Abstract—This is the second part of a two-part paper on data-based distributionally robust stochastic optimal power flow (OPF). The general problem formulation and methodology have been presented in Part I [1]. Here, we present extensive numerical experiments in both distribution and transmission networks to illustrate the effectiveness and flexibility of the proposed methodology for balancing efficiency, constraint violation risk, and out-of-sample performance. On the distribution side, the method mitigates overvoltages due to high photovoltaic penetration using local energy storage devices. On the transmission side, the method reduces N-1 security line flow constraint risks due to high wind penetration using reserve policies for controllable generators. In both cases, the data-based distributionally robust model predictive control (MPC) algorithm explicitly utilizes forecast error training datasets, which can be updated online. The numerical results illustrate inherent tradeoffs between the operational costs, risks of constraints violations, and out-of-sample performance, offering systematic techniques for system operators to balance these objectives.

Index Terms—stochastic optimal power flow, data-driven optimization, multi-period distributionally robust optimization, distribution networks, transmission systems

I. INTRODUCTION

A s penetration levels of renewable energy sources (RESs) continue increasing to substantial fractions of total supplied power and energy, system operators will require more sophisticated methods for balancing inherent tradeoffs between nominal performance and operational risks. This is relevant for both transmission and distribution networks, which have seen rapid recent increases in photovoltaic (PV) and wind energy sources. Here, we present extensive numerical experiments in both distribution and transmission networks to illustrate the effectiveness and flexibility of our data-based distributionally robust stochastic optimal power flow (OPF) methodology for balancing efficiency, constraint violation risk, and out-of-sample performance.

Y. Guo and T. Summers are with the Department of Mechanical Engineering, The University of Texas at Dallas, Richardson, TX, USA, email: {yi.guo2,tyler.summers}@utdallas.edu.
K. Baker is with the Department of Civil, Environmental, and Architectural Engineering, The University of Colorado, Boulder, CO, USA, email:kyri.baker@colorado.edu.
E. Dall’Anese is with the National Renewable Energy Laboratory, Golden, CO, USA, email:emiliano.dallanese@nrel.gov.
Z. Hu is with the Department of Electrical Engineering, Tsinghua University, Beijing, P.R. China, email:zechhu@tsinghua.edu.cn.

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A variety of stochastic OPF methods have been recently proposed to explicitly incorporate forecast errors of network uncertainties for modeling risk. These methods can be categorized according to assumptions made about forecast error distributions and metrics for quantifying risk. Many make specific assumptions about forecast error distributions and use chance constraints, which encode value at risk (VaR), conditional value at risk (CVaR), or distributional robustness with specific ambiguity sets [2]–[10]. Others handle uncertainty using scenarios approaches, sample average approximation, or robust optimization [11]–[24]. However, in practice all decisions about how to model forecast error distributions must be based on finite historical training datasets. None of the existing methods account for sampling errors inherent in such datasets in high-dimensional spaces.

Our proposed data-based distributionally robust stochastic OPF methodology, developed in Part I [1], explicitly incorporates robustness to sampling errors by considering sets of distributions centered around a finite training dataset. A model predictive control (MPC) approach utilizes Wasserstein-based distributionally robust optimization subproblems to obtain superior out-of-sample performance. Here in Part II we illustrate the effectiveness and flexibility of the methodology in both distribution and transmission networks. On the distribution side, the method mitigates overvoltages due to high photovoltaic penetration using local energy storage devices. On the transmission side, the method reduces N-1 security line flow constraint risks due to high wind penetration using reserve policies for controllable generators. In both cases, the data-based distributionally robust (MPC) algorithm explicitly utilizes forecast error training datasets, which can be updated online. The numerical results illustrate inherent tradeoffs between the operational costs, risks of constraints violations, and out-of-sample performance, offering systematic techniques for system operators to balance these objectives.

The rest of the paper is organized as follows. Section II illustrates the data-based distributionally robust stochastic AC OPF for mitigating overvoltages in a modified IEEE 37-node distribution feeder with high PV penetration using local energy storage devices. Section III illustrates the data-based distributionally robust stochastic DC OPF for reducing N-1 security line flow constraint risks due to high wind penetration using reserve policies for controllable generators. Section IV concludes.

