Online Model-Free Chance-Constrained Distribution System Voltage Control Using DERs

Preprint

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Online Model-Free Chance-Constrained Distribution System Voltage Control using DERs

Haoyi Wang, *Student Member, IEEE*, Yiyun Yao, *Member, IEEE*, Junbo Zhao, *Senior Member, IEEE*, Fei Ding, *Member, IEEE*

***Abstract*—This paper proposes an online data-driven distributed energy resource management system (DERMS) optimization method using chance-constrained formulation to address distribution system voltage regulation. This is achieved via the local sensitivity factor (LSF)-enabled reformulation of the DER control into a linear programming (LP) problem, which is easy and computationally efficient to solve. The LSF is estimated using online measurements and does not need the assumption of node load information. The latter is usually required for existing optimization-based methods but is difficult to obtain in practice. To mitigate measurement uncertainties, a scenario-based chance-constrained formulation is constructed. Compared with other control methods, the results carried out in a realistic distribution system show that the proposed method can effectively eliminate voltage violation issues.**

***Index Terms*—Distribution system voltage control, local sensitivity factor, chance-constrained optimization, DERs**

I. Introduction

Distributed energy resource (DER) has been increasingly deployed in distribution systems [1]. However, the high-level penetration of DERs could cause adverse impacts on the distribution system due to the lack of enough voltage support, and oscillation control. For example, voltage violations may degrade power quality, cause distribution line congestion, etc [2]. Typically, distribution systems are designed for unidirectional power flow in a radial structure, while PV integrations may trigger bidirectional power flow with smart inverters, especially at a high penetration level. On the other hand, implementing these smart inverters provides power grids with the opportunity for fast control.

Different from transmission systems, distribution systems are difficult to obtain an accurate model for coordinated control. Thus, the model-based optimization approaches [3], [4] face the practical challenge. To this end, data-driven methods [5], [6], [7] are paying increasing attention these days. It should be noted that the measurements (e.g., voltages and DER real and reactive power) are usually needed but they suffer from uncertainties, making obtained control decisions biased [8]. Two main approaches can be utilized to tackle that. One is via robust optimization while the other is through chance-constrained optimization, which enforces the constraints up to a pre-specified probability level [9]. DERs can be scheduled based on different objectives (e.g., the lowest active power losses, minimized curtailment of DERs, etc.) by solving a risk-based robust optimization problem [10] or chance-constrained programming [11]. In this paper, we develop the chance-constrained formulation to mitigate uncertainties from measurements for voltage control.

For DER control, most researches focus on the design of autonomous volt-var/watt control with predefined voltage-reactive/active power piecewise functions on each inverter [12]. Despite the effectiveness of local autonomous inverter controls in alleviating voltage violations, they cannot guarantee system-level optimality without system-wide coordination. A measurement-feedback online distribution system DER management system (DERMS) could fill the gap between system optimality and coordination control [13]. To control DERs for voltage violation reduction, a DERMS would coordinate the active and reactive power of DERs based on sensitivity factors, such as the local sensitivity factor (LSF) between power injections and voltage magnitudes. LSF is obtained before the optimization, which may lead to inadequate results [14], [15], [16] as it depends on not only the topology of distribution networks but also the power variations on each node.

This paper proposes a data-driven online DERMS control method. Unlike existing LSF-based approaches that rely on constant LSF values and ignorance of measurement uncertainties, a time-varying LSF-enabled scenario-based chance-constrained reformulation is proposed. The contributions are as follows:

(1) A measurement-feedback online DERMS with LSF-enabled LP formulation is proposed to coordinate DER controls for voltage regulation. The proposed scheme is model-free and does not need load information that distinguishes existing model-based and data-driven approaches, such as model-based OPF as well as those deep reinforcement learning-based DER control methods.

(2) The LSF is updated at each time step to guarantee adaptiveness to the changing system operating conditions.

(3) A scenario-based chance-constrained optimization is formulated to mitigate the impacts caused by the uncertainties from measurements. The proposed method is also verified by

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using a realistic distribution system.

