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Comparative Study on Wind Speed and Energy Forecasting Models

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ABSTRACT

The main objective of this paper is about the prediction of wind forecasting. Rapid growth in wind power is weather dependent, it is variable and intermittent over various time scales. Thus, accurate forecasting of wind power is recognized as a major contribution to reliable large-scale wind power integration. Wind power forecasting methods can be used to plan unit commitment, schedule, and dispatch by system operators, and maximize profit by electricity traders. The uncertainties in wind velocity forecasts are analyzed using the nonlinear regression method and compared with the Kalman-filter technique. The initial data is collected from the global data obtained from ARW (Advanced Research core of the Weather Research and Forecasting) for the region around the wind power plant. But now the trend was changed, there we have a lot of methods for wind power forecasting based on artificial intelligence techniques are introduced. The method requires as input past power measurements and metrological forecasts of wind speed and direction interpolated at the site of the wind farm. The proposed method is suitable for the operational planning of power systems with increased wind power penetration.

Keywords: Kalman filter, nonlinear regression method, CNLSTM, ARW:

1. INTRODUCTION

Globally, wind energy has grown quickly in recent years. However, because to the erratic nature of wind resources, weather and operational limitations have the potential to significantly reduce the output of large-scale wind farms [1]. Numerous wind-related observation data are produced, recorded, stored, and aggregated due to the rapid advancement of science and technology and the ongoing requirement for wind speed equipment updates. These data are referred to as big data in the wind energy industry since they originate from several sources and are of various forms, such as numerical values, text, and photos, as well as various frequencies, such as minute, hour, and daily [2]. The evaluation and detection techniques for wind power ramp occurrences have recently attracted the attention of numerous academics. provides a risk indicator based on the Monte Carlo method that may evaluate ramp events and risk assessment[1]. Although AI technology is used to predict wind speeds, it is still plagued by overfitting and a real risk of becoming trapped in the local optimum [3]. The WPF (Wind Power Forecasting) approaches can be divided into two categories: probabilistic (also known as interval forecasting), which provides a range of potential values at a particular time, and deterministic (also known as point forecasting), which produces one output for a certain time horizon. The deterministic WPF can be divided into groups according to the input data, forecasted results, time frame, and forecasting technique[4]. The evaluation and detection techniques for wind power ramp occurrences have recently attracted the attention of numerous academics. provides a risk indicator based on the Monte Carlo method that may evaluate ramp events and risk assessment[1]. Although AI technology is used to predict wind speeds, it is still plagued by overfitting and a real risk of becoming trapped in the local optimum [3]. The WPF (Wind Power Forecasting) approaches can be divided into two categories: probabilistic (also known as interval forecasting), which provides a range of potential values at a particular time, and deterministic (also known as point forecasting), which produces one output for a certain time horizon. The deterministic WPF can be divided into groups according to the input data, forecasted results, time frame, and forecasting technique[4-8].

1.1 Quantities

WIND SPEED: A fundamental atmospheric quantity in meteorology known as wind speed, sometimes known as wind flow speed, is produced when air moves from a high to a low-pressure area, typically as a result of temperature changes. Anemometer is now frequently used to measure wind speed. The weather forecast is impacted by wind speed. The local weather has a significant impact on wind speed. Monsoons and cyclones, as extreme meteorological events, can significantly alter the speed of the wind.

WIND POWER: A cost-effective approach to produce energy is through wind power. A utility-scale, land-based wind farm is one of the most affordable energy sources available to us right now. Most installations cost six cents per kilowatt hour using current production methods and transportation efficiency. Variable renewable energy is wind power. In order to balance supply and demand, power management techniques like hydroelectric power and wind hybrid power systems are used. More dispatchable power sources, excess capacity, geographically dispersed turbines, power import and export to nearby regions, grid storage, and lowering demand during periods of poor wind production are some other options. A region may need to improve its system as the amount of wind energy grows.

WIND SPEED Vs POWER

It changes over time and is influenced by local weather patterns and the landscape's features. Relationship between wind speed (m/s) through the wind turbine's swept area (A) and wind power (P) per unit of time (W).

