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Research Article

Wind Speed Prediction Based on Statistical and Deep Learning Models

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Abstract. Wind is a dominant source of renewable energy with a high sustainability potential. However, the intermittence and unstable nature of wind source affect the efficiency and reliability of wind energy conversion systems. The prediction of the available wind potential is also heavily flawed by its unstable nature. Thus, evaluating the wind energy trough wind speed prevision, is crucial for adapting energy production to load shifting and user demand rates. This work aims to forecast the wind speed using the statistical Seasonal Auto-Regressive Integrated Moving Average (SARIMA) model and the Deep Neural Network model of Long Short-Term Memory (LSTM). In order to shed light on these methods, a comparative analysis is conducted to select the most appropriate model for wind speed prediction. The errors metrics, mean square error (MSE), root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE) are used to evaluate the effectiveness of each model and are used to select the best prediction model. Overall, the obtained results showed that LSTM model, compared to SARIMA, has shown leading performance with an average of absolute percentage error (MAPE) of 14.05%.

Keywords: Wind energy, Wind speed, Time series, Forecasting models, SARIMA, Deep learning, LSTM.

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1. Introduction

Renewable energies are a serious alternative to fossil fuels. these type of energy sources are sustainable, extremely abundant within nature and can be a reliable alternative to classic energy generation methods. Wind energy, particularly, is one of the most exploited energy sources; it is a clean source, with a high-performance coefficient, it assures a good energy independence. The most imposing drawback of wind energy is the high intermittence within the year cycle (Asari *et al.*, 2002). Because of its fluctuating nature, wind speed is an extremely unpredictable meteorological factor. Increasing the accuracy of wind forecasting is necessary to optimize wind farm operations, maximize their yield, and ensure a steady development (Devis *et al.*, 2018). Wind energy production plants use special equipment to determine wind direction in order to control the rotor axis direction (Kodjo *et al.*, 2008). However, The wind direction has a low influence on the energy production, especially since wind tends to have one or two dominant directions for which most of the energy is produced (Adekunle, 2017). Thus, the unpredictable nature of wind potential, affecting the yield of wind turbines is related to the variation of wind speed itself for a given direction.

Currently, there are two methods to forecast the wind speed. The first one, named indirect technique, involves predicting wind speed based on environmental data, such as wind direction, temperature, air humidity, etc. The second way is to use past wind speed data to forecast wind speed for the next hours or days. According to the time horizon, the time series prediction is divided into three categories: (*i*) an extremely short-term prediction, which is very useful for intraday market trading and it represents a few minutes to an hour, (*ii*) A short-term prediction approach that is suitable for maintenance planning and it is from one hour to 12 hours. Finally, (*iii*) a medium to long-term prediction, which is useful for maintaining non-renewable energy production. The prediction horizon ranges from several hours to several days.

To grasp wind speed forecasting, several approaches have been proposed. These methods can be separated into physical and statistical methods. Generally, the physical models require ample physical background information, so that they are not appropriate for wind speed forecasting in electric power systems (Mi *et al.*, 2019). In the statistical methods, the historical data are used to train time series models, e.g., auto-regression (AR) model, autoregressive moving average (ARMA) model (Erdem and Shi, 2011), Kalman filter, and artificial neural network (ANN) (Zhang *et al.*, 2016). The purpose of this article is to compare the predicting results of the Seasonal Auto-Regressive Integrated Moving Average (SARIMA) model with the deep neural network model of Long Short-Term Memory (LSTM) using the same dataset and diverse evaluation metrics.

In the first section of this paper, various kinds of forecasting models are described, and then compared based on the analysis of several contents in the literature. In the second section, wind

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speed time series data is studied using the time-series decomposition method. The third paragraph discusses a short-term wind speed forecasting using two of the most frequently employed time-series forecasting methods: SARIMA and the LSTM models. In the last section of the paper, the obtained results are carefully analyzed. To evaluate the performance of the wind speed forecasting model, data from three different velocity month were used, and four kinds of error metrics were considered: The Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE).

2. Related work

According to the methodology, there are three major types of weather forecasting systems namely, physical, deterministic and hybrid systems. Physical systems utilize probabilistic approaches to indicate weather event probability, Deterministic approaches produce more precise weather forecasts for a given location, and hybrid models which combine multiple individual prediction models to overcome several prediction limits (Jaseena and Kovoor, 2020). In the literature, all these approaches are applied for wind speed forecasting systems:

2.1. Physical models

In general, a physical model is an interpretable model, which permits the identification of causal relationships and has the possibility to generate data by performing various numerical simulation experiments. However, it can only approximate complex cases and only simulates well-known physical laws. Physical models are used to forecast the wind resource, beginning with meteorological data and adjusting it to local physical effects. The physical method does not require any training inputs from older data; they provide real-time physical information of wind farm, such as wind speed, wind direction, temperature, humidity, air pressure, air density (Bessac *et al.*, 2018). Combined with the information of topography around the wind farm (terrain, obstacle, contour etc.), the wind speed at the wind turbine's mast height is calculated, and the output of the turbine may then be determined. The use of inaccurate meteorological parameters induces system faults, which subsequently causes a cumulative impact of error, and reduce the forecast accuracy. The physical model uses the mathematical approaches of the atmosphere, they are mainly based on numerical weather prediction model; the NWP model is a program that resolves complex equations and describes atmospheric processes and how they evolve over time. Authors in (Lorenc, 1986), have proposed a NWP model that uses Bayesian Probabilistic Arguments. However, the model does not exhibit accurate results in short-term prediction. Indeed, the performance of the physical model is relatively weak when the wind speed is very random, it is only used for long-term forecasting or it is considered as an input for the statistical method. Evidence illustrates that, to achieve the objective of accurate wind speed prediction, the statistical model built based on probability theory and mathematical statistical method is identified as the most widely used model.