II. Problem Formulation

A. OPF Model for DER Control

In any realistic distribution system, power flow calculation needs to set $N+1$ buses denoted by the set $\mathcal{N}\cup\{0\}$, $\mathcal{N}:=\{1,...,N\}$ and branches by the set $\mathcal{L}:=\{(m,n)\subset(\mathcal{N}\cup\{0\})\times(\mathcal{N}\cup\{0\})\}$. The $(N+1)-th$ bus is taken to be the slack bus with a specific voltage magnitude and angle. Normally, a three-phase distribution system is defined by $\mathcal{P}:=\{a,b,c\}$ to represent the three phases, and one phase is regarded as a separate node. The analysis for the three-phase system could generalize to any multiphase cases by removing nonexistent phases. Assume the complex voltage and current vectors on each node as $\mathbf{V}=[V_{1,a},V_{1,b},...,V_{N,c}]\in\mathbb{C}^{3N}$ and $\mathbf{I}=[I_{1,a},I_{1,b},...,I_{N,c}]\in\mathbb{C}^{3N}$. The smart inverter power outputs from PVs are installed at nodes $\mathcal{H}\subseteq\mathcal{N}\times\mathcal{P}$. Typically, the OPF objective is to minimize either the total cost or system losses or DER curtailment. In this paper, we set the minimization of PV real power curtailment and reactive power usage as the objective:

$$f_i^t\left(P_i^t,Q_i^t\right)=-c_{P,i}\cdot P_i^t+c_{Q,i}\cdot\left|Q_i^t\right| \tag{1}$$

where P_i^t,Q_i^t present the real and reactive power injections of the $i-th$ PV inverter at time t. $c_{P,i},c_{Q,i}$ are constant cost coefficients. The constraints of this OPF problem contain two primary components: constraint region for each PV inverter and operation constraints of voltage and power on each node.

For each PV inverter, a power region $\mathcal{RE}_i^t$ for $\forall i\in\mathcal{H}$ is set as (2) after assuming the DC-to-AC ratio of the PV system is oversized and the power factor to be higher than 0.9:

$$\begin{aligned}\mathcal{RE}_i^t=\{P_i^t+jQ_i^t\mid 0\le P_i^t\le P_{i,\max}^t\\ \left(P_i^t\right)^2+\left(Q_i^t\right)^2\le\left(H_i\right)^2\\ power\ factor\ge 0.9\}\subset\mathbb{C}\end{aligned} \tag{2}$$

where $P_{i,max}^t$ is the maximum real power of the $i-th$ PV inverter at time t, $\mathcal{H}_i$ is the nameplate power size of the $i-th$ PV inverter.

The second part of constraints is related to the power and voltage on each node. The active and reactive power on each node need to be balanced based on Kirchhoff Current Law (KCL) and voltage magnitudes across all nodes must be maintained within a specific region for grid operation. Denote the load real and reactive power on node k at time t as $P_{load,k}^t,Q_{load,k}^t$, and the lower and upper limits for the voltage magnitudes as V_{min} and V_{max} (0.95 and 1.05 [17]), the AC load balance and voltage limits can be represented as:

$$V_i^t\left(I_i^t\right)^*=\left(P_i^t-P_{\text{load},i}^t\right)+j\left(Q_i^t-Q_{\text{load,i}}^t\right)\ \forall i\in\mathcal{H}, \tag{3}$$

$$V_k^t\left(I_k^t\right)^*=-P_{\text{load},i}^t-jQ_{\text{load},k}^t,\quad\forall k\in(\mathcal{N}\times\mathcal{P})/\mathcal{H}. \tag{4}$$

$$V_{\min}\leqslant\left|V_l^t\right|\leqslant V_{\max}\ \forall l\in\mathcal{N}\times\mathcal{P}, \tag{5}$$

B. LSF-based OPF Reformulation

As mentioned before, accurate information on loads across the network is difficult to access through measurements due to the limited number of real-time measurements for the distribution systems. A data-driven control scheme is advocated to compensate for the lack of timely load information. To realize a data-driven control, this paper introduces measurement feedback correction [18], [19] into the optimization problem. In most cases, voltages on all nodes $|V^t|$ work as auxiliary variables in the OPF formulations, which requires us to construct the relationship between PV power outputs and voltage magnitudes on each node. However, this is not doable due to the absence of full visibility of load information in distribution networks. Instead, PV inverters can change their power injections P_i^t and Q_i^t to mitigate voltage violations.