P = (1/2) *ρ*A*υ^3

where is the air's density (kg/m3), which depends on the air's temperature and pressure. This graph demonstrates the nonlinear, essentially cubic nature of the relationship between wind speed and power.

1.2 Types of wind forecasting

Table 1 Forecasting Methods

METHOD	DATASETS	ALGORITHM
ULTRA SHORT-TERM METHOD	FEW MINUTES TO 1Hr	BACK PROGRESSION NEUTRAL NETWORK METHOD
SHORT TERM METHOD	ONE HOUR TO SEVERAL HOURS	CNN-LSTM APPROACH
MEDIUM TERM METHOD	SEVERAL HOURS TO 1WEEK	HYBRID APPROACH
LONG TERM METHOD	1 WEEK TO ONE YEAR AHEAD	M.L. APPROACH [TREEE BASED ALGORITHM]

1.3 Types of wind speed forecasting models

The forecasting models can be classified as,

- ✓ Physical model
- ✓ Statistical and computational model
- ✓ Hybrid model

1.4 Types of wind energy forecasting models

ULTRA-SHORT-TERM FORECAST: The dispatching of the power grid, the operation and administration of wind farms, and finally the appropriate operation of the power system can all be supported technically by the ultra-short term wind power forecasting. Higher expectations are placed on the predicting accuracy and computing efficiency for the ultra-short term wind power forecasting, which offers results from zero to four hours and should be updated every fifteen minutes [9].

SHORT-TERM- FORECAST: The literature uses a variety of methodologies to accomplish short-term load forecasting (STLF). These procedures can be roughly classified into two categories, such as traditional and techniques based on artificial intelligence. Most classic approaches rely on statistical methodologies. Exponential smoothing, multiple linear regression, and autoregressive integrated moving average (ARIMA) techniques are some of these [10].

MEDIUM-TERM FORECAST: For power generators, there is still a significant commercial risk associated with the work of medium-term planning from a few weeks to several months in advance. Planning the availability of production facilities with seasonal weather risks affecting both demand and supply, with volatile fuel prices necessitating careful forward purchasing and hedging, as well as the unpredictability of competitor behaviour in the market, all combine to require forecasts that go beyond point estimates to provide at least interval, if not full density, estimates of market price risks [11]. The task of creating hourly-granular medium-term projections, taking into account market-wide structural and regulatory changes, and defining a complete probability density for electricity pricing.

LONG-TERM-FORECAST: The ability to arrange the connection or disconnection of wind turbines or conventional generators results in minimal spinning reserves and the lowest possible running costs. A time horizon of up to two or three days in the future is mentioned along with hourly statistics. In these situations, the statistical characteristics of the wind are ineffective, so we must rely on the national meteorological services' approximations of wind forecasts. It is necessary to reduce these forecasts to the site of interest because they are based on some specified reference points rather than necessarily the location of the park[4].

2. Medium-term-forecasting

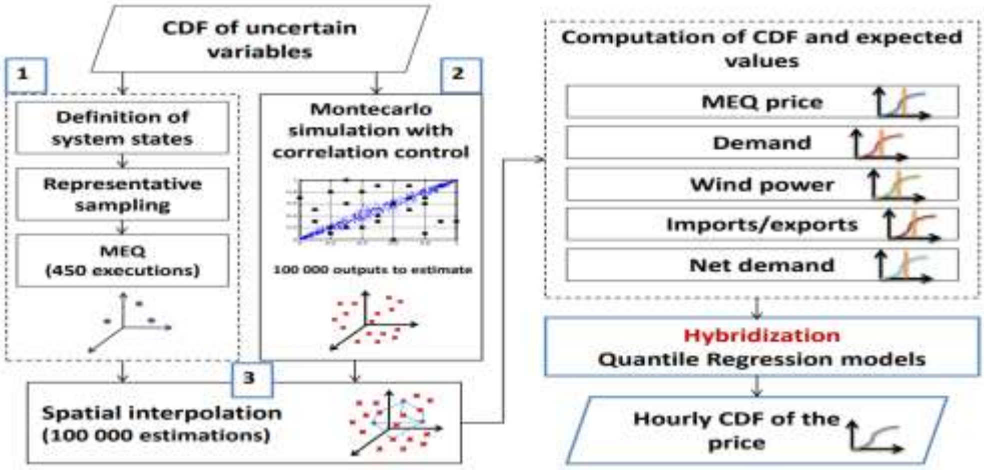

Fig-1: Over view of methodology[7]

