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Stochastic Dynamic Optimal Power Flow Integrated with Wind Energy Using Generalized Dynamic Factor Model

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Abstract: Integrating large wind power to power grid complicates the system operation due to the intermittency of wind. To address the challenges associated with wind power this paper formulates a stochastic dynamic optimal power flow to consider the uncertainty of wind power forecast in the power system operation. The goal of the system operation is to minimize the expected operational cost. The uncertainty of wind power forecast can be represented by a set of scenarios. For accurate forecasting, the generalized dynamic factor model (GDFM) is proposed to synthesize the forecasted wind power outputs while it preserves the correlation structure among wind power outputs from closely located wind farms under similar weather condition. In this paper, the GDFM was developed by the raw data of 94 wind farms in Texas and we use the model to predict hourly wind power outputs for 24 hours. This work also emphasizes on AC optimal power flow and is solved by a novel heuristic method, artificial bee colony (ABC). Such method is chosen because of its effective nature of handling hard constraints. Case studies are conducted on modified IEEE-30 system.

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Keywords: Wind energy, Generalized dynamic factor model (GDFM), Stochastic optimization, AC optimal power flow (ACOPF), Artificial bee colony (ABC).

1. INTRODUCTION

The high penetration of wind power to grid has complicated the system operation significantly because of the intermittent nature of wind (Su and Wang, 2012). The uncertainty of wind power forecast can have a tremendous impact on the system operations even by small errors. Such impact can be reflected in ancillary services such as reactive power compensation, voltage regulation, and operating reserves. Therefore independent system operators (ISO) in competitive electricity markets seek for optimization methods for managing the system under reliable and economically friendly conditions by utilizing wind power (Khattam et al., 2003).

Deterministic operation approaches such as unit commitment (UC) or optimal power flow (OPF) is appropriate for short-term generation scheduling (Lyu et al., 2013). However with large wind energy penetration, stochastic/probabilistic approaches are in urgent need of development due to the intermittent nature of wind power. The representation of wind power forecasting (WPF) uncertainty in the UC problem has been investigated (Wang et al., 2011). It is shown that the stochastic approach has advantages over deterministic one in providing a rational and adaptive way to provide operating reserves. The security-constrained UC with volatile wind power generation was formulated and the wind power was represented by several possible scenarios (Wang et al. 2011). Wind power scenarios are generated through Monte Caro simulation assuming that the forecast error is under normal distribution. However such assumption fails to consider the correlation among wind farms.

Economists and forecasters have tried to analyze the relationship between explanatory and response variables to build accurate forecasting model. Explanatory variable is any factor that influence the response variables, and response variable (wind power output in this study) is the quantity we want to know. The first challenge of analyzing the relationship is when an unobservable explanatory variable arises, such as weather conditions (wind speed, wind direction, air mass, etc.) in wind power system. The factor analysis overcomes this obstacle by assuming that response variables are loaded by the linear combination of unobservable factors with different weighted parameter, which is a factor loading (Burns et al., 1946). In the factor analysis, the factors and factor loadings are estimated by analyzing the response variables. The second challenge is to design multi-dimensional explanatory and response variables by considering the correlation structure among them. The multivariate time-series model can design the explanatory and response variables through the polynomial matrix, where the correlation structure is preserved. However, as the size of dimension increases linearly, the number of parameters increases exponentially, so the advantage of the factor analysis to represent the system parsimonious is faded away.

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Therefore, the possible solution to both obstacles is to construct the multivariate time-series model on factors in order to reduce the number of variables and describe the dynamic relationship between the factor and factor loadings.

The generalized dynamic factor model (GDFM) becomes one of solutions (Forni et al., 2000). The pre-processing step of the GDFM is to extract from the observation data the common component, which is directly affected by weather conditions, so that the GDFM ignores unrelated errors obtained in a measurement process. There are multiple types of load and generation scenarios: generating point values, scaling time series, and utilizing the power curve of wind farm (Wang et al., 2011). However, these scenarios did not systematically considered the correlation structure among raw data. Since wind farms in Texas are under the same weather condition, wind power outputs are highly correlated, so dynamic factors of correlated wind power outputs might share co-movements. The role of the GDFM is to analyze these co-movements and synthesize correlated wind power forecasts. In this paper, GDFM is proposed to generate wind power forecasting scenarios based on the power output data of 94 wind farms.