2.2. Deterministic models

Deterministic models can be classified into statistical models and Artificial Intelligence models. (i) The statistical methods consider the training of history of wind speed data and produces a result without considering the effect physical phenomena. A statistical method contains Kalman filters model; in this method, wind speed is considered a state variable leading to the establishment of state space representation. Kalman filters algorithm is then used to forecast the future wind speed. This approach commonly increases the accuracy of NWP models predictions (Cassola and Burlando, 2012). The fuzzy logic model, is a polyvalent statistical approach for wind forecasting, which the values of variables are real numbers between 0 and 1. It is based on qualitative variables to model complex systems, it is generally best suited for systems and phenomenon, for which it's not possible to establish an exact model (Damousis *et al.*, 2004). Another statistical method is the conventional statistical model; they are similar to the direct random time-series model. Model identity, parameter estimation, and model validation are used to develop a mathematical solution to the problem. These models can be categorized into the following categories: Autoregressive model (AR), moving average model (MA), autoregressive moving average model (ARMA), auto regressive integrated moving average model (ARIMA) (Yatiyana *et al.*, 2017). (ii) Artificial intelligence (AI) models have proven to be more accurate and efficient at handling nonlinear data sets and providing better forecasting results. These models are divided between machine learning (ML) approaches for forecasting and deep learning predictors. Among the most commonly used machine-learning predictors for forecasting are ANN and Support Vector Machine (SVM) models. Thanks to its ability to convey non-linear correlations between previous weather patterns and future weather conditions, ANN-based models (Faniband and Shaahid, 2020) are one of the most common approaches for weather prediction. Neural networks are non-linear regression models that can rapidly process large amounts of data and efficiently match input and output variables. SVM are supervised machine learning models focused on solving mathematical discrimination and regression problems. SVMs are appreciated for their simplicity of application, they can handle classification and regression issues (Brereton and Lloyd, 2010). Deep Learning is a subcategory of machine learning that uses an artificial neural network approach to extract intelligence from big data sets. This technique employs supervised or unsupervised methods in deep architectures to create hierarchical representations. RNNs are employed in deep learning and in the generation of models that simulate the activity of the human brain system. They are particularly powerful in forecasting results. For classical RNNs, the absence of the gradient is a severe issue, since the neural network, unable to be properly trained, would surely lose performance. LSTM (Long Short-Term Memory) units are one of the solutions to this problem (Tokgöz and Ünal, 2018). LSTM based architectures are capable of capturing long-term dependencies with much more precision.

2.3. Hybrid models

Hybrid predictive models were introduced to address the limits of single models and increasing the performance of wind speed forecasting, a single model is not sufficient to handle complex real-world systems with unknown mixed models. Such as the combination of ANN and ARIMA model forecasts proposed in (Li *et al.*, 2011) (Nair *et al.*, 2017), the combination of long short-term memory (LSTM) network and the decomposition methods using the grey wolf optimizer (GWO) (Altan *et al.*, 2021).

In literature, the most common and extensively used hybrid models are parameter optimization and data preprocessing based models (Hajirahimi and Khashei, 2019). The data preprocessing-based hybrid models, generally rely on data preparation approaches, the time series is converted split into many subsets of data. Authors in (Nguyen and Novák, 2019) created a hybrid model based on preprocessing to forecast seasonal time series.

Table 1
Comparison of wind speed forecasting models

Wind speed forecasting model	Strengths	Weaknesses
Models based on Bayesian approach. (Miranda and Dunn, 2006) (Tascikaraoglu and Uzunoglu, 2014).	It offers a high flexibility in the modeling, allowing the inclusion of information from physical phenomena that may have an influence on the variable studied.	This approach demands more work and time and requires a certain level of skill on the part of the user.
NWP models (Yang *et al.*, 2018) (Bennitt and Schueler, (2012).) (Martinez-García *et al.*, 2021).	Provides good results for longer prediction terms. The spatial resolution of numerical weather prediction models is continuously growing, providing a better representation of weather characteristics.	Requires longer processing times and advanced computational resources. Not appropriate for short forecast times. Difficult to model. Requires the analysis and understanding of a variety of conditions.
Kalman filter models (Wu *et al.*, 2004) (Babazadeh *et al.*, 2012) (Hide *et al.*, 2003)	Good performance in linear regression methods Because of its recursive form it is not needed to store historical data	Needs extensive previous information of the system. Divergent filter estimates due to stability problems.
Fuzzy logic models (Bououden *et al.*, 2012).	Appropriate for structures that are harder to model precisely.	Very complicated, and needs a considerable processing time when there are numerous rules.
Time series models (AR, ARMA, ARIMA) (Torres *et al.*, 2005) (Eldali *et al.*, 2016)	The structure is relatively simple, it's possible to correct local trends in data,	Requires a much longer historic records, difficult to model nonlinear problems.
ANN-based models (Navas *et al.*, 2020) (Nazir *et al.*, 2020).	Before analysis, there is no requirement to establish a mathematical model, not very susceptible to input data errors, better adaptability to online measures.	Needs a training process and a large number of training data sets.
SVM-based models (Ranganayaki and Deepa, 2017) (Pinto *et al.*, 2014)	Good efficiency in generalization	Requires a good setting of parameters, using a complicated optimization approach, and long training time.
LSTM based models (Araya *et al.*, 2020) (Geng *et al.*, 2020).	Capable of capturing long-term dependencies more precisely.	Needs a training process and a big number of training data sets.
Hybrid models (Soman *et al., 2010)* (Zhang *et al., 2020).*	Achieves a good prediction ability with higher precision, and maximizes the approximation of the actual value. Achieves excellent Stability performance.	Difficulty of analyzing correlated observations and their temporal orders. Sequential nature of the data. Require complex and specific resolution techniques.

The parameter optimization models are established using optimization algorithm, specifically Meta heuristic techniques, thanks to its ample searching benefits (Qian *et al.*, 2019)

2.4. Literature synthesis

Different forecasting models have been used trough literature. Each model includes a special set of strengths and weaknesses. Table 1 summarizes numerous references with an explication of the strengths and weaknesses of the methods used.

Based on this literature analysis, numerous researches work related to wind speed forecasting and power using various models have been used; these approaches often produce credible results, and each method has strengths and weaknesses. The appropriate model is chosen based on the specific data characteristics of the site and the application area of the method, though, the developed prediction models are typically site-specific and greatly influenced by the change in the prediction times required.

3. Mathematical fundamentals

3.1. Problem formulation

The problem consists of predicting the future wind speed values from historical wind data. Assuming that W denotes the input set that includes the recorded wind speed data in the past up to the time t, and $\widehat{W}$ means the output vector that refers to the predicted wind speed values over a given prediction horizon h. Figure 1 shows the wind speed forecasting paradigm. W And $\widehat{W}$ are defined below:

$$\begin{cases} W = [w_{t-N}, w_{t-(N-1)}, \dots, w_t] \\ \widehat{W} = [\widehat{w}_{t+1}, \widehat{w}_{t+2}, \widehat{w}_{t+3}, \dots, \widehat{w}_{t+h-1}, \widehat{w}_{t+h}] \end{cases} \quad (1)$$

