Short-Term Spatio-Temporal Wind Power Forecast in Robust Look-ahead Power System Dispatch

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Abstract—We propose a novel statistical wind power forecast framework, which leverages the spatio-temporal correlation in wind speed and direction data among geographically dispersed wind farms. Critical assessment of the performance of spatio-temporal wind power forecast is performed using realistic wind farm data from West Texas. It is shown that spatio-temporal wind forecast models are numerically efficient approaches to improving forecast quality. By reducing uncertainties in near-term wind power forecasts, the overall cost benefits on system dispatch can be quantified. We integrate the improved forecast with an advanced robust look-ahead dispatch framework. This integrated forecast and economic dispatch framework is tested in a modified IEEE RTS 24-bus system. Numerical simulation suggests that the overall generation cost can be reduced by up to 6% using a robust look-ahead dispatch coupled with spatio-temporal wind forecast as compared with persistent wind forecast models.

Index Terms—Data-driven forecast, look-ahead dispatch, spatio-temporal statistics, wind generation.

I. NOMENCLATURE

The notations are summarized in Table I.

II. INTRODUCTION

U NCERTAINTIES and variabilities in renewable generation, such as wind energy, pose significant operational challenges to power system operators [1]–[5]. While conventional wisdom suggests that more spatially dispersed wind farms could be aggregated and "smooth out" total wind generation at any given time, the reality is that wind generation tends to be strongly correlated in many geographical regions [6], [7]. As many regions/states are moving toward renewable portfolio standards (RPS) in the coming decade, the role of *accurate wind prediction* is becoming increasingly important for many regional transmission organizations (RTOs) [8].

The major uncertainty in conventional power grid operation comes from the demand side [9]–[11]. Nowadays, in power systems with high presence of intermittent generation, the main

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TABLE I NOTATIONS

G	Set of conventional power plants					
D	Set of inelastic loads					
n	Number of wind farms installed in system					
k	Time step in a look-ahead horizon with k_0 as its initial step					
C_{G_i}	Generation cost function of power plant i					
C_{W_i}	Generation cost function of wind farm i					
C_{Rs_i}	Reserve cost function of power plant i					
C_{U_i}	Start-up cost of generator i					
C_{D_i}	Shut-down cost of generator i					
$P_{G_i}^k$	Scheduled generation of power plant i at time k					
$P_{W_i}^k$	Scheduled generation of wind farm i at time k					
$P_{D_i}^k$	Forecasted load level of bus i at time k					
$P_{Rs_i}^k$	Scheduled reserve capacity of power plant i at time k					
\mathbf{F}^{k}	Vector of branch flow at time k					
F ^{max}	Vector of capacity limits of transmission lines					
$\triangle T$	Energy Market scheduling interval					
P_i^R	Ramping constraints of power plant i					
$P_{G_i}^{min}$	Lower operating limit for power plant <i>i</i>					
$P_{G_i}^{max}$	Higher operating limit for power plant <i>i</i>					
$P_{W_i}^{min}$	Lower operating limit for wind farm <i>i</i>					
$P_{W_i}^{max}$	Higher operating limit for wind farm i					
$\hat{P}_{W_i}^k$	Forecasted wind availability for wind farm i at time k					
$\hat{\mathbf{P}}_W$	The vector of forecasted wind availability					
$\tilde{\mathbf{P}}_W$	The vector of historical wind data					
x_i^k	On/off status of generator i at time step k					
$x_{U_i}^k$	Binary indicators of starting-up and shutting down generator i					
$x_{D_i}^k$	Binary indicators of shutting-down generator i					
YR,t	Wind speed at location R at time t					
$\theta_{R,t}$	Wind direction at location R at time t					
$\mu_{R,t+k}$	Center parameter of the predictive distribution at location R at time $t + k$					
$\sigma_{R,t+k}$	Scale parameter of the predictive distribution at location R at time $t+k$					
$\mu_{R,t}^r$	Residual of wind speed location R at time t					
$\theta_{R,t}^r$	Residual wind direction at location R at time t					
$D_{R,h}$	Daily component in wind speed at location R at hour h					
W	Set of wind farms					
T	Look-ahead window size					

source of uncertainty comes from both demand and supply sides [1]. State-of-the-art load forecasts could achieve high accuracy in the day-ahead stage [12]. Compared with load forecasting, accurate forecast of wind generation still remains an open challenge. There exists a large body of literature on wind power forecasting, and state-of-the-art day-ahead wind forecast based on numerical weather prediction (NWP) models has enabled relatively accurate wind forecast with approximately 15%-20% of wind speed forecast mean absolute error (MAE) [13]–[16]. As the operating time moves closer to the near term (e.g., hourahead or 15 minute-ahead), at a high spatial resolution, the computation complexity (in terms of simulation time and memory requirements) often renders NWP models intractable [16].

In sharp contrast, data-driven statistical model is thought to be the most competitive method for near-term wind forecasting problems being able to capture the rapidly changing dynamics of the atmosphere and with nice model interpretation [17]. Statistical forecasting models could potentially provide *accurate* and efficient wind forecasts with MAE reduced to the range of around 5% or less [13]. A good set of references can be found in [18]. Our proposed spatio-temporal wind forecast model is directly targeted at *computationally efficient near-term* wind forecasts.