It is known that the static OPF is a non-linear, non-convex and mixed-integer problem and in order to make a day-ahead operation, dynamic OPF needs to be introduced for the optimization over 24 hours. In addition, when considering the WPF uncertainty through scenarios, an efficient solving algorithm is in urgent need. A common method to tackle the stochastic dynamic OPF is to decompose the main problem into master energy scheduling problem and a power flow sub-problem (Su et al., 2014). In master problem stage, control variables are solved without considering power flow, ramp rate and bus voltage constraints; then the control variables are passed into the sub-problem stage where all constraints are verified. Another perspective of methodology is from heuristic methods. It is demonstrated that the static OPF can be efficiently solved by heuristic methods (such as genetic algorithm and particle swarm optimization) without simplifying the system, and promising results can be obtained (Park et al., 2010; Lee et al., 2008; Sivasubramani and Swarup, 2011). Therefore in this paper, we adopted artificial bee colony (ABC) and modified it to solve dynamic OPF. The objective is to minimize the expected total cost under all forecasting scenarios over 24 hours.

The paper is organized as follows: Section II formulates the stochastic dynamic OPF integrated with wind power, and Section III describes methodology and the implementation of ABC into dynamic optimization. In Section IV the proposed algorithm is tested in simulation, and the performance of stochastic approach was evaluated. Finally, the conclusion is provided in Section V with recommendation for future works.

2. PROBLEM FORMULATION

In this section the traditional optimal power flow (OPF) is introduced first, followed by the modified dynamic OPF integrated with wind power. Lastly the generalized dynamic factor model (GDFM) is proposed to generate wind power forecast scenarios and the stochastic optimization is formulated to minimize the total expected operational cost.

2.1 Traditional Optimal Power Flow

The objective of traditional OPF is to minimize fuel cost for power generation by determining a setting of control variables while satisfying network constraints and operational requirements. Its mathematical formulation is:

$$\text{Min } f(x,u) \tag{1}$$

$$\text{s.t. } g(x,u)=0 \tag{2}$$

$$h(x,u)\le 0 \tag{3}$$

where vector u represents decision/control/independent variables and it includes generator real power P_G except at slack bus, generator bus voltage V_G, transformer tap T, and shunt compensator Q_C at selected buses. The vector x is state/dependent variables which include real power P_{G1} at slack bus, voltages V_L at load bus, reactive power Q_G at generator bus, and loadings S_L of transmission lines. The objective functions f from (1) considered in the study are the total fuel cost:

$$f=\sum_i a_i P_{Gi}^2 + b_i P_{Gi} + c_i \tag{4}$$

where a_i, b_i, c_i, and P_{Gi} denote for the fuel cost coefficients and real power of the i-th unit. The equality constraints g from (2) are the AC power flow balance equations at each bus representing that the power flowing into that specific bus is equal to the power flowing out, and the equations are defined as:

$$\begin{aligned} P_i &= V_i\sum_{j=1}^{N} V_j Y_{ij}\cos(\delta_i-\delta_j-\theta_{ij}) \\ Q_i &= V_i\sum_{j=1}^{N} V_j Y_{ij}\sin(\delta_i-\delta_j-\theta_{ij}) \quad \forall i,\forall j \end{aligned} \tag{5}$$

Inequality constraints h in (3) are listed as generator limits, tap position of transformers, shunt capacitor constraints, security constraints, load bus voltage and transmission line flows.

Generator limits:

$$\begin{aligned} &P_{Gi,\max}\le P_{Gi}\le P_{Gi,\max} \\ &Q_{Gi,\max}\le Q_{Gi}\le Q_{Gi,\max} \\ &V_{Gi,\max}\le V_{Gi}\le V_{Gi,\max} \quad i\in N_G \end{aligned} \tag{6}$$

Tap positions of transformers:

$$TP_{i,\min}\le TP_i\le TP_{i,\max} \quad i\in N_T \tag{7}$$

Shunt capacitors constraints:

$$Q_{ci,\min}\le Q_{ci}\le Q_{ci,\max} \quad i\in N_c \tag{8}$$

Static Security constraints on the limits of load bus voltage and transmission line flows:

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