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Modelling wind power spatial-temporal correlation in multi-interval optimal power flow: A sparse correlation matrix approach

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HIGHLIGHTS

- Spatial and temporal correlation of wind power and uncertainty considered.
- Sparse correlation matrix efficiently models the spatial-temporal correlation.
- Distributionally robust chance constrained OPF model considers economics and security.
- Considering spatial-temporal correlation leads to lower system operating cost.
- Comparison with scenario-based stochastic model shows efficiency of proposed model.

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ABSTRACT

The significantly increasing deployment of wind power necessitates that system operation considers the spatial-temporal correlation of power forecast from different wind power plants. How to model this spatial-temporal correlation in the actual system dispatch is challenging. In this paper, a sparse correlation matrix is utilized to efficiently model the spatial-temporal correlation of wind power forecast in the generation dispatch model. A novel, adjustable, and distributionally-robust chance-constrained multi-interval optimal power flow (ADRCC-MIOPF) model is proposed to obtain reliable economic dispatch (ED) solutions. The spatial-temporal correlation of wind power plants power forecasts is represented by the sparse correlation covariance matrix obtained from historical, time series wind power forecast error data. The chance constraints in the ADRCC-MIOPF model are transformed into a set of second-order-cone (SOC) constraints in which an adjustable coefficient in the chance constraints controls the robustness of the ADRCC-MIOPF model to the wind power forecast errors distribution. Case studies performed on the PJM 5-bus system and IEEE 118-bus system verify the proposed method to improve the system security and reduce the cost especially under the high wind penetration levels. All the cases can be solved within several minutes for both the small and large cases which validates the efficiency of the proposed sparse matrix model. In addition, considering the spatial-temporal correlation of wind power forecast and the distributional robustness of wind power forecast error leads to a more reliable economic dispatch with lower system violations.

All the other variables and parameters are explained in the manuscript text.

1. Introduction

Wind power has substantially increased in power systems worldwide because of environmental concerns and the continually decreasing capital costs of the technology due to technology innovations [1]. In the United States, obtaining 20% of energy provided from wind at the end of 2030 has been set as a target by the U.S. Department of Energy [2]. Consequently, the penetration of wind power has increased significantly in many power systems in the United States [3].

In power system operations considering high-penetration wind power, the correlation among wind power plants forecast errors should be considered because the power output of each individual wind power plant is not independent from adjacent wind power plants, as has been

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Nomenclature

t	time index
i, j, k	index for network node
$c_{i,t}$	price of generator at bus i ($/MWh) at time t
$G_{i,t}$	generation power output at bus i (MW) at time t
G_i^{max}/G_i^{min}	maximum/minimum generation level of generator i (MW)
$D_{i,t}$	demand quantity (MW) at bus i at time t
$P_{i,t}$	wind power output (MW) at bus i at time t
GSF_{l-i}	generation shift factor of bus i to line l
LU_l	line limit of line l
$G_{exp,i,t}$	expected generation output of generator i (MW) at time t
$P_{exp,i,t}$	wind power point forecast (MW) at bus i at time t
$\beta_{i,t}$	generation balancing factor at bus i of time t
$\Delta P_{i,t}$	uncertain wind power output at time t
$\Delta G_{i,t}$	generation i's response to the system uncertainty at time t
$PF_{l,t}$	power flow on line l at time t
f_{obj}	system generation cost considering uncertainty
Ξ	sparse covariance matrix of wind power forecast errors
$\sigma_{i,t}$	standard deviation of wind power plant i's forecast error
$\sigma_{PF,l,t}$	standard deviation of the transmission l-th line power flow
$\sigma_{g,i,t}$	standard deviation of the generation i-th output at time t
R_i^U/R_i^D	ramp-up/-down capability (MW/minutes) of generation i
$\Delta\ t$	length of the time interval (minutes)
$Ramp_{i,t}$	ramp capacity of the generation i-th power at time t
$r_{g,i,t}$	standard deviation of the generation i-th ramp at time t

