in phase ϕ and the corresponding lower and upper limits, which are determined by its own management system based on its needs. Equations (11) and (12) correspond to the constraints on the active and reactive power consumption of the smart loads.

The equality constraints (6) and (7) correspond to the active and reactive power balance equations at bus i phase ϕ, where $\Re\{\cdot\}$ and $\Im\{\cdot\}$ denote the real and the imaginary parts of a complex number, respectively. Operational constraints on system voltages are also included in the OPF problem, which are modeled as soft constraints in (8). The nonnegative slack variable s_{i}^{ϕ} is used to quantify the violation of the voltage constraint at bus i phase ϕ.

The objective function is to minimize the weighted sum of all voltage violations while penalizing the relative deviations of the load consumption from the desired values with the penalization coefficient ω_L. The weighting parameter ω_{i}^{ϕ} associated with the voltage violation at bus i phase ϕ is dynamically determined by the forecast system voltages. If the voltage magnitude at a certain bus and phase is forecast to have a higher violation in the next 5 minutes than those at other buses and phases, the weighting parameter associated with this voltage will be increased. With a higher penalization on the specific bus and phase with a potential larger voltage violation, the severe voltage violation which may occur in the near future will be alleviated by controlling the available resources accordingly.

V. Simulation Results

A 12-bus system shown in Fig. 2 is used to test the proposed state forecasting-based OPF approach. In the following, the forecasting results of the near-future system states are first shown, and then the state forecasting-based OPF results are presented.

A. State Forecasting

The simulations are executed using a server with a 3.60-GHz Intel Xeon CPU and 32-GB RAM.

1) Results of ELM-based System State Forecasting: In this paper, the collected system states are divided into two sets: the training data set and the testing data set. The size of the testing data set is 20% of the training data set with a sliding window algorithm, which is used to traverse all the collected data sequentially and evaluate the proposed approach comprehensively.

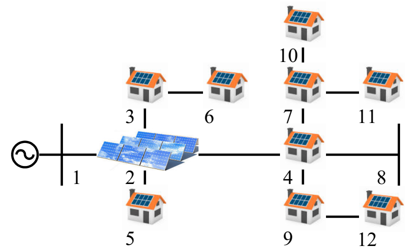

Fig. 2. A 12-bus distribution system.

TABLE I
Performance of Proposed Approach: MAPE

Forecasting Type	Voltage (%)	Angle (%)
1 hour-ahead	1.157	1.640
2 hours-ahead	1.271	1.772

TABLE II
Performance of Proposed Approach: Kurtosis and Skewness

Forecasting Type	Voltage (%)	Angle (%)
Kurtosis	1.131	1.578
Skewness	1.182	1.628

In this study, a short-term distribution system state forecasting approach is studied at 1-hour-ahead and 2-hour-ahead time horizon to cooperate with the next steps. The results are presented in Table I and Table II, which contain the mean average percentage error (MAPE), the kurtosis, and the skewness to evaluate the forecasting results. The kurtosis and skewness indicate the asymmetry and the outliers-prone of the probability distribution of the forecast errors [19]. According the forecasting performance in Table I, the MAPEs of the voltage forecasting are less than 1.50%, and the average is 1.214%. The MAPEs of the angle forecasting are less than 2.00%, and the average is 1.706%.

The histograms of the voltage and angle forecasting errors are presented in Fig. 3 and Fig. 4. As shown in Fig. 3, in the histogram of the voltage forecasting error, it is noticed that more than 85% of the errors are accumulated between -2.5% and 2.5%. Similarly, as shown in Fig. 4, in the histogram of the angle forecasting error, it is noticed that more than 85% of the errors are accumulated between -2.9% and 2.9%. In Table II, the results of the skewness of the proposed approach indicate that the error distribution is very close to normal distribution. And the results of the kurtosis of the proposed approach indicates that the accuracy of the proposed approach is very high [19].

2) Compared to Other Approaches: In this part, the forecasting approaches in [8], [9], [20], [21] are compared to the proposed state forecasting approach in 2-hour-ahead state forecasting. As shown in Table III, the MAPE and time consumption are the average of the voltage and angle forecasting results. As shown in Table III, although the ANN has a similar forecast accuracy to the proposed approach, the proposed approach has the shortest time consumption.