Notation: The inner product of two vectors $a, b \in \mathbb{R}^m$ is
denoted by \( (a, b) := a^\top b \). The \( N_s \)-fold product of distribution \( \mathcal{P} \) on a set \( \Xi \) is denoted by \( \mathcal{P}^{N_s} \), which represents a distribution on the Cartesian product space \( \Xi^{N_s} = \Xi \times \ldots \times \Xi \). We use \( N_s \) to represent the number of samples inside the training dataset \( \Xi \). Superscript \( \ast \) \( \ast \) is reserved for the objects that depend on a training dataset \( \Xi^{N_s} \). We use \( \{ \cdot \}^\top \) to denote vector or matrix transpose. The operators \( \mathbb{R}\{ \cdot \} \) and \( \mathbb{Z}\{ \cdot \} \) return the real and imaginary part of a complex number, respectively. The operator \( \{ \cdot \}_{[a,b]} \) selects the \( a \)-th to \( b \)-th elements of a vector or rows of a matrix.

II. OVERVOLTAGE MITIGATION IN DISTRIBUTION NETWORKS

In this section, we apply the data-based distributionally robust stochastic OPF methodology to mitigate overvoltages in distribution networks by controlling set points in RESs and energy storage devices. We provide further modeling details of the loads, inverter-based RESs, and energy storage devices. The set points of controllable devices are repeatedly optimized over a finite planning horizon within a MPC feedback scheme. The risk conservativeness of the voltage magnitude constraints and the out-of-sample performance robustness to sampling errors are explicitly adjustable by two scalar parameters.

A. System model

1) Loads: We use \( P_{l,n}^t \) and \( Q_{l,n}^t \) to denote the active and reactive power demands at bus \( n \in \mathcal{N}_R \subseteq \mathcal{N} \), where the set \( \mathcal{N}_R \) denotes all buses with RESs. With high RES penetration, overvoltages can cause power quality and reliability issues. By intelligently operating set points of RES and energy storage, operators can optimally trade off risk of constraint violation and economic efficiency (e.g., purchase of electricity from the main grid, active power curtailment costs, and reactive compensation costs). The active power injections of RESs are controlled by adjusting an active power curtailment factor \( \alpha_{l,n}^t \in [0,1] \). Reactive power set points of RESs can also be adjusted within a limit \( S_n \) on apparent power as follows:

\[
\sqrt{(1-\alpha_{l,n}^t)P_{av,n}^t)^2 + (Q_{av,n}^t)^2} \leq S_n, n \in \mathcal{N}_R.
\]

B. Data-based stochastic OPF implementation

We now use the methodologies presented in Part I Section IV, and the models of loads, RESs and energy storage devices to develop a data-based stochastic AC OPF for solving a voltage regulation problem. This stochastic OPF aims to balance the operational costs the total CVaR values of the voltage magnitude constraints. We consider an operational cost that captures electricity purchased by customers, excessive solar energy fed back to the utility, reactive power compensation costs and penalties for active power curtailment:

\[
J_{\text{Cost}}(\alpha^t, Q^t, p_{B}^t, \xi_t) = \sum_{n \in \mathcal{N}} \left[ a_{1,n}^t \left[ P_{l,n}^t + P_{B,n}^t - (1-\alpha_{l,n}^t)P_{av,n}^t \right] + a_{2,n}^t \left[ (1-\alpha_{l,n}^t)P_{av,n}^t - P_{l,n}^t - P_{B,n}^t \right] + a_{3,n}^t \left| Q_{l,n}^t \right| + a_{4,n}^t \alpha_{l,n}^t P_{av,n}^t \right].
\]

We collect all decision variables into \( \mathbf{y}_t = \{ \alpha^t, Q^t, p_{B}^t, \mathbf{b}^t \} \), and all RES and load forecast errors into the random vector \( \xi_t \). Now the MPC subproblems take the following form:

\[
\inf_{\mathbf{y}_t, \alpha_{l,n}^t, Q_{l,n}^t, \mathbf{b}_t} \sum_{t=1}^{t+H_t} \left\{ E[J_{\text{Cost}}] + \rho \sup_{Q_{l,n}^t \in P_{Q,n}} \sum_{o=1}^{N_o} E^{Q_{l,n}^t} [Q_{l,n}^t] \right\},
\]

where \( \rho \) is a positive parameter. The convexity of the problem is then ensured by adjusting the parameter \( \rho \).