Starting from our preliminary work [19], [20], the main objective of this paper is to exploit a novel short-term spatio-temporal wind forecast model and quantify the dispatch benefits from improved short-term wind forecast. Wind generation is driven by wind patterns, which tend to follow certain geographical spatial correlations. For large-region wind farms, the wind generation forecast of the wind could significantly benefit from upstream wind power generation. Enabled by technological advances in sensing, communication, and computation, spatially correlated wind data could be leveraged for accurate systemwide short-term wind forecasts. This is potentially applicable to large-scale wind farms. The performance of such wind forecast model is critically assessed.

In order to fully exploit the advantage of spatio-temporal wind forecast, advanced power system scheduling is needed. In recent years, there are many valuable pieces of work along this direction. Currently, two major schools of methodologies exist: 1) based on stochastic optimization and 2) robust optimization. A security-constrained unit commitment algorithm is formulated by J. Wang et al., which considers the intermittency and volatility of wind power generation [21]. A two-stage stochastic programming model for reserves commitment in power systems with high penetration of wind generation is proposed by A. Papavasiliou et al. [22]. A stochastic optimization model is developed by P. Meibom et al. to study the operational impacts of high wind generation in Europe [23], [24]. An adaptive robust optimization is proposed by D. Bertsimas et al. to solve security constrained unit commitment problems [25]. A robust unit commitment model is presented by Y. Guan et al. to schedule wind power and pumped hydro storage [26].

The advantage of the stochastic programming approach is to fully utilize the distribution of the uncertainty set to achieve optimal expected benefits. Compared with the stochastic approach, a robust optimization, focusing on optimal benefits under worst scenarios, has advantages in computation efficiency and low requirement for knowledge of full distribution [27], [28]. The spatio-temporal forecast presented in this paper is aiming at short-term power system application such as near-term (hourahead) or real-time economic dispatch which have high requirement of computation efficiency. Therefore, we propose and formulate a robust optimization based look-ahead economic dispatch model to quantify the economic benefits of improved forecast under uncertainties. The suggested contributions of this paper are:

 We propose to use two spatio-temporal correlated forecast models for short-term wind generation in power system operations, the TDD (trigonometric direction diurnal) and the TDDGW (TDD with geostrophic wind information) models. Both forecasting models take into account local and nearby wind farms' historical wind information. Additionally, based on atmospheric dynamic principles, the latter incorporates geostrophic wind information and has better forecasts than the former one. Both methods are tested with realistic wind data obtained in Texas, and they demonstrate improved forecast accuracy.

2) We incorporate our spatio-temporal wind forecast into a robust look-ahead economic dispatch framework. Numerical study in a revised IEEE RTS 24-bus test system shows improved benefits compared with conventional static dispatch with time-persistent wind forecast models.

The rest of this paper is organized as follows. In Section III we provide an overview of statistical wind forecast models, which is followed by the introduction of the proposed spatio-temporal wind forecast models. In Section IV we compare the performance of spatio-temporal wind forecasts using realistic wind farm data obtained from West Texas. Section V presents the day-ahead reliability unit commitment model as well as a robust look-ahead economic dispatch formulation by incorporating available wind forecast. Numerical illustrations of the economic benefits of incorporating spatio-temporal wind forecast with robust look-ahead dispatch are presented in Section VI. Conclusions and future work are presented in Section VII.

III. STATISTICAL WIND FORECASTING

In this section, we provide an overview and critical assessment of several statistical approaches to short-term wind forecasting. Whereas NWP models play the key role in day-ahead to several hour-ahead wind forecasting, the computational burden and forecasting accuracy of NWP are still challenging in near-term forecasts (minutes-ahead to hour-ahead). As an alternative, data-driven statistical wind forecasting has gained increasing attention for near-term forecasts. Extensive research has been devoted to wind power forecasting problems [18], [29]-[31]. In short-term wind speed forecasting, statistical models that incorporate spatial information are the most competitive methods [17], [18]. A regime-switching space-time model [32] improved forecasts by 29% and 13% compared with persistence forecasts and autoregressive in terms of root mean squared error (RMSE). It was generalized by the TDD model [33] by treating wind direction as a circular variable and including it in the model. Regime-switching models based on wind direction and conditional parametric models with regime-switching substantially reduced variance in the forecast errors [34]. Adaptive Markov-switching autoregressive models [35] were developed for offshore wind power forecasting problems in which the regime sequence is not directly observable but follows a first-order Markov chain.

For wind speed forecasting problems, more realistic metrics that have penalization on underestimates and forecasts for small true values are desired for model evaluation [18] instead of RMSE and mean absolute errors (MAE). Power curve error [33] was proposed as a loss function, which links prediction of wind speed to wind power by a power curve and evaluates the loss based on the wind power with penalty on underestimates. The pros and cons of the mean absolute percentage error and the mean symmetric absolute percentage error as loss functions to penalize both underestimates and forecasts for small true values were also discussed [18].



Fig. 1. Map of the four locations in West Texas.

TABLE II SITE INFORMATION



Fig. 2. Wind roses of the four locations in West Texas.