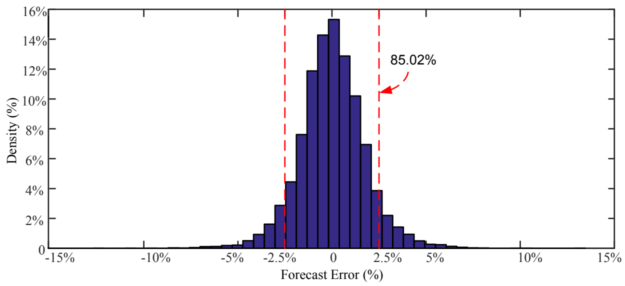

Fig. 3. Percentage error of distribution system forecasting: voltage.

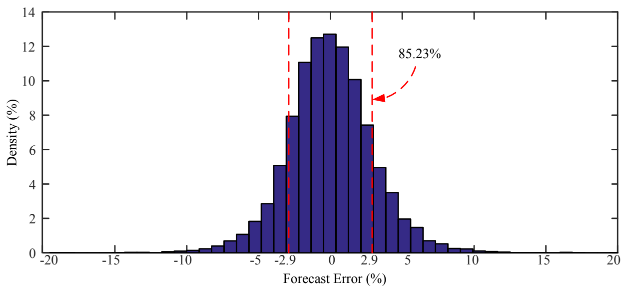

Fig. 4. Percentage error of distribution system forecasting: angle.

TABLE III
COMPARISON TO OTHER APPROACHES

	ANN	ARIMA	GA-SVR	Proposed Approach
MAPE	1.542%	8.211%	2.516%	1.521%
Time	120.3s	16.14s	156.3s	8.45s

B. OPF

As shown in Fig. 2, a utility-scale PV plant is connected at bus 2, which has a rated capacity of 300 kVA. All loads in the system are considered to be smart loads, and their active power consumption values are assumed to be adjustable within $\pm 20\%$ of the desired values. The lower and upper limits for the voltage magnitude are set to be 0.95 p.u. and 1.05 p.u., respectively. The penalization coefficient on the load deviations ω_L is chosen to be 1.

Every 5 minutes, the developed ELM-based state forecaster predicts the voltage magnitudes and angles in the system for the next 1 hour. If any voltage violations are forecast to occur in the next 5 minutes, 5 locations with the highest forecast voltage violation are identified and the weighting parameters associated with these locations are increased to be five times the weighting parameters for the voltage violations in the rest of the system. By solving the proposed OPF problem, the PV plant and smart loads are optimally controlled to mitigate the severe voltage violations in the next 5 minutes.

1) 5-Minute Results: In the following, one 5-minute time step is used as an example to demonstrate the proposed state forecasting-based OPF approach. By employing the developed state forecasting algorithm, system voltages for the next 5 minutes are predicted. Fig. 5 shows the average forecast voltage violations at all buses in the considered 5-minute time interval. The voltage magnitudes at buses 12, 9, 7, 10, and 8 in phase C have the largest predicted violations of the voltage lower bound. Therefore, the weighting parameters for the voltages at these buses in phase C are increased to be five times the weights associates with other buses in the system.

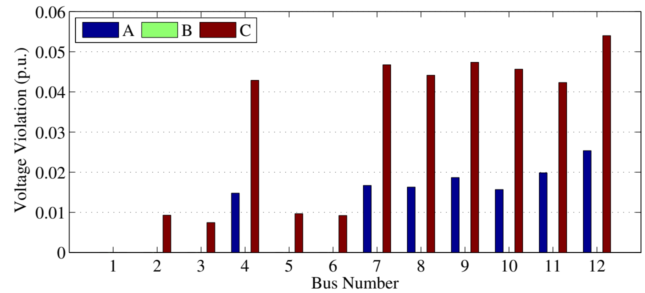

Fig. 5. Forecast voltage violations.

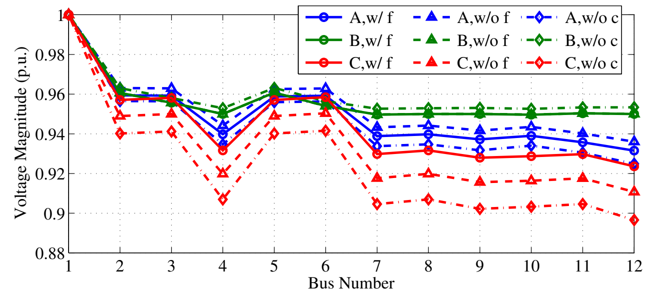

Fig. 6. Voltage magnitude of buses.