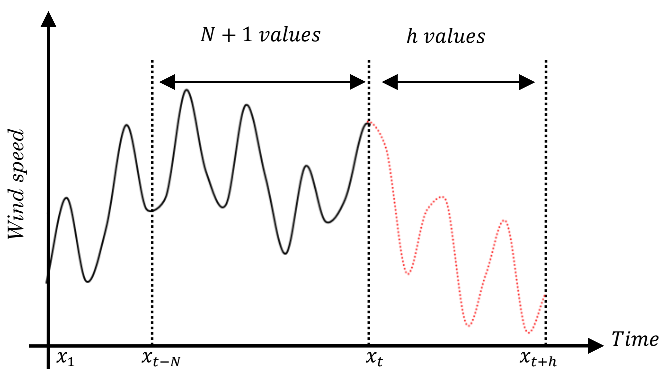


Fig. 1 Wind speed forecasting paradigm

The prediction operation consists to forecast the $\widehat{W}$ values from the known W records with the objective to minimize the prediction error $(w_{t+i} - \widehat{w}_{t+i})$ for each $i = 0\ to\ h$. Thus, the prediction problem can be formulated as follow:

$$[\widehat{w}_{t+1}, \widehat{w}_{t+2}, \dots, \widehat{w}_{t+h-1}, \widehat{w}_{t+h}] = \hat{f}(w_{t-N}, w_{t-(N-1)}, \dots, w_t) \quad (2)$$

Where $\hat{f}$ denotes the forecasting method.
In this study, SARIMA and LSTM methods are used to predict the time related wind speed. Those models would be compared based on several metrics as detailed below.

3.2. ARIMA model

ARIMA model, which means Auto-Regressive Integrated Moving Average is the most popular stochastic models in time series forecasting (Siami-Namini *et al.*, 2018). ARIMA is a time series model that can be employed to analyze and forecast next values in the series. ARIMA models are determined by the combination of three different features (p,d and q). The parameters p, d and q are integers superior or equals to 0 and are described as follow:

p: represents the seasonality, it's specifying the number or order of the AR terms.
d: the trend, it's the number or order of the differences
q: the noise, it represents the number or order of the MA, moving average terms.

The fundamental forecasting equation in terms of y is:

$$\hat{y}_t = \phi_1\, y_{t-1} + \dots + \phi_p\, y_{t-p} + e_t \; - \theta_1 e_{t-1} \; - \cdots \theta_q e_{t-q} \quad (3)$$

Where ϕ_i are the auto-regression coefficients, θ_j are the moving average coefficients of the model, e_t is the noise, and y_t represents the wind speed value at time t.

A more detailed version of the ARIMA model is seasonal ARIMA (SARIMA), this technic proposes to model the seasonality of the time series by adding the period parameter S and the coefficients P, D and Q equivalent to the parameters p, d and q of the differentiated time series (Farida and Zeghdoudi, 2020)

The factors p, d, q, S, P, D and Q are fixed by improving the Akaike information criteria (AIC). This measure is based on striking a balance between a model's complexity and its fit (Mantalos *et al.*, 2010).

3.3. Deep learning models

3.3.1. Recurrent neural network (RNN)

A recurrent neural network (RNN) is a developed branch of artificial neural network (ANN) that aids in sequence modeling. The recurrent neural networks have the capacity to build on previous types of networks.

In RNN, an input sample is added to previously recorded outputs that are included as new inputs. Although RNNs are efficient, they are affected by the vanishing gradient problem, which makes learning large data sequences very difficult. The gradient transmits information used in updating the RNR parameters and when the gradient becomes significantly smaller, the parameter updates become inconsequential, indicating that no meaningful learning is done. Instead, better variation of RNNs is used: Long Short-Term Networks (LSTM) (Tian *et al.*, 2018).

3.3.2. Long Short-Term Memory (LSTM)

LSTM networks are a category of RNN that employs a combination of special and standard units. A "memory cell" in a LSTM unit can store information and keep it for lengthy periods, and a collection of gates is used to manage information. As a result, they use an activation function to determine the activation of a weighted sum. The structure of LSTM cell is shown in Figure 2. The LSTM cell contains the following components: Forget Gate f, candidate layer c, input Gate i, output Gate o, hidden state h, memory state c, inputs of the LSTM cell at any step are X_t (current input), h_{t-1} (previous hidden state) and c_{t-1} (previous memory state).

The LSTM cell produces two outputs: h_t (current hidden state) and c_t (current memory state). Firstly, the LSTM cell get the prior memory state c_{t-1} and performs by element multiplication with the forget gate f. If the forget gate value is 0, the prior memory state is totally forgotten; if it is 1, the previous memory state is completely transferred to the cell. (f gate values are between 0 and 1).

$$c_t = c_{t-1} \times f_t \quad (4)$$

Calculating the new memory state:

$$c_t = c_t + (i_t \times c'_t) \quad (5)$$

Thus, the output is

$$h_t = tanh(c_t) \quad (6)$$

3.4. Evaluation metrics

Validating a prediction model is indispensable to ensure that the model is indeed capable of accurately predicting the values of a variable of interest. The focus is on whether the values predicted by the model are close to the true values in the validation data set. The statistical error metrics described in the following are the most commonly reported indicators: The mean square error (MSE), the root mean square error (RMSE), mean absolute error (MAE) and mean absolute percentage error (MAPE) (Botchkarev, 2019):

- MSE and RMSE

The mean square error of an estimator of a parameter is a measure characterizing the precision of this estimator; it measures the average of the square of the error's deviancies. However, the RMSE is the square root of the second sampling moment of discrepancies between forecasted and observed values. Because the influence of each error is proportional to the amount of the error squared, greater errors have a disproportionate effect on RMSE. (Hossin and Sulaiman, 2015), (Kamble and Deshmukh, 2017).

$$RMSE_{y,\hat{y}} = \sqrt{\frac{1}{n}\sum_{j=1}^{n}(y_j - \hat{y}_j)^2} \quad (7)$$

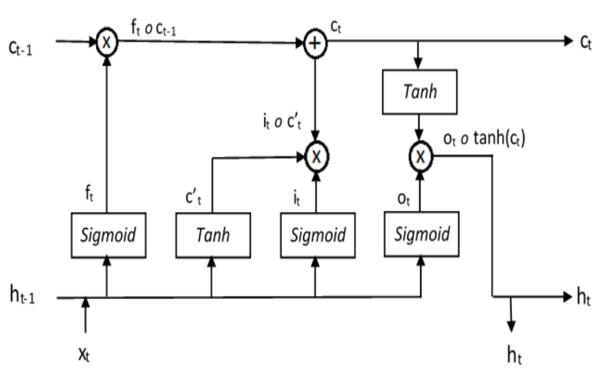


Fig. 2 The structure of LSTM cell

- MAE

Mean absolute error (MAE) is a statistical measure for comparing two continuous variables. Given that, y and y_1 are variables of paired observations expressing the same phenomena. Comparisons of expected against observed, subsequent time versus starting time, and one measuring technique versus another measurement technique are examples of y_1 versus y (Botchkarev, 2019):

$$MAE_{y,\hat{y}} = \frac{1}{n}\sum_{j=1}^{n}\left|y_j - \hat{y}_j\right| \quad (8)$$

The mean absolute error is one of the main methods used for comparing predictions with their eventual results.