We consider $\mathcal{M}\subset\mathcal{N}\times\mathcal{P}$ as the set of necessary nodes, $|V_k^t|_{meas},\forall k\in\mathcal{M}$ as voltage magnitude measurements and $P_{i,meas}^t,Qi,meas^t,\forall i\in\mathcal{H}$ as PV power measurements. Correspondingly, constraints (3)-(5) can be linearized as (6)-(10) with LSF:

$$P_i^t=P_{i,\text{meas}}^t+\Delta P_i^t,\forall i\in\mathcal{H}, \tag{6}$$

$$Q_i^t=Q_{i,\text{meas}}^t+\Delta Q_i^t,\forall i\in\mathcal{H}, \tag{7}$$

$$\Delta\left|V_k^t\right|_{\text{meas}}=\sum_{i\in\mathcal{H}}\left(\frac{\partial\left|V_k\right|}{\partial P_i}\cdot\Delta P_i^t+\frac{\partial\left|V_k\right|}{\partial Q_i}\cdot\Delta Q_i^t\right),\forall k\in\mathcal{M}, \tag{8}$$

$$\text{if }\left|V_k^t\right|_{\text{meas}}>1.05:\Delta\left|V_k^t\right|_{\text{meas}}\le 1.05-\left|V_k^t\right|_{\text{meas}}, \tag{9}$$

$$\text{if }\left|V_k^t\right|_{\text{meas}}<0.95:\Delta\left|V_k^t\right|_{\text{meas}}\ge 0.95-\left|V_k^t\right|_{\text{meas}}, \tag{10}$$

where ΔP_i^t and ΔQ_i^t are the power changes on PV setpoints. $\partial\left|V_k\right|/\partial P_i$ and $\partial\left|V_k\right|/\partial Q_i$ denote LSF of voltage magnitude at node k to real and reactive power injections at node i. $\Delta|V_k^t|_{meas}$ represents the modified value for the voltage magnitude at node k because of power changes ΔP_i^t and $\Delta Q_i^t,\forall i\in\mathcal{H}$.

The above formulation still has two issues:

a. Time-variant power distribution. The practical power distribution of each node varies over time, and power injections on the PV nodes change due to solar irradiance variations. Although LSF mainly depends on the topology structure of networks, the impacts of nodal power injection changes on LSF may not be negligible, especially on nodes with large power injections.

b. Uncertainties in measurements. In any data-driven control method, measurements are essential to realizing control operations. Unfortunately, even the most advanced measuring instruments can never avoid uncertainties. Such uncertainties may lead to biased DERMS actions, which would reduce the efficiency of the proposed scheme and increase operating costs.

This paper proposes a novel data-driven DERMS framework to address them, which is shown below.

III. Proposed DERMS Online Solution

In this section, the PV inverter control region is analyzed, and then the importance of time-varying LSF updating is emphasized and a recursive method to achieve that is presented.

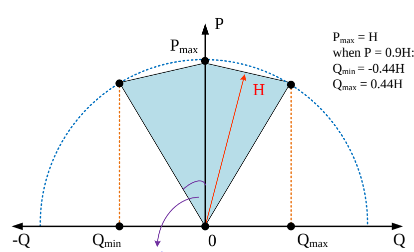

Fig. 1. Illustration for the linearization of the PV inverter control region.

Finally, the chance-constrained reformulation and its solution method are proposed.