Finally, we formulate the problem as a two-stage stochastic optimization problem with recourse:

\[
\inf_{\mathbf{y}_t, \alpha_{l,n}^t, Q_{l,n}^t, \mathbf{b}_t} \sum_{t=1}^{t+H_t} \left\{ E[J_{\text{Cost}}] + \lambda_{\epsilon^t} \epsilon_{\epsilon^t} + \frac{1}{N_s} \sum_{s=1}^{N_s} s_{\epsilon} \right\},
\]

(1a)
subject to:
\[
\rho(\tilde{b}_{ok}(k_{\tau}^r)) + (\tilde{a}_{ok}(y_{\tau}), \xi_{i,o}^r) + (\xi_{i,o}, d - H_{i,o}^r)) \leq s_{i,o}, \quad (1b)
\]
\[
\|HT_{i,o} - \rho(\tilde{a}_{ok}(y_{\tau}))\|_{\infty} \leq \lambda_{i,o}^r, \quad (1c)
\]
\[
\xi_{i,o} \geq 0, \quad (1d)
\]
\[
\frac{1}{N_s} \sum_{i=1}^{N_s} \left[ \left(1 - \alpha_{i,n}^r\right) \tilde{P}_{av,n}^r, \right]^2 \left(\sum_{n=1}^{N_s} \frac{1}{N_s} \sum_{i=1}^{N_s} \left[ \tan(\theta_{n}) \left(1 - \alpha_{i,n}^r \right) \tilde{P}_{av,n}^r - [Q_{n}^r] + \omega_{1,n}^r \right] \right) \leq \omega_{1,n}^r \mu, \quad (1e)
\]
\[
B_{n}^{\min} \leq B_{n}^r \leq B_{n}^{\max}, \quad (1f)
\]
\[
P_{B,n}^{\min} \leq P_{B,n}^r \leq P_{B,n}^{\max}, \quad (1g)
\]
\[
B_{n+1}^r = B_n^r + \eta_{B,n} P_{B,n}^r \Delta, \quad (1h)
\]
\[
0 \leq \alpha_{i,n}^r \leq 1, \quad (1i)
\]
\[
\forall i \leq N_s, \forall o \leq N_{\ell}, n \in N^r, k = 1, 2, \tau = t, \ldots, t + H_{\ell}, \quad (1j)
\]

where \(\omega_{1,n}^r\), \(\omega_{2,n}^r\), and \(\kappa_{i,o}^r\) are CVaR auxiliary variables, and \(\lambda_{i,o}^r\), \(\xi_{i,o}^r\), \(\xi_{i,o}^r\) are auxiliary variables associated with the distributionally robust Wasserstein ball reformulation. For simplicity, the power factor constraints and apparent power limitation constraints are not treated as distributionally robust constraints, and instead are handled using direct sample average approximation.

C. Numerical results

We use a modified IEEE-37 node test feeder to demonstrate our proposed data-based stochastic AC OPF method. As shown in Fig. 1, the modified network is a single-phase equivalent and the load data is derived from real measurements from feeders in Anotlalia, CA during the week of August 2012 [25]. We place 21 photovoltaic (PV) systems in the network. Their locations are marked by yellow boxes in Fig. 1, and their capacities are summarized in Table I. Based on irradiation data from [25], [26], we utilized a greedy gradient boosting method [27] to make multi-step ahead predictions of solar injections, and then computed a set of forecast errors from the dataset. In general forecast errors increase with the prediction horizon. Other parameters of the network, such as line impedances and shunt admittances, are taken from [28]. The total nominal available solar power \(\sum_{n} P_{av,n}^r\) and aggregate load demand over 24 hours is also shown in Fig. 2.

The energy storage systems are placed with PV systems at certain nodes, as shown in Fig. 1. Their locations and capacities are listed in Table I. We select the capacities in the range of typical commercial storage systems, or aggregate of 10-12 residential-usage batteries (e.g., electric vehicles), which are connected to the same step-down transformer. The lower limit of SOC, \(B_{n}^{\min}\), is set to be zero for all batteries. The charging/discharging rate \(P_{B,n}^r\) is also limited by 10% of their respective energy capacity \(B_{n}^{\max}\). Voltage limits \(V_{\max}^r\) and \(V_{\min}^r\) are 1.05 p.u. and 0.95 p.u., respectively. The cost function parameters are \(a_{1,n}^r = 10, a_{2,n}^r = 3, a_{3,n}^r = 3\), and \(a_{4,n}^r = 6\). The decision making time period is 5 minutes.