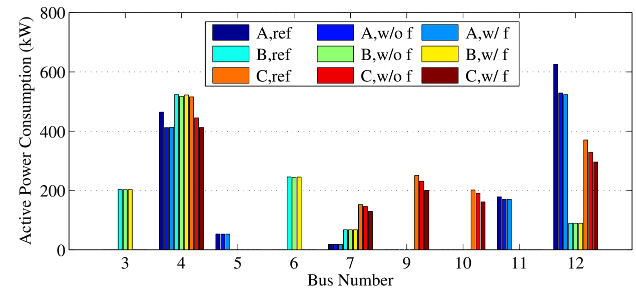

Fig. 7. Active power consumption of smart loads.

Fig. 6 depicts the voltage violations in the following three cases: 1) forecast of the system voltages used ('w/ f'), 2) no forecast of the system voltages ('w/o f') and 3) no control over the PV plant and loads ('w/o c'). In the case with no control over the PV plant and loads, the PV plant is producing as much active power as possible with a constant power factor 1, and the power consumption of all loads is not flexible. In the case without the forecast of the system voltages, the weighting parameters for all voltages are set to be the same.

Compared to the case without control over the PV plant and loads, the voltage violations in phases A and C in the other two cases are significantly smaller if the PV plant and smart loads are optimally controlled. Since the weights for the buses 12, 9, 7, 10, and 8 in phase C which have the lowest predicted voltage magnitudes are larger than the weights for the voltages at other buses in other phases, with forecasting the system voltages, the most severe voltage violations at buses 4 and 7 to 12 in phase C are reduced significantly compared to the voltage violations without the voltage forecasting, while the violations in phase A slightly increase with forecasting the system voltages. For phase B, the voltage magnitudes are lower if the available resources are optimally controlled, however, no violations of the voltage lower limit occur.

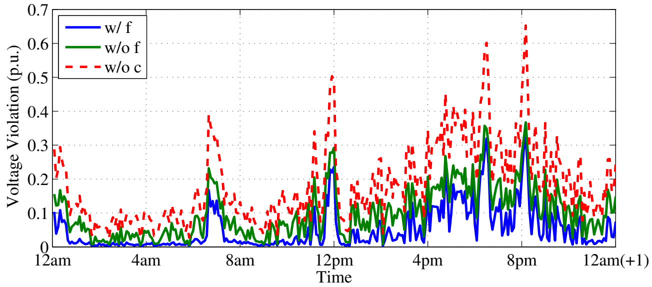

Fig. 8. Comparison of voltage violations.

Fig. 7 shows the desired active power consumption ('ref') and actual active power consumption of the smart loads with ('w/ f') and without the state forecasting ('w/o f'). Compared to the case without the voltage forecasting, the active power consumption of the smart loads connected in phase C is further reduced in order to reduce the large voltage violations which occur at the end of the distribution feeder in phase C.

2) 24-Hour Results: The proposed state forecasting-based OPF approach for voltage regulation has been tested for a whole day. Fig. 8 depicts the total voltage violation in the system for the whole day in the aforementioned three cases: with ('w/ f') and without state forecasting ('w/o f') as well as no control over the PV plant and loads ('w/o c'). As shown in Fig. 8, the total voltage violation values are significantly smaller if the state forecasting is employed compared to the total voltage violation values in the other two cases. One interesting observation is that when the total voltage violations are really high, i.e., around 6 p.m. and 8 p.m., the reduction in voltage violations by using the state forecasting is not significant. The reason for that is the active power consumption of each load is flexible only within $\pm 20\%$ of its desired consumption. When extremely severe voltage violations occur, purely curtailing the load consumption may not be good enough to significantly alleviate the voltage violations. Other mitigation methods need to be considered.

In summary, by employing the proposed state forecasting-based OPF approach, the most severe voltage violations are mitigated, and the overall voltage profile is improved.

VI. Conclusion

In this paper, a state forecasting-based OPF approach is developed to mitigate the potential severe voltage violations in distribution systems. The developed ELM-based short-term state forecaster accurately predicts the near-term system voltage magnitudes and angles in a computationally efficient manner. By employing the state forecasting results, the distribution system operator is able to prioritize its control needs and optimally control the available resources to improve the overall voltage profile by solving a dynamically weighted OPF problem. Simulation results show that the proposed approach is able to significantly reduce the voltage violations and achieve a better overall voltage profile in the system.

The OPF problem developed in this paper only considers system states in the next 5 minutes. Future work includes extending the single-step optimization problem into multistep problem by taking into account the potential system states in the future 1 or 2 hours. Further development is also needed to integrate short-term state forecasting into the optimal operation of distribution systems for different control objectives.

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