A. Linearize PV Inverters Control Region

Neither a centralized nor distributed approach could solve the non-linear problem (2) at a fast speed to satisfy the online control requirement. To update PV power output at each time step, piecewise linearization is utilized to simplify this non-linear power constraint into linear constraint, and the linearization process is illustrated in Fig. 1.

$$\mathrm{Lin}-\mathcal{RE}_i^t = \{P_i^t + jQ_i^t \mid 0 \leq P_i^t \leq P_{i,\max}^t \tag{11a}$$
$$0 \leq P_i^t \leq H_i \tag{11b}$$
$$-0.44H_i \leq Q_i^t \leq 0.44H_i \tag{11c}$$
$$P_i^t + 0.23Q_i^t \leq H_i \tag{11d}$$
$$P_i^t - 0.23Q_i^t \leq H_i \tag{11e}$$
$$-P_i^t + 2.05Q_i^t \leq 0 \tag{11f}$$
$$-P_i^t - 2.05Q_i^t \leq 0, \} \subset \mathbb{C} \tag{11g}$$

If PV inverters work at "night mode" to provide reactive power support, where power factor limitation can be relaxed and P_i^t is zero, the modified piecewise linearization can be represented as the bottom line of the semicircle in Fig. 1.

B. Time-Varying LSF

Based on the formulation proposed in (6)-(10), LSFs are the key elements to realize a data-driven online control scheme with smart inverters. Once voltage violations are sensed, the proposed constraints (6)-(10) would adjust the power injections of PV nodes across the whole system depending on LSF combined with existing grid voltage and PV power measurements. The Jacobian inverse matrix of the distribution system power flow is shown below:

$$\begin{bmatrix} \Delta\delta_4 \\ \vdots \\ \Delta\delta_n \\ \Delta V_4 \\ \vdots \\ \Delta V_n \end{bmatrix} = \begin{bmatrix} J_{11}^{-1} & J_{12}^{-1} \\ J_{21}^{-1} & J_{22}^{-1} \end{bmatrix} \begin{bmatrix} \Delta P_4 \\ \vdots \\ \Delta P_n \\ \Delta Q_4 \\ \vdots \\ \Delta Q_n \end{bmatrix} \tag{12}$$

where submatrices J_{11}^{-1}, J_{12}^{-1}, J_{21}^{-1}, J_{22}^{-1} represent sensitivities between power (active and reactive) and voltage (angle and magnitude) respectively (i.e., $\partial\delta/\partial P$ for J_{11}^{-1}, $\partial V/\partial Q$ for J_{22}^{-1}). J_{21}^{-1}, and J_{22}^{-1} of the Jacobian inverse matrix are the LSFs in constraints (8). The inverse of the Jacobian matrix is hard to accomplish since it is a sparse matrix in the distribution system. The perturb-and-observe approach is adopted to derive LSF by injecting small power on a specific node (i.e., ΔP_i^t and ΔQ_i^t) and measuring voltage violations across all nodes(i.e., $\Delta\left|V_k^t\right|$).

In an actual distribution system, both load and PV injections change over time: electric vehicles move after charging, and solar panel has the feature of intermittency. Time-variant power injections will change the relationship between power and voltage, so the LSF must be updated before solving the OPF problem. To this end, a "forgetting factor" $\lambda \in [0, 1]$ is introduced to prioritize recent data over historical data. The factor λ gives a small weight to older samples in the LSF observation. When $\lambda = 0$ no datum prior to the current timestep is considered, while when $\lambda = 1$, all historical data have the same weights. Typical values of λ lie between 0.95 and 0.99.

The updating equation of LSF at timestep T can be formulated as:

$$\begin{aligned} LSF\left(T\right) &= \frac{1}{T}\sum_{t=1}^{T} \lambda^{T-t} LSF\left(t\right) \\ &= \frac{1}{T}\left[LSF\left(t\right) + \lambda\left(T-1\right)LSF\left(T-1\right)\right] \end{aligned} \tag{13}$$

where $LSF(t)$ is the sensitivity matrix observed from perturbation at timestep t, and $LSF(T)$ is the sensitivity matrix obtained through both perturbation and iteration at timestep T, which is used to control PV power injections at the corresponding moment.

C. Scenario-based Chance-Constraint Optimization

The proposed online control scheme is a measurement feedback method to mitigate the lack of load information. Measurements from sensors suffer from uncertainties, which degrade the optimization solutions. Two approaches are widely used in the existing works to offset the impact of uncertainties: robust optimization and chance-constrained optimization.