shown in [4]. In actual system operation, ignoring this correlation leads to underestimation of the risks on the system [5]. In [6], the spatial correlation of wind power in the security-constrained unit commitment and security-constrained economic dispatch problem was studied. In this study, the wind power correlation was modelled by a set of correlated scenarios which was also deployed in [7] or by a correlation covariance matrix, while the temporal correlation was usually modelled by generating dynamic scenarios considering the probability transfer matrix between consecutive time intervals [8]. In [9], a Copula based method was proposed to decide the system reserve considering wind power plant correlation. The conditional probabilistic distribution of wind power forecast was derived under different power levels while the temporal correlation was not explicitly modelled. The wind power forecast errors conditional model and the scenario creation considering this interdependency was introduced in [10]. The wind power density distribution considering the geographical information was studied in [11] which includes the spatial correlation information. The generation dispatch considering the spatial-temporal correlated wind power forecast was investigate in [12]. It demonstrated that the system cost could be reduced through considering the spatial-temporal correlation in the wind power forecast [13]. Although the forecast considered the spatial-temporal correlation, point forecasts were used and the impact of wind power forecast uncertainty on the system operation was not modelled.

To maintain system reliability considering the uncertainty associated with the wind power forecast, chance-constrained optimal power flow (CC-OPF) has been studied in economic dispatch [14] considering the impact of the variable and uncertain characteristics of wind power output. In chance-constrained optimization, the system's physical constraints, such as transmission power flow and generation output, are modelled as chance constraints to represent the impacts of renewable power output uncertainties on transmission overloading and generation violations [15]. Previously, Gaussian distribution was used to represent the short-term wind power forecast uncertainty, but it might lead to an estimation error for the system condition [16]. Distributionally-robust CC-OPF was proposed in [17], which needed only the forecast mean and variance information, but it can lead to a conservative dispatch and high generation cost because the dispatch was robust to all possible distributions of the forecast error. Robust optimization is also applied in system operation problems in [18]. In robust optimization, system reliability is maintained through the consideration of the worst-case scenario at the cost of a more conservative dispatch solution [19]. In stochastic optimization [20], the uncertainty is represented through a set of probabilistic scenarios to obtain a minimized expected system cost, given the probabilities of the varied scenarios which might need high computational capability to solve [21]. Therefore, how to efficiently consider both the spatial-temporal correlation of wind power forecast and the uncertainty of wind power forecast in the system operation is still challenging.

To address this problem, this paper proposes a sparse correlation matrix based adjustable and distributionally-robust chance-constrained multi-interval optimal power flow model (ADRCC-MIOPF). In this model, the wind spatial-temporal correlation is modelled through a sparse matrix which is efficient to solve and only the first-order and second-order moments of the wind power forecast errors are needed for the distributional robustness, which can be obtained from historical chronological wind forecast data. The chance constraints in the proposed ADRCC-MIOPF model are reformulated as a set of second-order cone (SOC) constraints, then the model is transformed into a quadratically constrained programming (QCP) problem. Both the impacts of the spatial-temporal correlations on the system generation and reserve dispatch are analytically analyzed. The robustness of the chance constraints to the distribution of wind power forecast errors is controlled through an adjustable coefficient in the chance constraints. The major contributions of this paper are:

(1) It considers both the spatial and temporal correlation of wind power plants power output uncertainty in the optimal power flow model.
(2) It utilizes a sparse correlation matrix to efficiently model the spatial-temporal correlation of wind power forecast instead of large number of dynamic scenarios.
(3) An ADRCC-MIOPF model is proposed to control the robustness of chance constraints to the forecast errors and tradeoff between economics and system security.
(4) Comparison with the scenarios-based stochastic model demonstrates the efficiency of the proposed model.

The rest of this paper is organized as: Section 2 presents the sparse spatial-temporal correlation covariance matrix construction from historical wind power forecast error data; Section 3 proposes the ADRCC-MIOPF model, the formulation into the QCP model, and the choice of the adjustable coefficients in chance constraints to control the robustness; Section 4 performs the case studies on the PJM 5-bus and IEEE 118-bus systems to verify the proposed method; and Section 5 concludes the paper.

2. Spatial-temporal correlation of short-term wind power forecast error

In this section, the spatial-temporal correlations among different wind power plants power forecast error at different time intervals are analyzed. The spatial correlation is directly driving the joint probability distribution of the total power output of all wind power plants, which has a significant impact on the system generation cost [6]. The temporal correlation of wind power plants' power output among different time intervals determines the ramping capacity among adjacent time intervals, which also impact the system's generation cost implicitly.

The historical (time series) data used here for wind power forecasting errors is from the California Independent System Operator (CAISO). There are 16 wind units with forecast errors in 2010 [16].