A. Wind Data Source in West Texas

The wind data we use here are the 5-minute averages of 3-second measurements of wind speed and direction collected by monitors placed at 10 meters above the ground from four sites in West Texas labeled ROAR, SPUR, PICT, and JAYT. Their locations are indicated by the red crosses in Fig. 1, and more specific geographic information is listed in Table II. The period of the wind data covers three years from January 1, 2008 to December 31, 2010. (The data sets are available at http://www.mesonet.ttu.edu/wind.html).

Winds in this area are mainly from the south or north as shown by the wind roses in Fig. 2, where the petals are the frequencies of wind blowing from a particular direction, and the colored bands are the ranges of wind speed. Given the flatness in this area, the spatial correlation in wind can be captured when a southerly wind is blowing: wind at ROAR will mostly be just a shift from wind at SPUR. This means that to forecast the future wind speed at ROAR, it is definitely helpful to use the current and just past wind information at SPUR. Similarly, when the wind is blowing from the south or southeast, wind information at JAYT and PICT help in predicting the wind speed at ROAR. A good forecasting model should take into account both spatial and temporal correlations in wind.

B. Space-Time Statistical Forecasting Models

We used four statistical models, PSS, AR, TDD and TDDGW, to forecast short-term wind speed at each of the four sites. In the first two models, only the temporal correlation in wind is considered, while the TDD and TDDGW models utilize wind information from the other three locations so that both spatial and temporal correlations in wind are taken into account. Moreover, the TDDGW model incorporates geostrophic information into the TDD model.

To make it simple, we describe the four models in the setting of forecasting wind speed at ROAR. Let $y_{R,t}$, $y_{S,t}$, $y_{J,t}$, and $y_{P,t}$ denote the wind speed at time t at ROAR, SPUR, JAYT, and PICT, respectively, and $\theta_{R,t}$, $\theta_{S,t}$, $\theta_{J,t}$, and $\theta_{P,t}$ denote the wind direction at time t. The goal is to estimate $y_{R,t+k}$, or the k-step-ahead wind speed at ROAR, denoted as $\hat{y}_{R,t+k}$, where each step is 5 minutes.

1) Persistent Forecasting: In the PSS model, it is assumed that the future wind speed is the same as the current one. For example, if $y_{R,t}$ is the wind speed at time t at ROAR, then the k-step future wind speed is predicted as $y_{R,t}$, or $\hat{y}_{R,t+k} = y_{R,t}$. PSS works very well for very short-term forecasting, such as 10-minute-ahead. The PSS model is usually treated as a reference and an advanced forecasting model is thought to be good if it outperforms PSS.

2) Autoregressive Models: AR models predict the future wind speed as a linear combination of past wind speeds. In our case, we apply AR to model the center parameter, $\mu_{R,t+k}$, in (2) (defined in the next part) as follows:

$$\mu_{R,t+k}^{r} = \alpha_0 + \sum_{i=0}^{p} \alpha_{i+1} \mu_{R,t-i}^{r}.$$
 (1)

The AR model assumes that future wind speed is related to historical wind information only at the same location, without considering the spatial correlation. Bayesian Information Criteria is used to select the order p.

3) Spatio-Temporal Trigonometric Direction Diurnal Model: The TDD model is an advanced space-time statistical forecasting model. It generalizes the Regime-Switching Space-Time model [32] by including wind direction in the model. As a probabilistic forecasting model, the TDD model estimates a predictive distribution for wind speed at time t + k, thus providing more information about the uncertainty in wind. More recently, the TDDGW model, which incorporates geostrophic wind information into the TDD model, was proposed [36] and more accurate forecasts are obtained than from the TDD model.

In the TDD model, it is assumed that $y_{R,t+k}$ follows a truncated normal distribution on the nonnegative real domain, that is, $y_{R,t+k} \sim N^+(\mu_{R,t+k}, \sigma_{R,t+k}^2)$ (this can be detected by the density plots in Fig. 3), with center parameter $\mu_{R,t+k}$ and scale Density of Wind Speed at ROAR 2008-2009

Daily Pattern of Wind Speed at ROAR 2008-2009



Fig. 3. Wind speed density at ROAR 2008-2009.

parameter $\sigma_{R,t+k}$. The key to achieve accurate forecasts lies in modeling these two parameters appropriately.

The center parameter, $\mu_{R,t+k}$, is modeled as

$$\mu_{R,t+k} = D_{R,h+k} + \mu_{R,t+k}^r$$

where $D_{R,h+k}$ is made of trigonometric functions to fit the diurnal pattern of the wind speed. Specifically,

$$D_{R,h} = d_0 + \sum_{j=1}^{2} \left\{ d_{2j-1} \sin\left(\frac{2\pi jh}{24}\right) + d_{2j} \cos\left(\frac{2\pi jh}{24}\right) \right\}$$

where h = 1, 2, ..., 24; see Fig. 4. Fig. 4 is the functional boxplot [37] of daily wind speed from 2008–2009 with the solid white line as the mean wind speed over 24 hours, the solid black line as the median, and the dashed green line as the fitted daily pattern.