- MAPE

The mean absolute percentage error (MAPE) is one of the most widely used indicators of prediction performance. It was used as the primary measure in the M-competition (Kim and Kim, 2016).

$$MAPE_{y,\hat{y}} = \frac{1}{n}\sum_{j=1}^{n}\left|\frac{y_j - \hat{y}_j}{y_j}\right| \quad (9)$$

MAPE has a severe disadvantage in generates undefined values when the real values are null or near to zero (Tayman and Swanson, 1999).

4. Materials and methods

4.1.Methodical approach for the work process

A methodical approach was developed to better implement and assess the two methods for wind speed prediction; the work process is depicted in the diagram shown in Figure 3.

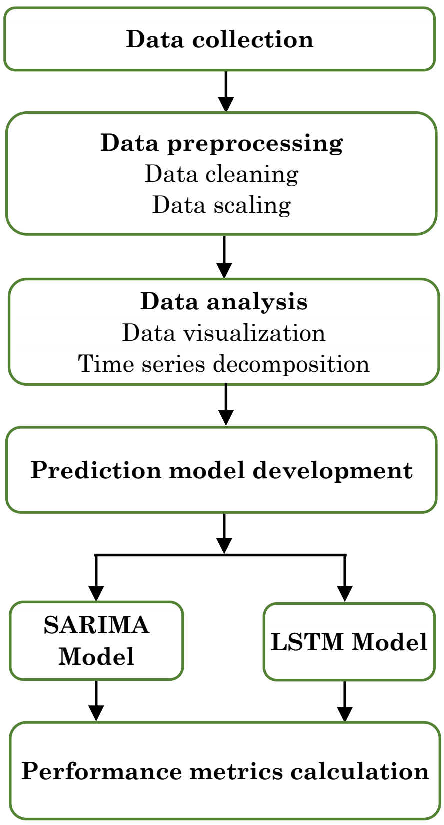


Fig. 3 Methodical approach for the work process

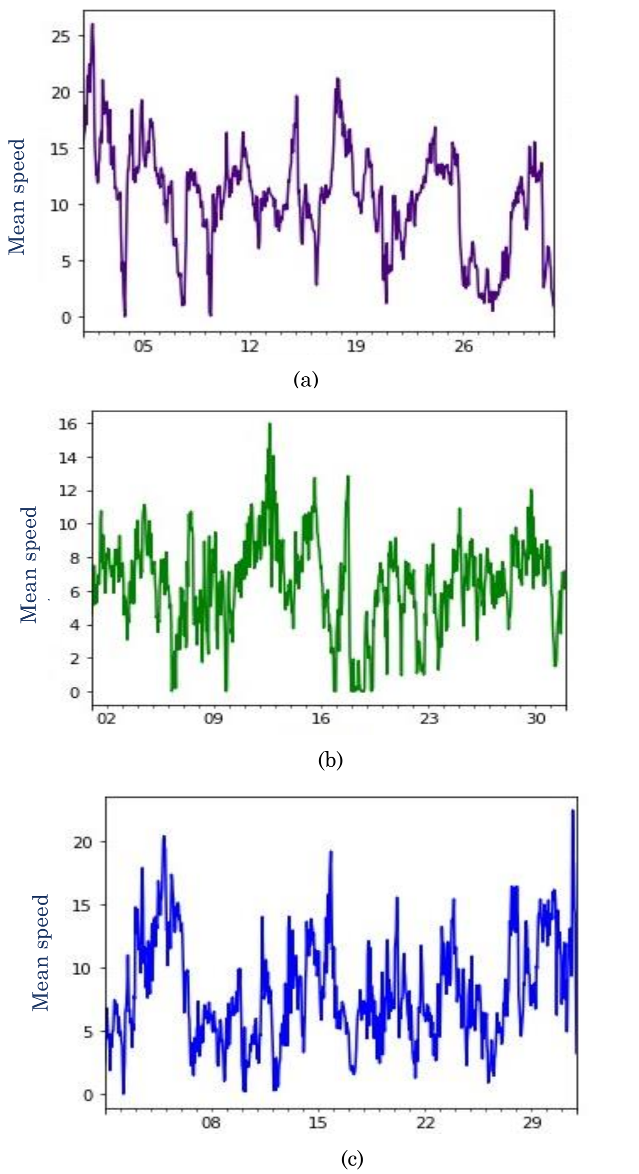


Fig. 4 Wind Data Visualization : (a) March 2018, (b) July 2018 and (c) October 2018

4.2.Data preparation

The meteorological data for this study was recorded at the site "Abdelkhalak Torres" in "Al Koudia Al Baida -Tetouen" located at (Latitude: 35° 45' 35.1, Longitude: -5° 41' 19.9"). The data used in this is recorded daily with a 10 *min* sampling period at a height of 100 m above the ground. The data that was specifically used for this study was recorded between January 1st and December 31st of the year 2018. Records includes date, time of the record and the wind speed. The data that was considered for the validation of the prediction model is related to three months: March, July and October of the year.

Data cleaning is a crucial step of data preparation. Missing data might be the result of an instrument malfunction or a discrepancy with previously recorded data. In the suggested method, the mean of the previous five observations is used to fill in the missing data.

The analysis and processing of the data was carried out by the python 3.8 programming language, with the Spyder 5.0.0 application available on the graphic interface of the Anaconda distribution.

4.3. Time series wind data analysis

A time series is defined as a sequence of numerical values indexed in time, habitually with the same time step separating two successive observations. In this paper, the data is a univariate time-series data. After importing the data set from the recorded CSV file, and to better apprehend the data recording for each studied month, the data is plotted as a time series with the date along the x-axis and the wind speed on the y-axis. The data visualization is showed in Figure 4.

Time-series forecasting is the process of fitting a model to previous data and employing it to forecast future observations. Decomposition is a time series analysis technique, it gives a systematic method of thinking about a time series forecasting issue, in terms of modeling complexity and in terms of how to effectively capture each of these components in a given model. A time series must be decomposed to systematic and non-systematic components. Systematic components are time series components with consistency or recurrence that can be characterized and modeled. Non-systematic components are time series components that cannot be directly represented. Time series have three systematic components: level, trend, and seasonality, with an additional non-systematic noise component.