3. Methodology

The hybrid strategy's central component is a thorough model for market price formation that is based on fundamentals. We employ a market equilibrium model (MEQ) that is specifically designed for the Spanish system and is based on conjectural variants. Contrary to econometric methods, this model allows for the simultaneous calculation of prices (represented by the Greek letter), firm profits, generation levels, emissions, and transmission flows even when fundamental changes to the underlying market conditions have taken place. Each generating firm, or market agent, in the model aims to maximize profit by creating quantities qi at particular times. The model is formulated as a conventional cost-based optimization problem. In such an oligopolistic framework, the market equilibrium is calculated using an equivalent quadratic optimization problem[11].

Step 1: Data framing

Step 2: Constructing multistep time series

Step 3: Building forecasting model

Step 4: Training the proposed model

Analysis

The hybrid approach's variations provided a number of technical insights. The accuracy was increased by using inputs to the quantile regression that were expressed as quantiles rather than the mean, such as the 1% level of the predicted wind output distribution. Several of the quantiles, such as the 1% 50% and 90%, were also occasionally helpful as predictors for particular price quantiles. In general, we discovered that, in order to have enough data and a complete seasonal spread, a rolling window of a year is best suitable for the re-calibration of the core model to offer correct tail risk estimations.

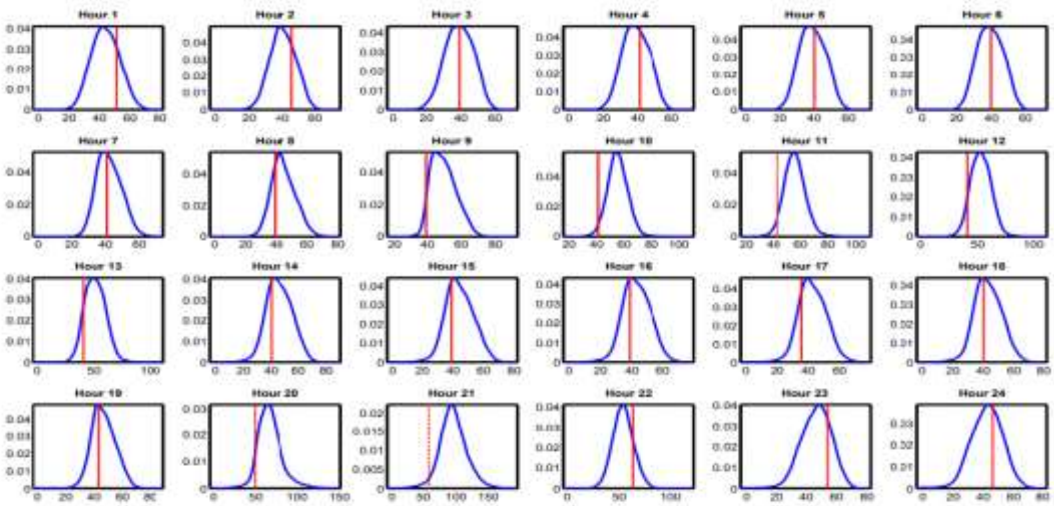

Fig-2: The model of predicted probability function per hour of a typical day :x [12]

Conclusion

The wind speed and power relation were discussed how they are related to each other. The approaches of finding the wind velocity are also discussed. This paper presented a review on forecasting of wind speed and generated power considering different time scales. Several forecasting models were discussed and a lot of researches on the models, which have their own characteristics, were presented. The major focus was on emphasizing the diversity of various forecasting methods available and also on providing a comparison of present mechanisms to determine the best available. And ensuring the safe and economical operation of the power grid is a core goal of wind power. the designing issues while establishing a plant the different nations are proposed their own models to use for their prediction. There are some errors finding methods are also discussed in this paper.

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