Robust constraints would undoubtedly provide us with a more reliable constraint region since it has taken all possible instances caused by uncertainties into consideration. However, robust constraints will harm the proficiency of calculation, especially in an online control scheme. Therefore, chance-constrained optimization is utilized in this paper to generate N scenarios by sampling the measurements from sensors and constraining these scenarios to get a final constraint region. Two preprocessing should be adopted before applying chance constraints into practice:

a. Risky node selection. A distribution network can have many nodes, but over-voltage typically happens on some nodes, where voltages are more sensitive to power injection than others. These risky nodes are necessary for producing scenarios in chance-constrained optimization and could be highlighted through an optimal problem shown below:

$$\begin{aligned} &(OPT)\ \max : \left|V_k^{t_0}\right|_{meas} + \Delta V_k^t \\ &s.t. : \Delta V_k^t \ = \sum_{i=1}^{|\mathcal{H}|}\left(\frac{\partial\Delta V_i^t}{\partial\Delta P_i^t}\Delta P_i^t + \frac{\partial\Delta V_i^t}{\partial\Delta Q_i^t}\Delta Q_i^t\right) \\ &\left(P_i^t - P_i^{t_0}\right)_{\min} \geqslant \Delta P_i^t \geqslant \left(P_i^t - P_i^{t_0}\right)_{\max} \\ &\left(Q_i^t - Q_i^{t_0}\right)_{\min} \geqslant \Delta Q_i^t \geqslant \left(Q_i^t - Q_i^{t_0}\right)_{\max} \end{aligned} \tag{14}$$

where $\left|V_k^{t_0}\right|$ is the reference voltage on node k at timestep t_0, ΔV_i^t, ΔP_i^t and ΔQ_i^t are the deviations of voltage, active and reactive power respectively at node i in the period of t_0 to t, $\forall i \in \mathcal{H}$.

By solving the OPT problem in different timescales, nodes with over-voltage issues will be highlighted as risky ones and utilized in sampling to generate needed scenarios for chance-constraints. *b. Corollary sample number N.* Another problem we need to solve is how many scenarios are corollary for the desired probabilistic level in the solution. Intuitively, a large number of scenarios can guarantee a sturdy constraint region, but it will affect the computation efficiency.

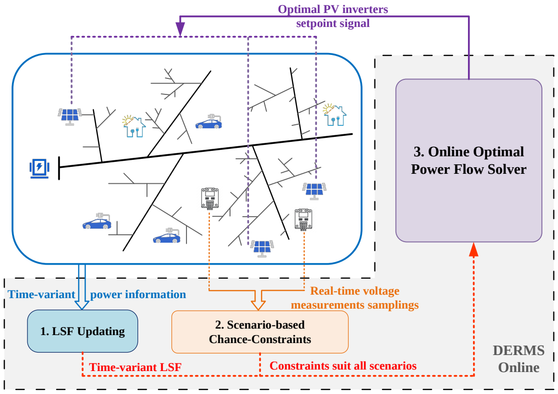

Fig. 2. Proposed online OPF-based DERMS architecture.

Two real numbers for risk level parameter $\varepsilon \in [0,1]$ and confidence parameter $c \in [0,1]$ are set for the derivation of number N. Then, with a probability no smaller than c, the chance-constraints return an optimal solution $\hat{x}_N$ that is $\varepsilon-$level robustly feasible.

The Markov inequality is used to provide a boundary for number N with ε, c, and n, n is the size of risky node highlighted before as decision variables [9]. The Markov inequality is noted as:

$$P^N\left\{V\left(\hat{x}_N\right)>\varepsilon\right\} \leqslant \frac{1}{\varepsilon} E_{P^N}\left[V\left(\hat{x}_N\right)\right] \leqslant \frac{1}{\varepsilon} \frac{n}{N+1} \tag{15}$$

where P^N $(= P \times ... \times P, N\ times)$ is the probability measured in the space Δ^N of multi-sample extractions. To achieve a specific probability with the confidence parameter c, P^N should satisfy the inequality below:

$$P^N\left\{V\left(\hat{x}_N\right)>\varepsilon\right\} \leqslant 1-c \tag{16}$$

The corollary number N can be derived from (16) as:

$$N \geqslant \frac{n}{\varepsilon(1-c)}-1 \tag{17}$$

The number N of random samples that need to be drawn can be managed to achieve a reasonable probabilistic level with respect to ε, c and n.