Due to high PV penetration, overvoltage conditions can emerge during solar peak irradiation. For simplicity, we model only the upper voltage limitations over the solar peak hours 6AM to 5PM as distributionally robust (1b)-(1d). The lower voltage limitations and other constraints during the 6AM to 5PM are handled with empirical sample averaging, as in [6], [20]. The power factor PF limit is 0.9 in (1f). The risk
level parameter $\eta$ is set to 0.01 for quantifying 1% violation probability of constraints (1e)-(1f). To emphasize the effect of sampling errors, the number of forecast error samples $N_s$ included in the training dataset $\Xi^N_s$ is limited to 30. The forecast errors are not assumed bounded, so the parameters of the support polytope $\Xi_t := \{\xi_t \in \mathbb{R}^{N_{\xi}} : H_{\xi_t} \leq d\}$ are set to zero in (1b)-(1c). We solved (1) using the MOSEK solver [29] via the MATLAB interface CVX [30] on a laptop with 16 GB of memory and 2.8 GHz Intel Core i7. Solving each time step during solar peak hours with distributionally robust constraints takes 4.84 seconds. Note that our implementation is not optimized for speed and in principle could easily be sped up and scaled to larger problems since the problem is ultimately convex quadratic.

In our framework, there are two key parameters, $\rho$ and $\epsilon$, that explicitly adjust trade offs between performance and constraint violation risk, and robustness to sampling errors. Fig. 3 illustrates the basic tradeoffs between operational cost and CVaR values of voltage constraint violations during a 24-hour operation for various values of $\rho$ and $\epsilon$. It can be readily seen that as $\rho$ increases, operational cost increases, but CVaR decreases since the risk term is emphasized. Similarly, as $\epsilon$ increases, we see that CVaR decreases, since a larger Wasserstein ball leads to higher robustness to sampling errors. These parameters offer system operators explicit data-based tuning knobs to systematically set the conservativeness of operating conditions.

Fig. 4(a)-4(c) shows the aggregated solar energy curtailment and substation power purchases for varying risk aversion $\rho$ and Wasserstein radius $\epsilon$. In order to prevent voltages over 1.05 p.u., the available solar energy must be increasingly curtailed as the risk aversion parameter $\rho$ increases. As a result, the network must import more power from the substation. The increasing curtailment of solar energy and purchase of power drawn from the substation lead to significantly higher operational cost. However, these decisions will also lead to more stable voltage profiles, as shown in Fig. 5. When $\rho$ is small, there is almost no curtailment, causing overvoltages at several buses. As $\rho$ increases, more active power is curtailed, and all voltages move below their upper limit. Similar comments apply for varying the Wasserstein radius $\epsilon$. For example, fixing $\rho$ and increasing $\epsilon$ also results in more curtailment and lower voltage magnitude profiles, which leads to better robustness to solar energy forecast errors.

Finally, we evaluate out-of-sample performance by implementing the full closed-loop distributionally robust MPC scheme over the 24 hour period with a 15 minute planning horizon. Monte Carlo simulations with 100 realizations of forecast errors over the entire horizon are shown in Fig. 6. We subsampled new solar energy forecast errors from the training dataset. The closed-loop voltage profiles based on MPC decisions for all scenarios at node 28 are shown (other nodes with overvoltages show qualitatively similar results). Again, it is clearly seen that larger values of $\epsilon$ and $\rho$ yield more conservative voltage profiles.

In summary, we conclude that the proposed data-based distributionally robust stochastic OPF is able to systematically assess and control tradeoffs between the operational costs, risks, and sampling robustness in distribution networks. The benefits of the open-loop stochastic optimization problems are also observed in the closed-loop multi-period distributionally robust model predictive control scheme.

