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Metaphorical Study on Wind Speed and Energy Forecasting Models

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ABSTRACT

This paper focuses on enhancing wind power forecasting, crucial for the growing wind energy sector, which is inherently variable and intermittent due to weather conditions. Accurate wind power predictions play a pivotal role in ensuring reliable integration of large-scale wind power. These forecasts are essential for system operators in planning unit commitment, scheduling, and dispatch, as well as for electricity traders aiming to maximize profits. The study examines the uncertainties in wind velocity predictions, comparing the nonlinear regression method with the Kalman-filter technique. Initial data is sourced globally from the Advanced Research core of the Weather Research and Forecasting (ARW) for the region surrounding the wind power plant. However, the current trend involves the introduction of various artificial intelligence techniques for wind power forecasting. These methods utilize past power measurements and meteorological forecasts of wind speed and direction at the wind farm site as input. The proposed approach proves suitable for operational planning in power systems experiencing increased wind power penetration.

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

1. INTRODUCTION

In recent years, global wind energy has experienced rapid growth. However, the unpredictable nature of wind resources poses challenges, with weather conditions and operational constraints having the potential to significantly impact the output of large-scale wind farms [1]. The wind energy industry generates extensive observation data due to advancements in science and technology, necessitating continuous updates to wind speed equipment. Referred to as big data in this context, these datasets originate from diverse sources, presenting various forms such as numerical values, text, and photos, and are recorded at different frequencies, including minute, hour, and daily intervals [2]. Academic interest in evaluating and detecting wind power ramp occurrences has increased, with one study proposing a risk indicator based on the Monte Carlo method for assessing ramp events and associated risks [1]. Despite the use of artificial intelligence (AI) technology for predicting wind speeds, challenges such as overfitting and the risk of being trapped in local optima persist [3]. Wind Power Forecasting (WPF) approaches fall into two categories: probabilistic (interval forecasting), which provides a range of potential values at a specific time, and deterministic (point forecasting), which produces a single output for a given time horizon. Deterministic WPF can further be categorized based on input data, forecasted results, time frame, and forecasting techniques [4-8].

1.1 Quantities

WIND SPEED: Wind speed, a fundamental meteorological parameter, is generated as air moves from areas of high pressure to low pressure, often driven by temperature variations. An anemometer is commonly employed for measuring wind speed. Wind speed plays a crucial role in influencing weather forecasts, with local weather conditions exerting a substantial impact on it. Extreme meteorological events such as monsoons and cyclones can profoundly alter the velocity of the wind.

WIND POWER: Wind power stands out as a cost-effective means of energy production. Currently, a utility-scale, land-based wind farm represents one of the most economical sources of energy. The cost for most installations averages six cents per kilowatt hour, taking into account current production methods and transportation efficiency. Wind power is categorized as variable renewable energy, prompting the use of power management techniques such as hydroelectric power and wind hybrid power systems to maintain a balance between supply and demand. Additional strategies include incorporating more dispatchable power sources, ensuring excess capacity, deploying geographically dispersed turbines, facilitating power import/export to nearby regions, implementing grid storage, and reducing demand during periods of low wind production. As the utilization of wind energy increases, regions may need to enhance their systems to accommodate the growth.

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: Ultra-short-term wind power forecasting plays a crucial role in technically supporting the dispatching of the power grid, the operation and management of wind farms, and ensuring the optimal functioning of the power system. There is a heightened demand for increased accuracy and computational efficiency in ultra-short-term wind power forecasting, which provides forecasts ranging from zero to four hours and requires updates every fifteen minutes [9].

SHORT-TERM- FORECAST: Various methodologies are employed in the literature to achieve short-term load forecasting (STLF), broadly categorized into traditional and artificial intelligence-based techniques. Traditional approaches predominantly utilize statistical methodologies, including exponential smoothing, multiple linear regression, and autoregressive integrated moving average (ARIMA) techniques [10].