The residual series after removing the diurnal pattern, $\mu_{R,t+k}^r$, is modeled as a linear function of current and past (up to time lag p) wind speed residuals and trigonometric functions of wind direction residuals at ROAR, as well as SPUR, JAYT, and PICT as follows:

$$\mu_{R,t+k}^{r} = \alpha_{0} + \sum_{s \in \{R,S,J,P\}} \sum_{i=0}^{p} \alpha_{i+1} \mu_{s,t-i}^{r} + \sum_{s \in \{R,S,J,P\}} \sum_{j=0}^{p} \left[\beta_{j+1} \sin(\theta_{s,t-j}^{r}) + \gamma_{j+1} \cos(\theta_{s,t-j}^{r}) \right].$$
(2)

The scale parameter, $\sigma_{R,t+k}$, is modeled as

$$\sigma_{B\ t+k} = b_0 + b_1 v_t,\tag{3}$$



Fig. 4. Functional boxplot [37] of daily wind speed at ROAR 2008-2009.



Fig. 5. The pressure gradient, Coriolis, and friction forces influence the movement of air parcels. Geostrophic wind (left) and real wind (right).

where $b_0, b_1 > 0$ and v_t is the volatility value:

$$v_t = \left[\frac{1}{8} \sum_{s \in \{R, S, J, P\}} \sum_{i=0}^{1} (\mu_{s,t-i}^r - \mu_{s,t-i-1}^r)^2 \right]^{1/2}$$

The coefficients in (2) along with b_0 , b_1 in (3) are estimated by the continuous ranked probability score method (see [38] for more details). Predictors in (2) are selected with the Bayesian Information Criteria (see [33]).

As we know, pressure and temperature also have significant effects on wind speed. If this information could be taken into account in wind forecasting problems, more accurate forecasts would be expected. However, it was found that adding surface pressure and temperature directly into the center parameter model in (2) brings no improvement to the forecasting accuracy. This is the motivation of the TDDGW model. It takes geostrophic wind, which extracts information on pressure and temperature, into the TDD model as a predictor.

Geostrophic wind is the theoretical wind that results from an exact balance between the pressure gradient force (horizontal components) and the Coriolis force if there were no friction above the friction layer, and this balance is called the geostrophic balance. It is parallel to straight isobars. Fig. 5 illustrates the difference between geostrophic wind (left) and real wind or surface wind (right).

The approximation of geostrophic wind is based on Newton's Second Law. It involves calculation of geopotential heights by referring to 850 hPa based on pressure, temperature and elevation, and fitting a plan of the geopotential height gradient in the region. Due to the space limitation, we refer readers to [36] for more detailed information.

The TDDGW model incorporates geostrophic wind into the TDD model, as shown in (4). This model not only includes important information on pressure and temperature, but it also has a clear and meaningful physical interpretation. Moreover, the TDDGW model keeps the advantage of the TDD model, namely to account for the spatio-temporal correlation in wind:

$$\mu_{R,t+k}^{r} = \alpha_{0} + \sum_{s \in \{R,S,J,P\}} \sum_{i=0}^{p} \alpha_{i+1} \mu_{s,t-i}^{r} + \sum_{k=0}^{p} c_{k+1} g w_{R,t-i}^{r} + \sum_{s \in \{R,S,J,P\}} \sum_{j=0}^{p} \left[\beta_{j+1} \sin(\theta_{s,t-j}^{r}) + \gamma_{j+1} \cos(\theta_{s,t-j}^{r}) \right]$$
(4)

where $gw_{R,t-i}^{r}$ s are the residuals of the geostrophic wind after removing the diurnal pattern and the c_{k+1} s are the coefficients. Since geostrophic wind is above the friction layer, it covers a large area. That means locations within the small area of our interests have very similar geostrophic values. We therefore use the geostrophic wind variable as a common predictor as shown in (4). The median of the truncated normal distribution is used as a point forecast:

$$z_{1/2}^{+} = \mu_{t+1} + \sigma_{t+1} \cdot \Phi^{-1} \left[\frac{1}{2} + \left(\frac{1}{2} \right) \Phi \left(\frac{-\mu_{t+1}}{\sigma_{t+1}} \right) \right]$$

where $\Phi(\cdot)$ is the cumulative distribution function of a standard normal distribution.

IV. FORECASTING RESULTS AND COMPARISON

In this section, the aforementioned four forecasting models are implemented to forecast 10-minute-ahead, 20-minute-ahead and up to 1-hour-ahead wind speed at the four locations in West Texas on one day each month except May 2010 (the days are chosen randomly). In the AR, TDD and TDDGW models, a 45-day sliding window of observations prior to the forecast is used to estimate coefficients in the models in which the variables are selected using the data from 2008 and 2009. For the diurnal pattern, the averages of 45 days' hourly wind speeds are used.

To evaluate the performance of the four forecasting models, mean absolute errors (MAE), defined below, are calculated from the forecasts on the 11 days and listed in Table III:

$$MAE = \frac{1}{T} \sum_{t=1}^{T} |y_{R,t+k} - \hat{y}_{R,t+k}|$$

where T = 3168 for 11 days.