III. N-1 SECURITY PROBLEM IN TRANSMISSION SYSTEMS

In this section, we apply the proposed methodology from Part I in a transmission system to handle N-1 line flow security constraints. The basic DC power flow approximation and device modeling is discussed in Part I. Here, we also incorporate N-1 security constraints and associated contingency reactions due to uncertain wind power injections.

A. System model

We consider a transmission system with $N_G$ generators (e.g., conventional thermal and wind) connected to bus subset $N_G \subseteq N$. There are $N_L$ loads, $N_l$ lines, and $N_b$ buses. The outages included for N-1 security consist of tripping of any single lines, generators or loads, yielding $N_{out} = N_G + N_L + N_l$ possible outages. We collect the outages corresponding to a generator, a line and a load in different sets $\mathcal{I}_G$, $\mathcal{I}_l$, and $\mathcal{I}_L$. The outages in total are $\mathcal{I} = \{0\} \cup \mathcal{I}_G \cup \mathcal{I}_L \cup \mathcal{I}_l$, where $\{0\}$ indicates no outage.

The formulation of a N-1 security problem is based on the following assumptions: 1) the power flow equations are approximated with DC power flow, as described in Part I (Section V); 2) each wind farm is connected to a single bus of the network; 3) load forecasting is perfect; 4) a single line outage can cause multiple generator/load failures.

The objective of the data-based distributionally robust stochastic DC OPF is to determine an optimal reserve schedule for responding to the wind energy forecast errors while taking the network security constraints into account. We define

![Fig. 3. Tradeoffs between operational cost, conditional value at risk (CVaR) of voltage constraints, and robustness to sampling errors, illustrated by varying the parameters $\rho$ and $\epsilon$ that control relative objective function weighting and Wasserstein ball radius, respectively.](image-url)
Fig. 4. Comparison of active power curtailment and power purchased from substation for various values of risk aversion $\rho$ and Wasserstein radius $\varepsilon$. As these parameters increase, more active power from PV is curtailed and more power is drawn from the substation, leading to lower constraint violation risk but higher operating cost.

Fig. 5. Optimal network voltage profiles for varying $\rho$ and $\varepsilon$. Overvoltages are reduced as $\rho$ increases.

$$P_{\text{mis}}^j \in \mathbb{R} \quad \text{for all } j \in \mathcal{I}$$

as the generation-load mismatch given by

$$P_{\text{mis}}^j = \begin{cases} P_L^j - P_G^j, & \text{if } j \in \{0\} \cup \mathcal{I}_t \\ +P_L^j, & \text{if } j \in \mathcal{I}_L \\ -P_G^j, & \text{if } j \in \mathcal{I}_G, \end{cases}$$

where $P_L^j, P_G^j \in \mathbb{R}$ denote the power disconnection corresponding to the outage $j \in \mathcal{I}$. Define $P_G \in \mathbb{R}^{N_G}$, and $P_L \in \mathbb{R}^{N_L}$ as nodal generation and load injection vectors. For the generator or load failures, the power disconnection $P_G^j$ or $P_L^j$ is corresponding to the components in the vector $P_G$ or $P_L$. In the case of line failures $j \in \mathcal{I}_t$, the power disconnection $P_{\text{mis}}^j$ or $P_L^j$ is the sum of the power loss caused by multiple failures. If there is no power disconnection caused by a line outage, or if $j = 0$ (no outage happens), the power mismatch is set to zero: $P_{\text{mis}}^0 = 0$.

To respond to contingencies, we can also define another reserve policy response matrix $R_{\text{mis},t}^{j,d} := [R_{\text{mis},t}^{1,d}, \ldots, R_{\text{mis},t}^{t,d}]^\top \in \mathbb{R}^t$, so that the affine reserve policy becomes

$$u_t^d = D_t^d \xi_t + R_{\text{mis},t}^{j,d} P_{\text{mis}}^d + \varepsilon_t^d, \forall j \in \mathcal{I}, d = 1, \ldots, N_t.$$

The general constraint risk function of the line flow in Part I (Section V, Equation (14c)) is then given by
wind energy forecast errors. The random vector \( \xi \) which captures nominal and reserve costs of responding to line flow constraints, and sampling error robustness. The goal is to balance tradeoffs between cost of thermal generation, CVaR values of the line flow constraints, and sampling error robustness. The generation with reserve policy in the cost function is given by

\[
P_d^t = D^d_t \xi_t + e^d_t,
\]

which captures nominal and reserve costs of responding to wind energy forecast errors. The N-1 security reserve cost is not included to simplify presentation, but this can also easily be included in our framework as an additional linear cost [15].

