A Computational Framework for Uncertainty Quantification and Stochastic Optimization in Unit Commitment With Wind Power Generation

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***Abstract*—We present a computational framework for integrating a state-of-the-art numerical weather prediction (NWP) model in stochastic unit commitment/economic dispatch formulations that account for wind power uncertainty. We first enhance the NWP model with an ensemble-based uncertainty quantification strategy implemented in a distributed-memory parallel computing architecture. We discuss computational issues arising in the implementation of the framework and validate the model using real wind-speed data obtained from a set of meteorological stations. We build a simulated power system to demonstrate the developments.**

***Index Terms*—Closed-loop, economic dispatch, unit commitment, weather forecasting, wind.**

NOMENCLATURE

Numerical Weather Prediction

γ	Ensemble inflation factor.
$\mathcal{M}$	Numerical weather prediction model.
M_x	Number of model states.
N_S	Number of ensemble members.
$\mathbf{Q}$	Covariance of the model error.
U, V, T	Horizontal wind components and the temperature atmospheric fields.
$\mathbf{V}, \mathbf{C}$	Covariance and correlation matrices of the initial ensemble.
x	Atmospheric field.
$\overline{x}, \mathbf{S}^2$	Ensemble sample average and covariance matrix.
x_{NARR}	Atmospheric state reconciled with observations.

Unit Commitment

a_j, b_j	Coefficients of production cost function of thermal unit j.
$cc_j, hc_j, t_j^{\mathrm{cold}}$	Startup cost function coefficients of thermal unit j.
$c_{j,k}^d$	Shutdown cost of thermal unit j in period k.
$c_{j,k}^p$	Production cost of thermal unit j in period k.
$c_{j,k}^u$	Startup cost of thermal unit j in period k.
C_j	Shutdown cost of thermal unit j.
D_k	Load demand in period k.
DT_j	Minimum down time of thermal unit j.
K_j^t	Cost of interval t of the stairwise startup function of thermal unit j.
N	Number of thermal units.
N_S	Number of wind-power scenarios.
N_{wind}	Number of wind units.
ND_j	Number of intervals of the stairwise startup function of thermal unit j.
$\nu_{j,k}$	On/off state of thermal unit j in period k.
$p_{s,j,k}$	Power output of thermal unit j in period k and scenario s.
$p_{s,j,k}^{wind}$	Forecasted power output of wind unit j in period k and scenario s.
$p_{s,j,k}^{wind,true}$	Observed power output of wind unit j in period k and scenario s.
$\overline{P}_j$	Maximum power output of thermal unit j.
$\underline{P}_j$	Minimum power output of thermal unit j.
R_k	Reserve in period k.
RD_j	Ramp-down limit of thermal unit j.

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RU_j	Ramp-up limit of thermal unit j.
SD_j	Shutdown limit of thermal unit j.
SU_j	Startup limit of thermal unit j.
T	Number of periods.
UT_j	Minimum up time of thermal unit j.

Inference Analysis

$\mathbf{A}, b$	Coefficients of first-stage constraints.
d	Coefficients of first-stage cost.
$\hat{f}^j_{N_S}$	Suboptimal sample average cost for batch j.
$L_{N_S,M}, s^2_{L,N_S,M}$	Mean and variance of lower bound.
M	Number of data batches.
q	Coefficients of second-stage cost.
$\mathcal{Q}, Q$	Second-stage cost and realization.
$\mathbf{T}, \mathbf{W}$	Coefficients of second-stage constraints.
$U_{N_S,M}, s^2_{U,N_S,M}$	Mean and variable of upper bound.
$\hat{v}^j_{N_S}$	Optimal sample average cost for batch j.
ξ_s	Realization s of random variable.
y	Second-stage decision variables for scenario k.
z	First-stage decision variables.

I. Introduction

WIND power is becoming worldwide a significant component of the power generation portfolio. In Europe, several countries already exhibit adoption levels in the range of 5%–20% of the total annual demand. In the U.S., an adoption level of 20% is expected by the year 2030 [1]. Such a large-scale adoption presents many challenges to the operation of the electrical power grid because wind power is highly intermittent and difficult to predict. In particular, unit commitment (UC) and economic dispatch (ED) operations are of great importance because of their strong economic impact (on the order of billions of dollars per year) and increasing emissions concerns.

Several UC studies analyzing the impact of increasing adoption levels of wind power have been performed recently. In [21], a security-constrained stochastic UC formulation that accounts for wind-power volatility is presented together with an efficient Benders decomposition solution technique. In [19], a detailed closed-loop stochastic UC formulation is reported. The authors analyze the impact of the frequency of recommitment on the production, startup, and shutdown costs. They find that increasing the recommitment frequency can reduce costs and increase the reliability of the system. None of these previous stochastic optimization studies present details on the wind-power forecast model and uncertainty information used to support their conclusions. In [12] and [15], artificial neural network (ANN) models are used to compute forecasts and confidence intervals for the total aggregated power for a set of distributed wind generators. A problem with empirical (data-based) modeling approaches [5], [20], [22], however, is that their predictive capabilities rely strongly on the presence of persistent trends. In addition, they neglect the presence of spatio-temporal physical phenomena that can lead to time-varying correlations of the wind speeds at neighboring locations. Such approaches can thus result in inaccurate medium- and long-term forecasts and over- or underestimated uncertainty levels [8], [13], [14], which in turn affect the expected cost and robustness of the UC solution. A comparison between uncertainty quantification techniques with empirical and physical weather prediction models for ambient temperature forecasting is presented in [23].

In this work, we seek to exploit recent advances in numerical weather prediction (NWP) models to perform UC/ED studies with wind-power adoption. The use of physical models is desirable because consistent and accurate uncertainty information can be obtained [13]. In a previous study, we have found that NWP models allow one to obtain much tighter uncertainty intervals of temperature forecasts that translate into lower operating costs in building systems [23]. On the other hand, we have also found that the practical capabilities of NWP models are limited. One of the major limiting factors is their computational complexity. For instance, performing data assimilation every hour at a high spatial resolution is currently not practical. In addition, extracting uncertainty information from NWP models quickly becomes intractable from the point of view of both simulation time and memory requirements. The question is: *From an operational point of view, how suitable and practical are the forecasting capabilities of state-of-the-art NWP models?* This is an important question because NWP models are expected to be used to make real-time operational decisions with important economic implications. To analyze this issue, we present a framework that integrates the Weather Research and Forecast (WRF) model with a closed-loop stochastic UC/ED formulation. In particular, we are interested in analyzing computational issues and the effects of wind uncertainty on UC/ED operations.

Arguably, more sophisticated hybrid methods that combine both NWP wind speed forecasts and empirical models are needed to map the resolution of NWP forecasts down to a specific domain and to account for system-specific characteristics (e.g., power curves, orography) [6], [13], [16]. We point out, however, that our approach offers several advantages over previous work involving wind forecast, such as [6] and [16]. The fact that we have control over both the UC/ED model and the WRF model allows us to refine the wind forecast with uncertainty as needed. In particular, as presented in Section IV-A, we can run the WRF at higher resolution than the data in [6] and [16], and we also have control over the number of scenarios used. The latter capability can have a large impact on the UC/ED solution feasibility and efficiency and can be used in conjunction with the confidence estimation described in Section III-D either to increase the number of scenarios in order to improve the uncertainty precision, if needed, or to use a more calculated conservative solution. Full quantification of