TABLE III MAE VALUES OF THE 10-MINUTE-AHEAD, 20-MINUTE-AHEAD AND UP TO 1-HOUR-AHEAD FORECASTS ON 11 DAYS IN 2010 FROM THE PSS, AR, TDD AND TDDGW MODELS AT THE FOUR LOCATIONS (SMALLEST IN BOLD)

Location	Model	10 min	20 min	30 min	40 min	50 min	60 min
PICT	PSS	0.56	0.72	0.84	0.92	1.00	1.08
	AR	0.55	0.70	0.80	0.87	0.94	1.00
	TDD	0.54	0.68	0.77	0.84	0.90	0.95
	TDDGW	0.54	0.68	0.77	0.83	0.89	0.94
JAYT	PSS	0.50	0.63	0.71	0.78	0.83	0.89
	AR	0.48	0.60	0.68	0.75	0.8	0.86
	TDD	0.47	0.57	0.64	0.69	0.73	0.78
	TDDGW	0.47	0.57	0.64	0.68	0.71	0.75
SPUR	PSS	0.51	0.64	0.73	0.81	0.86	0.92
	AR	0.49	0.61	0.69	0.76	0.80	0.86
	TDD	0.48	0.59	0.67	0.72	0.76	0.81
	TDDGW	0.49	0.59	0.67	0.71	0.75	0.79
ROAR	PSS	0.55	0.71	0.82	0.92	0.98	1.02
	AR	0.54	0.68	0.78	0.86	0.92	0.96
	TDD	0.54	0.67	0.77	0.85	0.90	0.93
	TDDGW	0.54	0.67	0.76	0.82	0.87	0.90

From Table III, we can see that MAE values increase by column, which means that the forecast accuracy reduces when the forecasting horizon, k, gets larger. Among the four models, the AR, TDD, and TDDGW models have smaller MAE values than the PSS and the space-time models, TDD and TDDGW, are more advanced than the PSS and AR models with smaller MAE values. As expected, by incorporating the geostrophic wind information, the TDDGW model increases its predictive accuracy. Its MAE values are reduced further compared with the TDD model, especially for 40-min-ahead or longer time lead forecasting. Relative to the MAE value of PSS, the TDDGW model obtains 15.7% reduction at JAYT for 1-hour-ahead forecasting, while it is 12.4% for the TDD model. This means that, by incorporating geostrophic wind information into the TDD model, we can further reduce the forecasting error up to 3.3%, based on the relative MAE value to PSS. The computational time for hour-ahead forecast using a laptop PC for one step of the TDDGW model is approximately 1.5 minutes, and the computational time for one step of TDD is approximately 1 minute. In contrast, recent literature suggests that it is currently impossible to compute the NWP models for hour-ahead scheduling purposes [16]. Therefore, data-driven statistical wind forecast models provide computationally feasible solutions for nearterm operations for system operators. In the next two sections, the economic benefits of improved forecast are quantified in look-ahead dispatch models.

V. POWER SYSTEM DISPATCH MODEL

With the spatio-temporal wind forecast models, we present in this section a critical assessment of the economic performance for power system operations. The power system scheduling framework formulated in this paper is designed with two layers: 1) Day-ahead reliability unit commitment (RUC) [39], [40] and 2) robust look-ahead real-time (every 5 minutes) scheduling.

A. Day-Ahead Reliability Unit Commitment

The structure of the two-layer dispatch model is described in Fig. 6. The models of day-ahead reliability unit commitment (RUC) and real-time scheduling are presented below.



Fig. 6. Two-layer dispatch model.

The day-ahead reliability unit commitment ensures the reliability of the physical power system after clearing the day-ahead market. It takes place 24 hours prior to the real-time operation, as shown in Fig. 6. Energy balancing and ancillary services (reserve services) are co-optimized with start-up/shut-down decisions. The model is formalized as follows:

$$\min_{\substack{P_{G_i}^k, P_{W_i}^k, P_{R_{S_i}}^k, x_i^k}} : \sum_{k=k_0}^T \sum_{i \in G} C_{G_i}(P_{G_i}^k) + \sum_{i \in W} C_{W_i}(P_{W_i}^k) \\
+ \sum_{i \in G} C_{R_{S_i}}(P_{R_{S_i}}^k) \\
+ \sum_{i \in F} C_{U_i}(x_{U_i}^k) + \sum_{i \in F} C_{D_i}(x_{D_i}^k)] \quad (5)$$

s.t.

$$\sum_{i \in G} P_{G_i}^k + \sum_{i \in W} P_{W_i}^k = \sum_{i \in D} P_{D_i}^k, \ k = k_0, \dots, T$$
 (6)

$$\sum_{i \in G} P_{Rs_i}^k \ge Rs^k, \ k = k_0, \dots, T \qquad (7)$$

$$|\mathbf{F}^k| \leqslant \mathbf{F}^{max}, \ k = k_0, \dots, T$$
 (8)

$$|P_{G_i}^k - P_{G_i}^{k-1}| \leqslant P_i^R \Delta T, i \in G, \ k = k_0, \dots, T$$
 (9)

$$x_i^k P_{G_i}^{\min} \leqslant P_{G_i}^k \leqslant x_i^k P_{G_i}^{\max}, i \in G, k = k_0, \dots, T \quad (10)$$

$$P_{G_i}^{\kappa} + P_{RS_i}^{\kappa} \leqslant x_i^{\kappa} P_{G_i}^{\max}, i \in G, k = k_0, \dots, T \quad (11)$$

$$x_{i}^{\kappa} - x_{i}^{\kappa-1} \leqslant x_{U_{i}}^{\kappa}, i \in G, k = k_{0}, \dots, T \quad (12)$$

$$x_i^{\kappa-1} - x_i^{\kappa} \leqslant x_{D_i}^{\kappa}, i \in G, k = k_0, \dots, T$$
 (13)

$$P_{W_i}^{min} \leqslant P_{W_i}^k \leqslant P_{W_i}^{max}, \ i \in W, k = k_0, \dots, T \quad (14)$$

$$P_{W_i}^k \leqslant \hat{P}_{W_i}^k = f(\tilde{\mathbf{P}}_W), \ i \in W, k = k_0, \dots, T \quad (15)$$

$$x_{i}^{k}, x_{U_{i}}^{k}, x_{D_{i}}^{k} \in Binary, i \in G, k = k_{0}, \dots, T.$$
 (16)