Fig. 2 depicts the architecture of the proposed online OPF-based DERMS control scheme, where both active and reactive power are measured to update LSF at each timestep.

Equipped with preprocessing of A, B and C, an OPF problem of the proposed online DERMS can be formulated as:

$$(OPF)^t \quad \min_{\{x_i^t\}_{i\in\mathcal{H}}} : \sum_{i=1}^{|\mathcal{H}|}\left(-c_{P,i}\cdot P_i^t + c_{Q,i}\cdot w_i^t\right) \tag{18a}$$

$$s.t. : w_i^t \geq 0, \forall i \in \mathcal{H} \tag{18b}$$

$$w_i^t \geq Q_i^t, \forall i \in \mathcal{H} \tag{18c}$$

$$w_i^t \geq -Q_i^t, \forall i \in \mathcal{H} \tag{18d}$$

$$x_i^t \in \mathrm{Lin}-\mathcal{R}\varepsilon_i^t, \forall i \in \mathcal{H} \tag{18e}$$

$$(6),(7),(8),(9),(10),(11) \tag{18f}$$

where w_i^t is a positive ancillary variable to equivalently substitute each of the absolute terms in (1). This problem can be solved with the assistance of updated LSF and chance constraints to provide all PV nodes with optimal setpoints.

IV. Numberical Results

The proposed method is tested using a real distribution system. It consists of 759 nodes (both primary and secondary nodes), and 40% of customers (69 of 224 load nodes) are randomly chosen to install PV systems. 40% is chosen because not all customers are suitable for PV system installation, among which some are EV chargers that may not have enough space for solar panels. One day in summer is chosen for this test as its strong solar irradiance may cause very severe over-voltage, and the result of all year-long tests can be shown with the statistical data. To simulate an over-voltage situation, each PV is randomly generated to be in the size of 0.5 to 1.5 times its nodal peak load value. The total load is 2,609 kW, including both EVs and normal load, and the total PV capacity is 1,044 kW (40% penetration). The data of load and solar are collected in the whole year 2019 with a 1-min resolution. Year-long QSTSs could use 1-min or 1-hour resolution, but in this paper, a linear interpolation is adopted on the selected day's data to have a 15-sec resolution for DERMS implementation. The voltage measurement of all nodes and the power measurement of all controllable PV inverters are assumed to be available. The tests are simulated with OpenDSS-Direct Module under Python 3.7, and OPF formulations for (14) and (18) are solved by an open-source Google ORTool-GLOP solver.

A. *Effectiveness of DERMS Online Framework*

To demonstrate the effectiveness of the proposed DERMS online control scheme, a comparison between the autonomous volt-var control and DERMS control is given. With a pre-defined piecewise function on each PV inverter, the volt-var control can regulate voltage magnitudes by changing reactive power injection. Different from transmission networks, both active and reactive power have an effect on voltage magnitudes in distribution networks. Generally, the "vars priority" operation mode aims to obtain more active power while the Q_i^t will be increased to meet the requirement of Q_i^t in the volt-var curve. To achieve an ideal voltage control as a reference, the volt-var control is set to compare with DERMS online scheme. For DERMS, sensors $|V|_{meas}$ at risky nodes are selected as shown before. Coefficients of c_P and c_Q are set to 1.

According to a rough estimation based on the statistical data, day 163 is the severest day of having voltage violation issues. Fig. 3 shows the voltage profile during that day, where the highest voltage magnitudes are also displayed. The node of the highest voltage magnitudes may change over time due to the time-variant load distribution and solar irradiance. The orange line depicts the over-voltage that occurred between 6:00 and 19:00 without any action/control since the solar irradiance was maintained long in summer. The highest value of voltage magnitudes is 1.095 on one node at noon. The volt-var control (vars priority) works when the highest voltage comes across the voltage limit (1.049). Although the volt-var