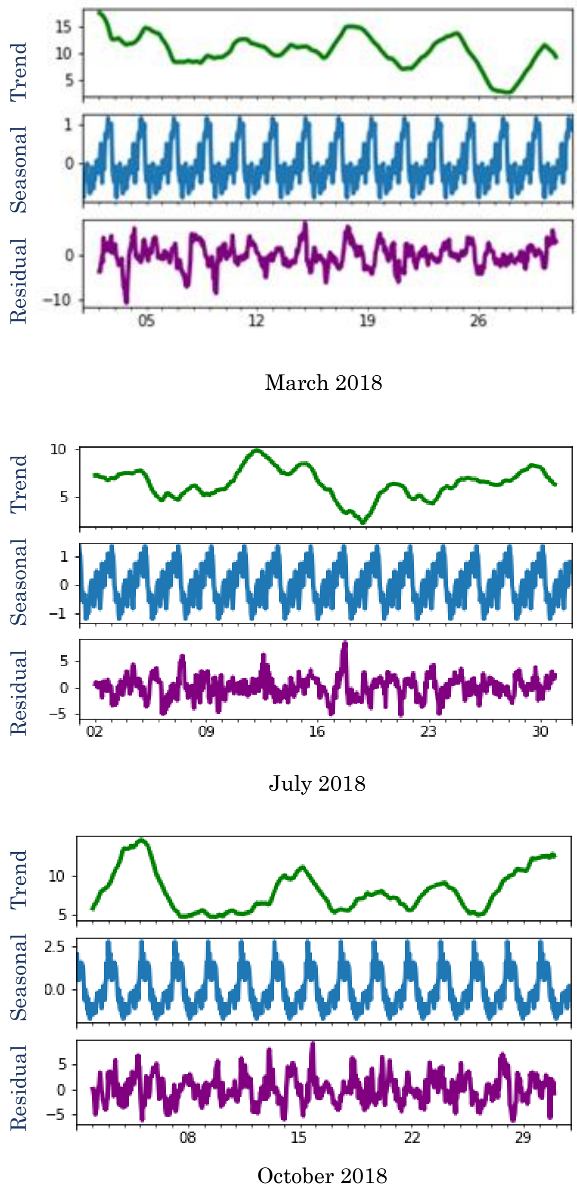


Fig. 5. Time series decomposition

The average value is called level; the trend in the series is the increasing or decreasing value. Seasonality is the recurring short-term cycle, while noise is the random fluctuation in time series (Athiyarath *et al.*, 2020). Results obtained for each month are shown in Figure 5.

For each month, the plot on Figure 4 shows clearly that the wind speed is unstable and extreme winds are rare. It is noted that the seasonal component is more significant on October and evolves slowly in time, because the data are from separate months of the year. However, for consecutive months these will be different seasonal patterns with more important seasonal components. In addition, random fluctuations are more frequent in October and appear to be approximately stable in size over time. According to the trend line, the data and the trend are on the same scale and there is no long-term evolution of the series.

5. Simulations and results

5.1 Wind speed forecasting based on SARIMA model

5.1.1 Parameter's selection and model fitting

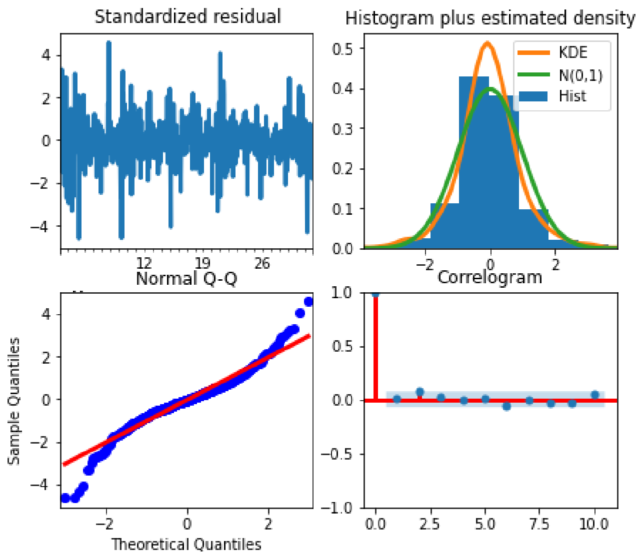
The objective of this subsection is to conduct a grid search to identify the best combination of parameters that generates the highest performance for the model. To accomplish this objective, time series predictive model SARIMA was used. The code's output indicates that respectively: SARIMA(1, 1, 1)x(0, 0, 1, 2) , SARIMA(1, 1, 1)x(0, 0, 1, 2), and SARIMA(1, 0, 1)x(0, 1, 1, 2) generate the lowest AIC (The Akaike Information Criteria) value of 14 869,12 for march, 9 443,72 for July, and 12 864,92 for October. Therefore, this optimal combination was adopted.

After fitting seasonal ARIMA models, it is important to run model diagnostics to ensure that the assumptions made by the model are correct. Figure 6 illustrates the diagnostics produced by the proposed model for each month.

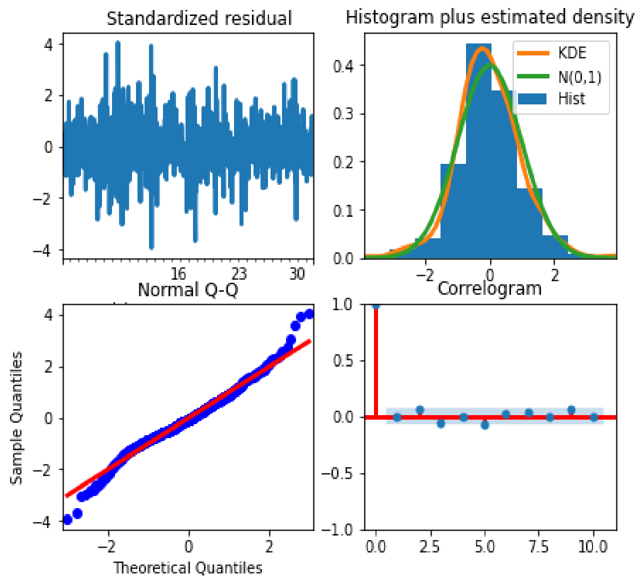
The conducted study has shown that the model residuals are normally distributed. The correlogram reveals that the autocorrelation of time series residuals are near to zero. This is confirmed by the plot of the residuals over time, which shows no significant seasonality. The Kernel Density Estimator (KDE) tracks tightly the normal distribution N (0, 1); this demonstrates that the residuals are distributed regularly. From the Q-Q plot, it can be observed that in the middle of the plot, the distribution of residuals closely follows the linear trend of the data obtained from a standard distribution; however, the residuals distribution diverges at the extremities, which corresponds to the extreme values of the data. Subsequently, the model generates a satisfactory fit that can be used to predict future values.