In the proposed formulation, the objective function (5) is to minimize the power system operating costs including generation cost, reserve cost and start-up/shut-down cost of units. This scheduling problem is subject to various security constraints. Equation (6) are the energy balancing (7) is the system reserve requirement, which is often assessed according to system reliability requirement. Equation (8) are the transmission capacity constraints. Equation (9) are the ramping constraints of all generation units. Equation (10) are the generators' capacity limits for generator units. Equation (11) are the combined capacity constraints of generator units for providing energy and reserve services. Equation (12) and (13) are start-up/shut-down indicator constraints. Equation (14) are the capacity limits of wind farms. In this paper, wind resources are assumed not to participate into ancillary services market providing reserve services. Equation (15) is the wind forecast for each wind farm at time k, the details of which are explained in Section III. Equation (16) gives the binary constraints to integer decision variables.

B. Robust Look-Ahead Economic Dispatch

Following the day-ahead scheduling from the previous subsection, we assume that system operators conduct a real-time dispatch every 5 minutes. We formulate this dispatch model as a multi-stage robust look-ahead economic dispatch to utilize the information of advanced spatio-temporal forecast. The robust look-ahead dispatch minimizes system operation cost over a horizon of multiple steps (e.g., one hour) for worst cases under predefined uncertainty set. As other look-ahead economic dispatch, only the dispatch decisions of the first step are executed. The updated information, such as wind forecast, load forecast and system conditions will be fed into the dispatch model for future decision-making. The robust look-ahead economic dispatch is formulated as

$$\max_{\mathbf{u}\in\mathbb{U}}\min_{P_{G_{i}}^{k}, P_{W_{i}}^{k}, P_{SU_{i}}^{k}, P_{SD_{i}}^{k}} : \sum_{k=k_{0}}^{T} \left[\sum_{i\in G} C_{G_{i}}(P_{G_{i}}^{k}) + \sum_{i\in W} C_{W_{i}}(P_{W_{i}}^{k})\right]$$
(17)

s t

$$\sum_{i \in G} P_{G_i}^k + \sum_{i \in W} P_{W_i}^k = \sum_{i \in D} \hat{P}_{D_i}^k, \ k = k_0, \dots, T \ (18)$$
$$|\mathbf{F}^k| \leq \mathbf{F}^{max}, \ k = k_0, \dots, T \ (19)$$

$$|\boldsymbol{k}| \leq \mathbf{F}^{max}, \ k = k_0, \dots, T$$
 (19)

$$|P_{G_i}^k - P_{G_i}^{k-1}| \leq P_i^R \Delta T, i \in G \cup W, \ k = k_0, \dots, T \ (20)$$

$$\sum P_{G_i}^k \geq SU_n^k(\mathbf{u}) \ k = k_0, \dots, T \ (21)$$

$$\sum_{i \in G} P_{SD_i}^k > SD_D^k(\mathbf{u}), \quad k = k_0, \quad T \quad (22)$$

$$P_{G_{i}}^{k} + P_{SU_{i}}^{k} \leqslant P_{G_{i}}^{\max}, i \in G, k = k_{0}, \dots, T$$
(23)

$$P_{G_i}^k - P_{SD_i}^k \ge P_{G_i}^{\min}, i \in G, k = k_0, \dots, T$$
 (24)

$$P_{G_i}^{min} \leqslant P_{G_i}^k \leqslant P_{G_i}^{max}, \ k = k_0, \dots, T$$
 (25)

$$P_{W_{\cdot}}^{min} \leqslant P_{W_{\cdot}}^{k} \leqslant P_{W_{\cdot}}^{max}, \ k = k_0, \dots, T$$
 (26)

$$P_{W_{*}}^{k} \leqslant \hat{P}_{W_{*}}^{k}, \ k = k_{0}, \dots, T$$
 (27)

$$\leq P_{cru}^k \leq P_{tr}^R \Delta T, k = k_0, \dots, T$$
 (28)

$$0 \leqslant P_{SD_i}^k \leqslant P_{Di}^D \Delta T, k = k_0, \dots, T.$$
(29)

The objective function (17) is to minimize the total operating cost for energy balancing. In real-time scheduling, various security constraints are considered. Energy balancing constraints are provided in (18). Transmission capacity constraints are given in (19). Ramping constraints of generators are presented in (20). We introduce short-term dispatchable (STDC) capacity to make sure the system has enough ramping capability to handle the uncertainty [41]. Equations (21) and (22) are the upward/downward STDC balancing equations. The STDC are constrained by the ramping capability of each unit as presented in (28) and (29). Capacity constraints of conventional generators and wind farms are described in (25) and (26), respectively. Equation (23) and (24) are combined capacity constraints between generation capacity and STDC. The dispatch points of wind generation

0

should be no larger than the forecasted wind production potentials, as is shown in (27).