With the proposed modeling in Part I (Section V), the updated data-based stochastic DC OPF is shown as follows. The decision variables are collected into \( y \)

\[
J^N_{\text{Cost}} = \sum_{d \in N_G} c_{1,d} [P^d_G]^2 + c_{2,d} [P^d_G] + c_{3,d},
\]

where \( \bar{y} \) maps the power injection of each device in the case of \( j \)-th outage.

**B. Data-based stochastic OPF implementation**

We now use the modeling here and in Part I and the affine control strategy (2) to formulate a data-based distributionally robust stochastic DC OPF for transmission systems that also incorporate N-1 security constraints. The goal is to balance tradeoffs between cost of thermal generation, CVaR values of the line flow constraints, and sampling error robustness. The generation with reserve policy in the cost function is given by

\[
P_d^t = D^d_t \xi_t + e^d_t,
\]

the operational cost of generators is

\[
J^N_{\text{Cost}} = \sum_{d \in N_G} c_{1,d} [P^d_G]^2 + c_{2,d} [P^d_G] + c_{3,d},
\]

which captures nominal and reserve costs of responding to wind energy forecast errors. The N-1 security reserve cost is not included to simplify presentation, but this can also easily be included in our framework as an additional linear cost [15].

With the proposed modeling in Part I (Section V), the updated data-based stochastic DC OPF is shown as follows. The decision variables are collected into \( y_t \) such that \( y_t = \{D_t, c_t, R_{\text{min}, t}\} \).

The random vector \( \xi_t \) comprises all wind energy forecast errors.

**Data-based distributionally robust stochastic DC OPF:**

\[
\inf \limits_{y_t, \sigma^2_t} \sum_{d=1}^{N_d} \{ E[J^N_{\text{Cost}}] + \rho \sup \limits_{Q_t \in P^2 \tau} \sum_{o=1}^{N_o} E[Q^o_t] \},
\]

subject to:

\[
\rho (\mathbf{b}_{ik}(\sigma^2_t) + \mathbf{b}_{ik}(\bar{y}_{ik}) - \mathbf{c}_{ik}(\bar{s}_{ik}, t - H_{\text{L}})) \leq s_{ik}, \quad (4b)
\]

\[
1 \geq \mathbf{c}_{i,k} \geq 0, \quad (4d)
\]

\[
\sum_{d=1}^{N_d} \sum_{t=1}^{T} \left( \sum_{d=1}^{N_d} \left( r_d^t + C^d_{i,k} A^d_0 D^d_{i,k} + B^d_{i,k} D^d_{i,k} \right) \right) \leq 0, \quad (4e)
\]

\[
\sum_{d=1}^{N_d} \left( G^d_{i,k} + C^d_{i,k} B^d_{i,k} D^d_{i,k} \right) = 0, \quad (4g)
\]

\[\forall t \leq N_t, \forall j \in J, \forall o \leq N_o, k = 1, 2, \tau = t, \ldots, t + H_{\text{L}}.\]

**C. Numerical results**

We consider a modified IEEE 118-bus test system to demonstrate our proposed data-based distributionally robust stochastic DC OPF shown in Fig. 7. For simplicity, we only show results of a single-period stochastic optimization problem. As with the distribution network, it is straightforward to extend to multi-period closed-loop stochastic control using MPC.

Three wind farms are connected to bus #1, bus #9, and bus #26, with the normal feed-in power 500 MW, 500 MW, and 800 MW, respectively. The corresponding conventional generators at bus #1 and bus #26 are removed. The wind power forecast errors are derived from the real wind sampling data from Fig. 6. Monte Carlo simulation results of the voltage profiles at node #28 resulting from the full distributionally robust closed-loop model predictive control scheme. We validate that in closed-loop larger values of \( \varepsilon \) and \( \rho \) yield more conservative voltage profiles.
hourly wind power measurements provided in 2012 Global Energy Forecasting competition (GEFCom2012) [31]. The wind energy forecast errors are evaluated based on a simple persistence forecast, which predicts that the wind injection in the following period remains constant. It can be seen the forecast errors are highly leptokurtic, i.e., that the errors have significant outliers that make the distribution tails much heavier than Gaussian tails. We scale the forecasting errors to have zero mean and the standard deviations of 200 MW, 200 MW and 300 MW for the wind farms at bus #1, #9 and #26, respectively. We consider five key lines, which deliver the wind power from the left side of the system to the right, as marked by the red crosses in Fig. 7. The line flow limits are shown in Table II. The line flow limits are shown in Table II.