5.1.2 Forecasting validation

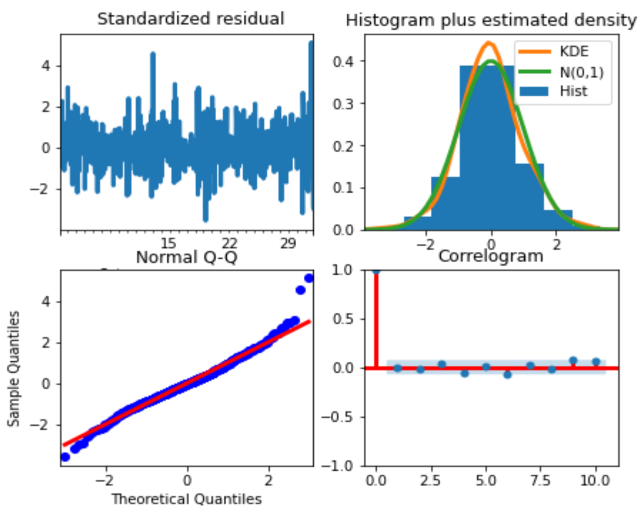
In order to evaluate the accuracy of the proposed forecasts, 25% of the time series data was used as a test set. The forecasted wind speed targeted by the present model is related to the periods between the 24th and the end of the months March, July and October 2018. The forecasts were generated at one-step forward, meaning that the forecasts at each date are compiled using the complete history up to that time. The graph in Figure 7, compares the actual values to the predicted values. Overall, the forecasted data tightly aligns with the actual values; this confirms that the proposed model produces reliable prediction results. This performance will be quantified using the errors metrics introduced previously.



(a)

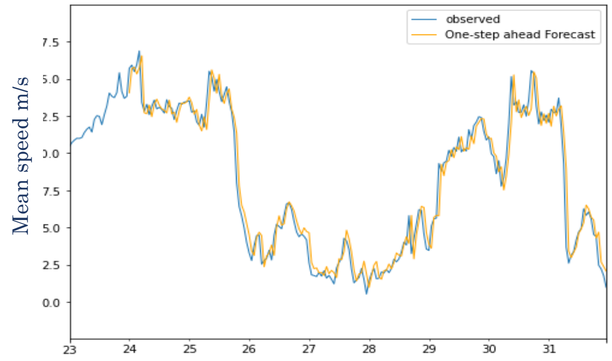


(b)

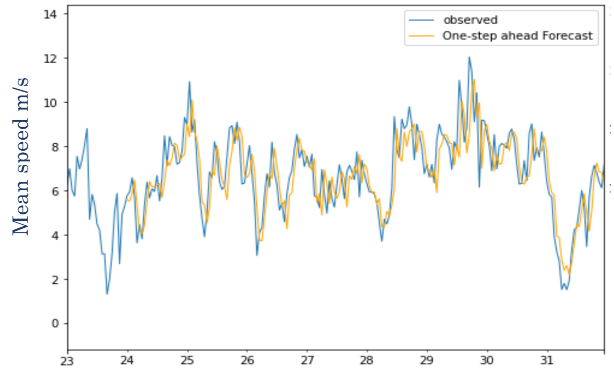


(c)

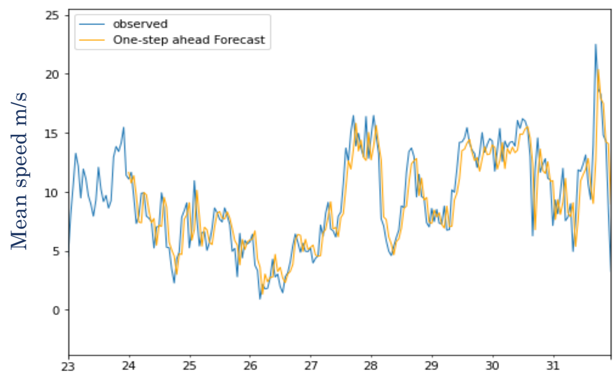
Fig. 6. The model diagnostics: (a) March 2018, (b) July 2018 and (c) October 2018



(a)



(b)



(c)

Fig. 7. SARIMA Forecasting validation: (a) March 2018, (b) July 2018 and (c) October 2018

5.2 Wind speed forecasting with the LSTM network

5.2.1 Experimental test setup

For each month, the global dataset is split in training dataset and test dataset of 75% and 25% of data respectively. A walk-forward validation forecasting model is used. Each step of the dataset test is browsed one at a time. Afterwards, the model is ready to make predictions. The new estimated value from the test data set is obtained and made available to predict the next time step.

5.2.2. LSTM data preparation

To create a LSTM model, the data must be processed. The time series data is therefore turned into a supervised learning model. Data is separated into input (X) and output (Y). The observation from the prior time step (t-1) is used as the input, while the observation from the current time step (t) is used as the output. The hyperbolic tangent function ($tanh$), having an average range (-1, 1), is the default activation function for LSTMs. Therefore, the training dataset was employed to generate the scaling coefficients (min and max) and then used the results to scale the test dataset and the observations were transformed to get a certain scale: the scale was reversed in order to restore the values to the original scale while computing error score in order to interpret and compare the acquired results.

5.2.3 LSTM model development

The LSTM layer requires that the inputs be arranged in a matrix with three following dimensions: samples, time steps, and features. Samples are sets of data in rows, time steps are discrete periods inside an observation, and features are distinct measurements taken at the time of the observation. Accordingly, each time step in the original sequence was treated as a distinct sample with a single time step and feature. The LSTM layer specifies the projected number of observations to be received in each batch. The frequency of updating the weights per time step is determined by the batch size and the number of epochs. The number of neurons is the last characteristic to define the LSTM layer, a number between 1 and 5 is sufficient. To forecast the wind speed at the following time step, the network requires a single neuron in the output layer. Once the network is described, it must be compiled into an appropriate symbolic representation. ADAM optimization algorithm was applied to compile the network since it is a realistic approach with advantages over other stochastic optimization methods (Chang *et al.*, 2019) (Zhou *et al.*, 2019). After, the network is fitted to the training data, which is taken in a supervised learning format. As be needed to make one-step predictions, the batch size is fixed to 1, the best configuration found is: Batch Size: 1, number of epochs: 50, number of neurons: 4. The number of epochs specifies how many times the learning algorithm will work on the training data set.

The result will be a two-dimensional array with a single value because they are supplied with a single input. At this point, the LSTM Network model for the wind speed dataset can be submitted for performance evaluation.

Table 2 shows an example of the expected and predicted values in the test dataset for each month studied. Figure 8 illustrates a line graph of the test values versus the predicted values. As observed, the forecasted data firmly aligns with the observed values, this, further confirms the model's forecasting capability.