The uncertainty set U is given by (30).

$$\begin{split} & \mathbb{U}(\hat{\mathbf{P}}_{W}^{k}, \bar{\mathbf{P}}_{W}^{k}, \hat{\mathbf{P}}_{D}^{k}, \bar{\mathbf{P}}_{D}^{k}, \overline{\mathbf{\Pi}}_{D}^{k}, \underline{\mathbf{\Pi}}_{W}^{k}, \overline{\mathbf{\Pi}}_{D}^{k}, \underline{\mathbf{\Pi}}_{D}^{k}, \bar{u}_{W}^{k}, \mathbf{u}_{W}^{k}, \bar{u}_{D}^{k}, \mathbf{u}_{D}^{k}) \\ & := \{\hat{\mathbf{P}}_{W}^{k} \in \mathbb{R}^{|\mathbf{W}|}, \hat{\mathbf{P}}_{D}^{k} \in \mathbb{R}^{|\mathbf{D}|} : \sum_{i \in \mathbf{W}} \frac{\hat{P}_{W_{i}}^{k} - \bar{P}_{W_{i}}^{k}}{\bar{u}_{W_{i}}^{k} - \bar{P}_{W_{i}}^{k}} \leqslant \overline{\mathbf{\Pi}}_{W}^{k}, \\ & \sum_{i \in \mathbf{W}} \frac{\bar{P}_{W_{i}}^{k} - \hat{P}_{W_{i}}^{k}}{\bar{P}_{W_{i}}^{k} - \mathbf{u}_{W_{i}}^{k}} \leqslant \underline{\mathbf{\Pi}}_{W}^{k}, \sum_{i \in \mathbf{D}} \frac{\hat{P}_{D_{i}}^{k} - \bar{P}_{D_{i}}^{k}}{\bar{u}_{D_{i}}^{k} - \bar{P}_{D_{i}}^{k}} \leqslant \overline{\mathbf{\Pi}}_{D}^{k} \\ & \sum_{i \in \mathbf{D}} \frac{\bar{P}_{D_{i}}^{k} - \hat{P}_{D_{i}}^{k}}{\bar{P}_{D_{i}}^{k} - \mathbf{u}_{D_{i}}^{k}} \leqslant \underline{\mathbf{\Pi}}_{D}^{k}, \hat{P}_{W_{i}}^{k} \in [\mathbf{u}_{W_{i}}^{k}, \bar{u}_{W_{i}}^{k}], \forall i \in \mathbf{W}, \\ & \hat{P}_{D_{j}}^{k} \in [\mathbf{u}_{D_{j}}^{k}, \bar{u}_{D_{j}}^{k}], \forall j \in \mathbf{D}\}. \end{split}$$

Here $\hat{\mathbf{P}}_W^k$ is the vector of wind production potential forecasts fed into the dispatch model as presented in (27). $\bar{\mathbf{P}}_W^k$ is the vector of expectations of wind forecast for each location at each time step. \bar{u}_W^k and u_W^k defines the upper bounds and lower bounds of wind forecast deviation from the expectation. $\overline{\Pi}_W^k$ is defined as the budget of uncertainty for wind forecast, which takes the value between 0 and $|\mathbf{W}|$, where $|\mathbf{W}|$ is the number of wind sources modeled in the system. If the budget is set to be 0, the problem formulation turns out to be deterministic. As $\overline{\Pi}_W^k$ grows, the uncertainty set \mathbb{U} enlarges, which indicates the system operation is toward more risk-averse, and the system is protected against higher degree of uncertain conditions.

Similarly, for the load forecast uncertainty, $\hat{\mathbf{P}}_D^k$ is the vector of load forecasts fed into the dispatch model. $\bar{\mathbf{P}}_D^k$ is the vector of expectations of load forecast for each bus at each time step. \bar{u}_D^k and u_D^k defines the upper bounds and lower bounds of load forecast deviation from the expectation. $\overline{\Pi}_D^k$ is defined as the budget of uncertainty for load forecast, which takes the value between 0 and $|\mathbf{D}|$.

VI. NUMERICAL EXPERIMENT

In this section, we conduct a numerical experiment on a 24-bus system to critically assess the *operational economic benefits* from improved short-term forecasts.

A. Simulation Platform Setup

The numerical example is modified from the IEEE Reliability Test System (RTS-24) [42]. The simulation duration is 24 hours. The operation interval in real-time scheduling is five minutes. The look-ahead horizon in real-time scheduling is 1 hour. Load profiles for 48 hours are collected from the ERCOT System [43]. Loads are scaled and factored out according to the portion of different buses. Wind forecasts are generated by various models discussed in Section III with forecast horizon which ranges from 10 minutes to 60 minutes. Then the wind power forecasts are converted from the wind speed forecasts based on the Nordex 2.5 MW power curve.