### TABLE II

| # of line | From bus | To bus | Line flow limitation [MW] |
|-----------|----------|--------|---------------------------|
| 7         | 8        | 37     | 600                       |
| 37        | 8        | 32     | 500                       |
| 38        | 26       | 30     | 500                       |
| 54        | 30       | 38     | 500                       |
| 96        | 38       | 65     | 300                       |

To simple our presentation, only these five lines flows are handled with distributionally robust optimization (4b)-(4d) in both directions; the remaining line flows are modeled by N-1 security constraints (4e) with nominal CVaR and sample average approximation (essentially equivalent to taking $\varepsilon = 0$), and no other local device constraint is included. Additionally, we assume no bounds on the wind power forecast errors $\xi_r$, hence $H$ and $\mathbf{d}$ in (4b)-(4c) are set to zero. It takes 10 seconds to solve (4) for each time step using the MOSEK solver [29] via the MATLAB interface with CVX [30] on a laptop with 16 GB of memory and a 2.8 GHz Intel Core i7.

Fig. 8(a) illustrates the solutions of the proposed data-based distributionally robust stochastic DC OPF for varying risk aversion and Wasserstein radius. Once again, the numerical results demonstrate fundamental tradeoffs between operational cost, CVaR values of line constraints violations, and robustness to sampling errors. The conservativeness of the generator policies are controlled by adjusting $\rho$ and $\varepsilon$. By explicitly using the forecast error training dataset and accounting for sampling errors, risks are systematically assessed and controlled. Since the forecast errors are non-Gaussian, existing methods may significantly underestimate risk [32]. Increasing $\varepsilon$ provides better robustness to sampling errors and guarantees out-of-sample performance. Note that CVaR values can be negative when the worst-case expected line flow is below the constraint boundary.

Fig. 8(b) illustrates the out-of-sample performance of the decisions via Monte Carlo simulations. For every risk aversion value $\rho$ shown in Fig. 8(a), we subsampled new values from the training dataset to operate our system based on the decisions from Fig. 8(a), and calculated the empirical CVaR of the line constraints violations. The number of scenarios for Monte Carlo simulations is 1000. From the simulation results, we conclude that larger $\varepsilon$ ensures smaller line constraint violation for all lines except line 38. This happens because the risk objective is the sum of all five CVaRs, and a lower overall risk is achieved for certain values of $\rho$ and $\varepsilon$ by trading off against risk of violating the flow limit of line 38. In general, it is possible to prioritize certain important constraints by weighting their associated risk higher compared to lower priority constraints. Again, Monte Carlo simulations demonstrate conservativeness of controlled explicitly by changing the Wasserstein radius $\varepsilon$ and the risk aversion $\rho$. Overall, our simulations illustrate the flexibility of our proposed data-based stochastic OPF for transmission systems.

### IV. Conclusion

We have illustrated the effectiveness and flexibility of our proposed multi-period data-based distributionally robust stochastic OPF methodology. We performed numerical experiments to balance overvoltages in distribution networks and $N-1$ security line flow risks in transmission networks. The flexibility of controllable devices was exploited to balance efficiency and risk due to high penetration renewable energy sources. In contrast to existing work, our method directly incorporates forecast error training datasets rather than making strong assumptions on the forecast error distribution, which allows us to leverage distributionally robust optimization techniques to achieve superior out-of-sample performance. Parameters in the optimization problems allow system operators to systematically select operating strategies that optimally trade off performance and risk.

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(a) Predicted tradeoffs between operational cost and CVaR of line constraint violation.  
(b) Out-of-sample performance is demonstrated by Monte Carlo simulation, the conservativeness is explicitly controllable.

Fig. 8. Five key line flow constraints are used to illustrate our proposed data-based distributionally robust stochastic DC OPF in a transmission system.