Table 2
The expected values versus predicted values

March	July	October
H=10, Pred= 8.523, Expec=11.068	H=10, Pred=4.226, Expec=5.700	H=10, Pred=10.553, Expec=13.057
H=11, Pred=11.109, Expec=11.534	H=11, Pred=5.820, Expec=6.169	H=11, Pred=13.191, Expec=12.621
H=12, Pred=11.545, Expec=10.359	H=12, Pred=6.173, Expec=5.354	H=12, Pred=12.745, Expec=11.590
H=13, Pred=10.248, Expec=10.107	H=13, Pred=5.164, Expec=7.654	H=13, Pred=11.738, Expec=11.424
H=14, Pred= 9.981, Expec=12.074	H=14, Pred=7.901, Expec=8.754	H=14, Pred=11.589, Expec=11.612
H=15, Pred=12.072, Expec=11.480	H=15, Pred=8.851, Expec=7.180	H=15, Pred=11.787, Expec= 9.983

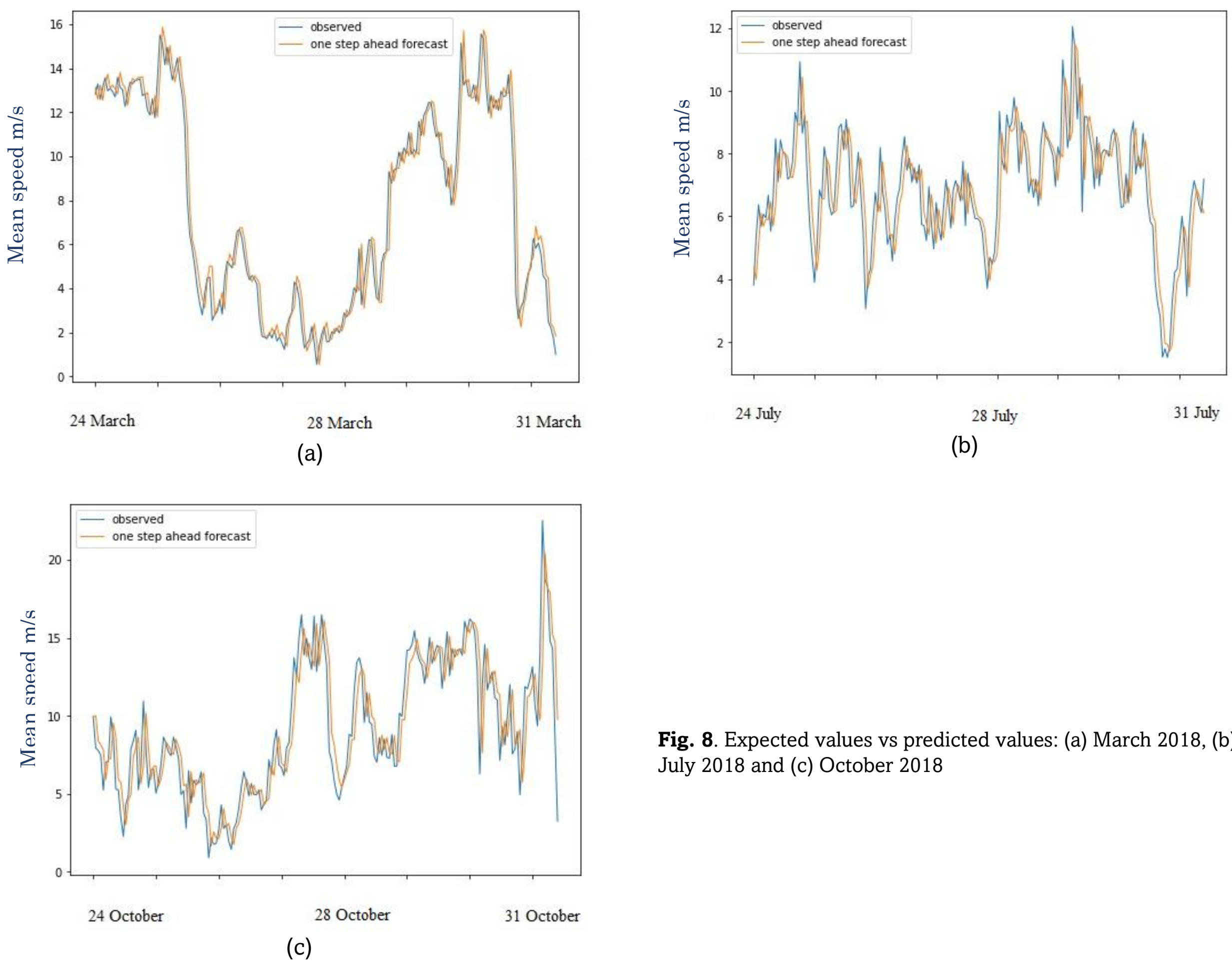


Fig. 8. Expected values vs predicted values: (a) March 2018, (b) July 2018 and (c) October 2018

5.2.4 Reinforcement of the model

The outputs of neural networks vary according to the initial conditions. For this specific problem, the experiment from the previous section were repeatedly conducted and the average of each error metric as a measure of the configuration performance envisaged on unknown data was used. In a loop with a set number of repetitions, the model's fit and walk-forward performance were validated. Every iteration, the executions of error metrics are captured. Next, a summary of the scores for all of the error metrics (MSE, RMSE, MAE, and MAPE) is produced. Table 3 shows the errors metrics results for 15 iterations for the three periods studied. The box and whisker graph of the distribution of test MAPE results for each of the 15 iterations is shown in Figure 9. MAPE values obtained with different periods for the same number of iterations show significant variances. However, it is interesting to note that the model produced the lowest MAPE value in JULY when compared to the other months. Looking at the three boxes medians, the median for March is closest to the minimum error, but for October, 50% of MAPE values are close to the maximum value. The lowest interquartile range (Q3-Q1) calculated, IQR = 0.060%, corresponds to the month of JULY, which indicates that the MAPE value distribution is the most homogeneous and the errors values are evenly distributed around the median.

5.3 Results discussion

The objective of this analysis section is to evaluate the numerical predictive models and determine which one performed better in terms of producing the lowest metrics error and minimal computation time. Overall, both, LSTM and SARIMA models offers good accuracy values of errors metrics comparing to results cited in the literature, for short term wind speed forecast (Liu *et al.*, 2021) (Haddad *et al.*, 2019) (Duan *et al.*, 2021). As shown in Table 4, besides the improvement, LSTM model still provides the highest predictive performance in terms of minimal metrics error in March and October the months with a high velocity and more extreme values.