The generator parameters are scaled according to [44]. The generator capacity portfolio (the installed capacity percentage of different technologies) is configured and scaled from the real

TABLE IV Generator Parameters

Bus	Type	Cap.	Cost	Ramping
Dus	Type	(MW)	(\$/MWh)	(MW/min)
1	Nuclear	140	15	1.12
2	Coal	540	20	10.8
4	Natural Gas	300	40	15
5	Natural Gas	510	37	33.15
6	Nuclear	150	11	1.35
7	Natural Gas	490	39	34.3
8	Coal	165	23	3.135
14	Natural Gas	170	38	15.3
16	Wind(JYAT)	200	6	18
18	Wind(PICT)	240	4	24
21	Coal	300	21	5.4
22	Natural Gas	725	36	79.75
23	Wind(SPUR)	70	5	7.7

TABLE V SAMPLE DAYS IN SIMULATION STUDY

Sample	Date	Sample	Date	Sample	Date
Day 1	10-Jan	Day 5	9-May	Day 9	8-Sep
Day 2	27-Feb	Day 6	16-Jun	Day 10	19-Oct
Day 3	12-Mar	Day 7	1-Jul	Day 11	22-Nov
Day 4	21-Apr	Day 8	17-Aug	Day 12	6-Dec

ERCOT system [44]. The ramping rates and marginal costs are applied as shown in Table IV.

In the numerical studies, simulations of twelve sample days¹ are conducted. The twelve days are randomly selected as representative days for each month in 2010, as shown in Table V.

B. Results and Analysis

In this section, the simulation results of the numerical experiments are presented. The distribution of the forecast errors of the wind generation reveals the accuracy of the forecast approach. The distribution of its errors for the perfect forecast (PF) with 100% accuracy is a concentrated spike at the zero origin of the x-axis. The better the forecast accuracy the closer the distribution pattern is to the central spike. A forecast model with poor accuracy has its errors distributed widely. The probability density distributions of the wind generation forecast errors (for a 200 MW wind farm) using the PSS, AR, TDD and TDDGW models under various simulation days are presented in Fig. 8. As we can observe, the distribution of the forecast errors of the PSS model is relatively spread out. The distribution of forecast errors of the TDD model is concentrated and has a higher central spike than do the AR and PSS models. The central spike of the TDDGW is higher than that of any other models. The shape of the forecast error distribution of the TDDGW model is closest to that of the perfect forecast. This is also verified by the wind speed forecast MAE presented in Table III.

By incorporating different forecast models into the power system economic dispatch, the economic performance differs. The economic performance results of Case A are presented in Fig. 9, which includes the total operating cost of each simulation day. The costs of the perfect forecast, PSS, AR TDD and

¹Day 5 for TDDGW model is not available due to the inaccessibility of measurement data. Therefore, for the averaged MAE comparison of wind speed forecasts, only 11 days are considered. For the independent studies of economic benefits in power system operation, Day 5 for models other than TDDGW are presented.



Fig. 7. The IEEE RTS-24 system (modified).



Fig. 8. Distribution of forecast errors under different forecast models.



Fig. 9. Total operating cost using different forecast models.

TDDGW models are represented by the blue bar, the red bar, the green bar, the purple bar and the cyan bar, respectively. As we can see, for most of the cases, the spatio-temporal forecasts (TDD and TDDGW) have lower operating costs than do the PSS and AR models.

Taking the PSS model as a benchmark, the reduction in operating cost by percentage using various forecast models is presented in Fig. 10. As we can see, the TDD and TDDGW models,



Fig. 10. Operating cost reduction using different forecast models.

which consider spatio-temporal wind correlation, outperform the AR model and the PSS model in most of the cases. By incorporating the effect of geostrophic wind, the TDDGW model can have a lower system operating cost than the TDD model. For most of the days, the AR model performs better than the PSS model. However, it is observed that for some days (Day 5), the AR model does not produce as good a forecast as does the PSS model. That is the limitation of wind forecast based on purely historical data. In contrast, by incorporating spatial correlations, the TDD model can produce more accurate forecasts than can the PSS model and enable lower system operating costs.

VII. CONCLUSIONS

Spatio-temporal wind forecast models (TDD and TDDGW models) are used and critically evaluated in this paper. It is shown that by incorporating spatial correlations of neighboring wind farms, the forecast quality in the near-term (hours-ahead) could be improved. The TDD and TDDGW models are incorporated into a robust look-ahead economic dispatch and a day-ahead reliability unit commitment. Compared with conventional temporal-only statistical wind forecast models, such as the PSS models, the spatio-temporal models consider both the local and geographical wind correlations. By leveraging both temporal and spatial wind historical data, more accurate wind forecasts can be obtained. The potential economic benefits of advanced wind forecast are illustrated using a modified IEEE RTS 24 bus system. It is observed that the spatio-temporal model can increase wind resources utilization, and reduce system costs against uncertainty. Such data-driven statistical methods for short-term wind forecast are also applicable in other similar regions with high wind penetration.

Future work will investigate the applicability of the proposed dispatch model to large-scale wind farms, such as offshore wind farms. Given the more consistent wind pattern over larger geographical areas, the potential benefits of the proposed method could be higher. Another important avenue for future research is to analyze the tradeoff between communication/computation burdens and the improved economic benefits by incorporating more spatially correlated wind data into power system dispatch models.

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