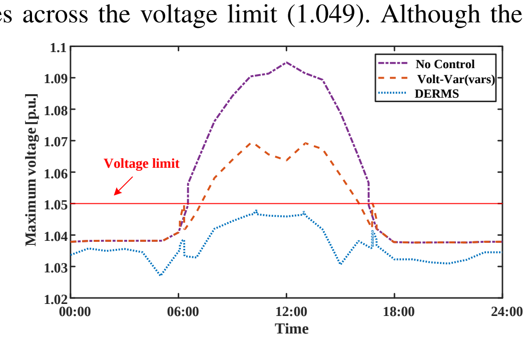

Fig. 3. Voltage profile during the selected day on the node that suffered from the worst overvoltage issues.

TABLE I
ONE-WEEK SIMULATION WITH DIFFERENT CONTROL SCENARIOS

	No Control	Volt-Var Control	DERMS
Total PV P (kWh)	27,641	26,516	**27,139**
Total PV P curt. (kWh)	-	1,125	**502**
Total PV P curt. (%)	-	4.07%	**1.82%**
Total PV Q (kVarh)	0	**7,806**	5,244

control can regulate the voltage at a certain level by actively providing reactive power support, it cannot regulate all over-voltage under the voltage limit (1.05) because of the constraint from predefined piecewise functions. Besides, the available bound of Q_i^t shrinks with the growing P_i^t because $(P_i^t)^2 + (Q_i^t)^2 \leqslant (H_i)^2$, and the inverter thus does not have sufficient reactive power to support voltage regulation. However, the proposed DERMS control shows excellent performance with updated LSF and chance constraints. DERMS may take actions before real over-voltage happens considering the uncertainties of measurements, which can be verified in Fig. 3, where the maximum value of all risky nodes is near 1.04 before sunrise, and an error of 1% is common in measurements. In realistic networks, this will not cause the misuse of DERMS since it will be set to work only during the daytime from 6:00 to 19:00 in summer and from 7:00 to 17:00 in winter. In this test, 19 risky nodes are highlighted to measure over-voltage values, and half of the nodes exceeded 1.06 during the daytime, which implies an ideal selection of the risky nodes. Table I reports a one-week generation of PV systems in different control scenarios. The proposed DERMS control can reduce 623 kWh active power curtailment and 2,562 kVarh reactive power usage compared to volt-var control.

B. Impacts of Chance-Constraints

TABLE II
CONTROL PERFORMANCE WITH OR WITHOUT CHANCE-CONSTRAINTS

Chance-Constraints Utilization	With	Without
Number of over-voltage **before control**	18	26
Highest voltage value during daytime	1.09	1.12
Number of over-voltage **after control**	0	4
Average computational time (sec)	0.014	0.022

For chance-constraints utilization, 1266 scenarios were sampled based on (17) with 0.3-risk level and 0.95-confidence level to eliminate the uncertainties in measurements. Table II reports the results of DERMS control with or without chance constraints in the forms of over-voltage numbers before and after control, respectively. All the over-voltages were regulated under 1.05 with chance constraints, and the maximum value of over-voltage is lower than in scenarios without chance constraints. This is because the impacts of uncertainties have not been fully mitigated before optimal problem-solving and have caused misuse of DERMS with inaccurate data, yielding biased results. The computing times are also shown, and it can be found that thanks to the LP formulation, even the chance constraints are considered, the proposed method only needs less than 0.1-sec to obtain the DER control set points. This is sufficient for real-time applications.

V. CONCLUSION

This paper proposes an online data-driven DERMS for dealing with voltage violation issues with updated LSF and scenario-based chance constraints. The proposed measurement feedback approach eliminates the dependence on load information and mitigates the uncertainties of the measurements. The control region of the PV system is linearized to formulate an LP OPF problem that is computationally efficient for large-scale system applications. Numerical tests on a day with severe voltage issues in a realistic distribution system demonstrate that the proposed method can effectively mitigate the voltage issues while being computationally efficient for online applications. Our future work will be on enhancing the robustness of the proposed method for dealing with time-varying distribution system topology changes, and alleviating the reliance on high measurement density without wrecking the performance of voltage regulation.

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