MEDIUM-TERM FORECAST: Power generators face considerable commercial risk when engaged in medium-term planning, spanning from a few weeks to several months ahead. Planning involves assessing the availability of production facilities amid seasonal weather risks impacting both demand and supply. Additionally, volatile fuel prices necessitate strategic forward purchasing and hedging. The unpredictability of competitor behavior in the market further underscores the need for forecasts that extend beyond point estimates. Instead, these forecasts should provide at least interval, if not full density, estimates of market price risks [11]. The challenging task at hand involves developing hourly-granular medium-term projections while considering market-wide structural and regulatory changes. The ultimate goal is to define a comprehensive 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

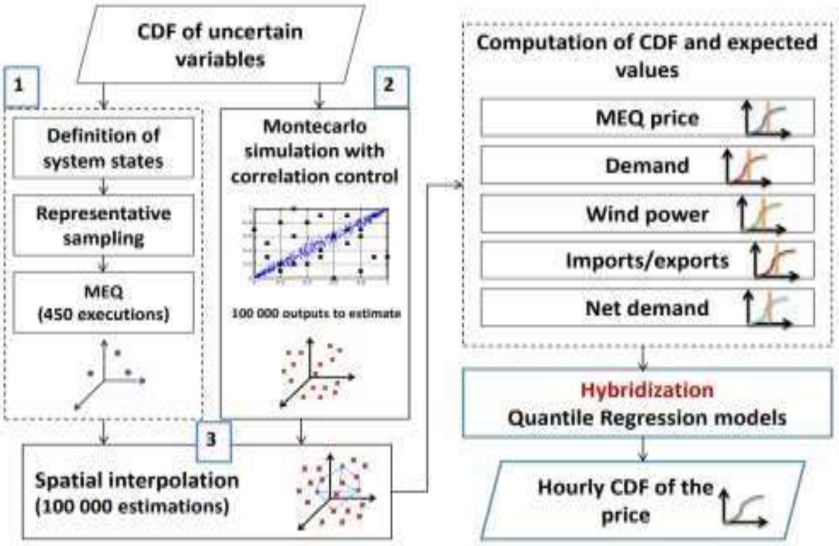

Fig-1: Over view of methodology[7]

3. Methodology

At the core of the hybrid strategy is a comprehensive model for market price formation based on fundamentals. We utilize a market equilibrium model (MEQ) specifically tailored for the Spanish system, relying on conjectural variations. Unlike 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 significant changes occur in the underlying market conditions. Each generating firm, or market agent, within the model seeks to maximize profit by determining quantities qi at specific times. The model is structured as a conventional cost-based optimization problem. In this oligopolistic framework, market equilibrium is computed 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

3.1 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.

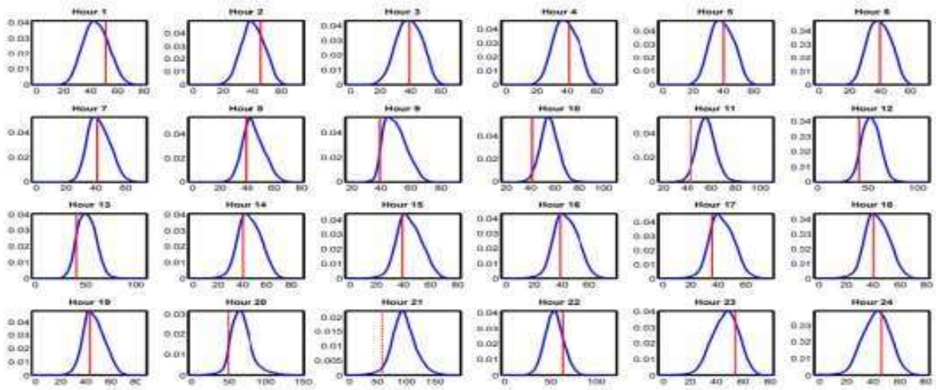

Fig-2: The model of predicted probability function per hour of a typical day :x [12]

4. Conclusion

This paper delves into the relationship between wind speed and power, exploring their interdependence. It addresses various approaches to determine wind velocity. The focus extends to a comprehensive review of wind speed and power forecasting across different time scales, encompassing discussions on numerous forecasting models. The paper highlights the distinctive characteristics of these models, presenting a plethora of research findings. The primary emphasis lies in underscoring the diversity of forecasting methods and offering a comparative analysis to identify the most effective ones. Safeguarding the secure and cost-effective operation of the power grid remains a central objective in wind power. The paper also addresses design considerations during plant establishment, with different nations proposing their unique models for prediction. Furthermore, the paper delves into error identification methods within this context.

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