Table 3
Error metrics values resulting from 15 iterations

	March				**July**				**October**			
	MSE	**RMSE**	**MAE**	**MAPE**	**MSE**	**RMSE**	**MAE**	**MAPE**	**MSE**	**RMSE**	**MAE**	**MAPE**
Minimum	1.1050	1.0449	0.7102	15.9400%	0.3947	0.6234	0.4544	10.5000%	1.5131	1.2298	0.9300	15.7000%
Q1	1.1177	1.0493	0.7147	16.0094%	0.4022	0.6270	0.4573	10.6704%	1.5240	1.2398	0.9350	15.7667%
Median	1.1203	1.0556	0.7164	16.0346%	0.4050	0.6310	0.4587	10.7006%	1.5295	1.2420	0.9370	15.8133%
Q3	1.1286	1.0567	0.7177	16.2518%	0.4070	0.6352	0.4599	10.7307%	1.5414	1.2442	0.9372	15.8309%
Maximum	1.1449	1.0586	0.7231	16.3737%	0.4089	0.6377	0.4889	10.9224%	1.5546	1.2464	0.9399	15.8926%
Mean	1.1238	1.0525	0.7168	16.1607%	0.4042	0.6313	0.4606	10.6982%	1.5318	1.2413	0.9360	15.8025%
Range	0.0399	0.0137	0.0129	0.4337%	0.0142	0.0143	0.0345	0.4224%	0.0415	0.0166	0.0099	0.1926%

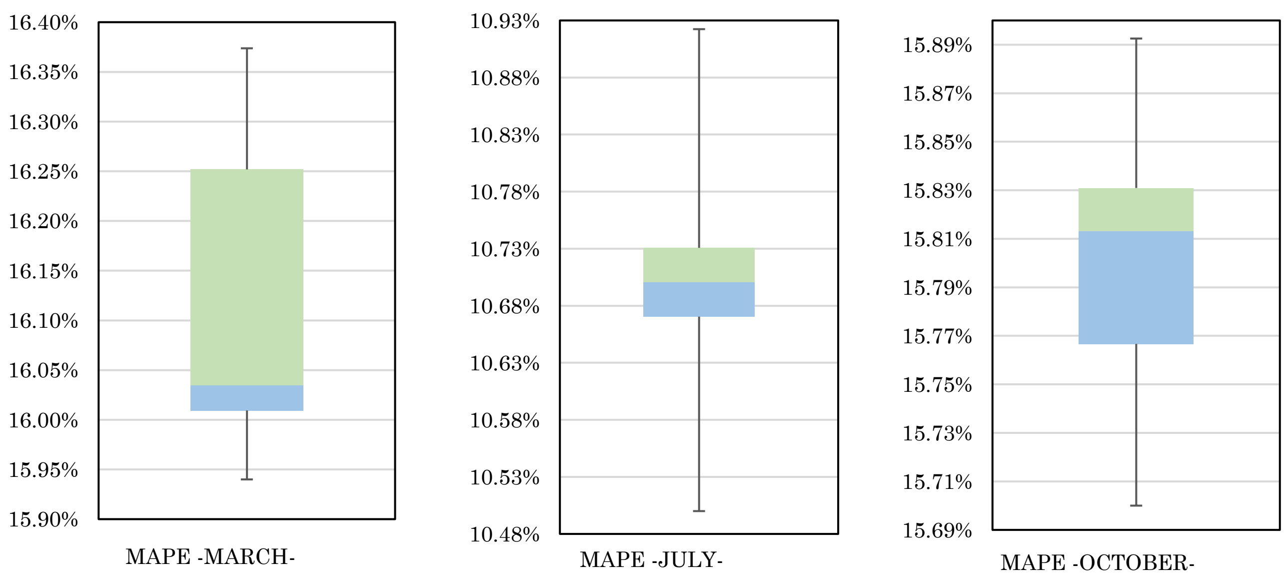


Fig. 9. LSTM Repeated Experiment Box and Whisker graph

Table 4
Errors comparison

	March		July		October	
	SARIMA	**LSTM**	**SARIMA**	**LSTM**	**SARIMA**	**LSTM**
MSE	1.19	1.10	0.38	0.39	1.54	1.51
RMSE	1.09	1.04	0.62	0.62	1.24	1.23
MAE	0.72	0.71	0.44	0.45	0.93	0.93
MAPE	16.10%	15.94%	10.67%	10.50%	16.03%	15.70%

The remarkable performance observed through LSTM -based approaches are related to the used iterative optimization algorithm, with the goal of finding the best results, Furthermore, taking a look at the RMSE values, the statistical SARIMA model gives slightly better results on July, than the LSTM model. Therefore, in periods with small fluctuations, the neural network achieved comparable performances to the traditional statistical models. It should be mentioned that LSTM would give more accurate results if the data contained structural changes with frequent fluctuation. In effect, the SARIMA method is unable to interpret the non-linear component of the wind speed time series data, thus, the model cannot capture all of the available details of the dataset. Contrarily, LSTM is a deep learning tool developed to learn temporal patterns, capture non-linear relations, and store relevant memory for a longer period. Furthermore, the required computational time for forecasting becomes critical to make any comparison. The LSTM based model is most computationally demanding than SARIMA, because of the optimization algorithm, 50 epochs were trained for each optimizer for 15 times and found that training and testing time ranges from 16 to 20 minutes, while the compilation time using SARIMA does not exceed 6 min. Previous study has also supported this (Shivani *et al*., 2019). Indeed, authors in (Makridakis *et al*., 2018), confirm that the complexity reported by ML approaches still substantially higher than statistical methods. The utility and advantage of a large data-learning model such as LSTM, is more solicited when the size of data is much larger (Liu *et al*., 2021). In this study, relatively small series data sets (one month) were used for predictive model training ant testing. Otherwise, the performance differences favoring the LSTM model would have been considerably more interesting. In previous academic research, the ARIMA model provided favorable performance with a smaller volume of data (Elsaraiti and Merabet, 2021).

6. Conclusion

The present study is a comparative analysis of SARIMA and LSTM forecasting models. The main goal is to evaluate the prediction performance of each one. The study uses wind speed time series recorded at three different months as common data. Furthermore, SARIMA and LSTM were compared based on the same evaluation metrics: MSE, RMSE, MAE and MAPE. The MAPE values ranges from 10.5% to 16.10% for both models which indicates that performance is acceptable in both cases. The results analysis shows that the LSTM exudes higher performance than the SARIMA model. This distinction is basically due to the use of iterative optimization algorithm in LSTM model. Practically speaking, The SARIMA model is more functional, because it requires the tuning of six unique parameters (p, q, d, P, Q, D), while the LSTM requires the evaluation of numerous additional hyper parameters, such as the number of units in each layer, the number of layers, the batch size, the number of epochs and the activation function. Regarding the forecasting operation conducted in this study, related to wind speed in particular, SARIMA model was faster to train and less complicated to implement. As a perspective study, the obtained results can be supported by extending the comparative analysis. Thus, in the future work, other machine learning prediction approaches are to be considered such as the support vector machine. The upcoming study will also use larger datasets that extend over a year, allowing us to assess the impact of seasons on the forecasting ability.

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