II. REVIEW OF RELATED LITERATURE

To forecast wind speed is possible to include spatial and temporal dependencies.
When only data of one place is available, temporal dependencies models could be performed by Autoregressive Models (AR) , Vector Autoregressive Models (VAR) or even some volatilities models such as ARIMA.

Orpia and Mappa (2014) modelled and forecast wind speeds of turbines in the Northwind Bangui Bay wind farm using VAR model using daily time series data. They used as explanatory variables of wind speed, humidity, temperature and pressure generated from the meteorological station in Laoag City in Filipines. They concluded that those factors highly affect the time series model of the wind speed in a wind turbine. In addition, the wind speed and the other weathers factors, using Augmented Dickey-Fuller test, were found to be stationary. They decided to make model with three lags VAR(3), and they also suggested that wind speed could be explained at AR(1). They found that any increase in the temperature or pressure incur a decrease in the wind speed and the Humidity affects wind speed on the same direction. This results were showed trough the impulse response function.

Dowell (2015) presented new statistical techniques for producing forecast at multiple locations using spatial-temporal information. The author developed a Sparse-VAR(sVAR) approach motivated by the desired to produce forecast on a large spatial scale, which is critical during periods of high instantaneous wind penetration. sVAR technique has been used to produce 5 minute ahead probabilistic forecasts of wind power at 22 wind farms in south-eastern Australia for a test period of 1 year. The study does not take other exogenous variables, five-minute-ahead probabilistic forecasts are produced using only power measurements as inputs to a sparse vector autoregressive model. The performance of the sVAR is compared to conventional VAR and AR models yielding improvement in terms of both deterministic and probabilistic skill scores, as well as in the reliability of the distributional forecasts.

Ewing, B. T., Kruse, J. B., Schroeder, J. L., & Smith, D. A. (2007) examined the interdependence in time series wind speed data measured in the same location at four different heights.Findings are based on analysis of contemporaneous wind speed time histories taken at 13, 33, 70 and 160 ft above ground level with a sampling rate of 10 Hz. They estimated a multiple-equation, VAR(3) model and utilized the corresponding innovation accounting method known as impulse response analysis. In addition, the paper employs the generalized impulse response function proposed by Pesaran and Shin and Koop et al. (1998) , which stablished that impulse response analysis have focused on responses that are not sensitive to the ordering of the variables in the VAR and thus provide more robust results. They found wind speed at 70 ft is the most volatile and persistent of the group. However, wind speed measured at 13 ft is the most interdependent, while wind speeds at 33 and 160 ft are the most independent. Besides, shocks at 13 ft were associated with responses that were the least persistent and smallest in magnitude. Finally, the greatest degree of persistence to an ‘‘own’’ shock is for 160, followed by 70, 33, and 13 ft.

He, M., Vittal, V., & Zhang, J. (2015) studied short-term wind farm power forecasting by exploting the spatio-temporal correlation between individual turbine's power output. A multivariate time series model for wind farm power generation is developed by using vector autoregression (VAR). In order to avoid the possible over-fitting issues caused by a large number of autoregressive coefficients and the impact on the forecasting performance of VAR models, they constructed a sparsified autoregressive coefficient matrix by utilizing the information on wind direction, wind speed and wind farm's layout. They found that the multi-variate turbine-level wind power data has great potential to improve wind farm power modeling and forecasting, as compared to using aggregate wind power data only.

Koivisto, M., Seppänen, et al (2016) worked on a Vector-Autoregressive-To-Anything (VARTA) process with a time-dependent intercept to model wind speeds in multiple locations. The model considers both temporal and spatial dependency structures in detail. The long term simulation and short term forecasting results are assessed using measurements from 21 locations in Finland. They conclude that the model properly assesses the temporal and spatial dependencies, and the monthly changing diurnal variations. The dependency structure specified by the VARTA model provides a good fit to the data. Through Monte Carlo simulations, the VARTAX model enables the estimation of the probabilities of very high or low wind speeds occurring contemporaneously in multiple locations. The modelling was also shown to perform well in short term forecasting, which can be useful in the short term operational planning of the power system.

Erdem, E., & Shi, J. (2011) employed four approaches based on autoregressive moving average (ARMA) to forecast wind speed and direction tuple. First, the decomposition of the wind speed into lateral and longitudinal components. Each component is represented by an ARMA model and the results are combined to obtain the wind direction and speed forecasts. Second, two independent ARMA models – a traditional ARMA model for predicting wind speed and a linked ARMA model for wind direction. Third, vector autoregression (VAR) models to forecast the tuple of wind attributes. Fourth, a restricted version of the VAR approach to predict the same. By employing these four approaches, the hourly mean wind attributes are forecasted 1-h ahead for two wind observation sites in North Dakota, USA. The performance of forecasts is evaluated using the metric of mean absolute error MAE. They concluded that the component model is a better choice than the traditional-linked ARMA model for forecasting the wind direction and the VAR models offer higher forecasting accuracy in wind direction and close performance in wind speed. Finally, they suggest that using restricted version of the VAR models would be a key for more parsimonious models.

Torres, J. L., et al (2005). used the ARMA (autoregressive moving average process) and persistence models to predict the hourly average wind speed up to 10 hours in advance in Spain . The authors in order to adjust the series made their transformation and standardization, given the non-Gaussian nature of the hourly wind speed distribution and the non-stationary nature of its daily evolution. Besides, in order to avoid seasonality problems, they have adjusted a different model to each calendar month. They concluded that for forecasts 10 h in advance, the errors with ARMA models are between 12% and 20% smaller than with persistence models. In addition, they found out three findings. Firstly, for wind speeds within a range of 4‑11 m/s the errors have relatively low values and are hardly affected by the extent of the forecast. Secondly, the biggest relative errors tend to fall within high wind speeds, higher than the rated speeds of most wind turbines. Thirdly, the lowest obtained RMSEs correspond to the highest observed wind speeds.

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