Electron: Jurnal Ilmiah Teknik Elektro
p-ISSN 2830–523X | e-ISSN 2622–6588

Deep Learning and Traditional Models for Wind Speed Forecasting in Saudi Arabia

Deep Learning dan Model Tradisional untuk Peramalan Kecepatan Angin di Arab Saudi

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[Received: 14 February 2025, Revised: 28 May 2025, Accepted: 31 May 2025]
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ABSTRACT — This study evaluates the performance of traditional statistical methods, specifically the Seasonal Autoregressive Integrated Moving Average (SARIMA), in comparison to advanced deep learning models—Long Short-Term Memory (LSTM), Bidirectional LSTM (BiLSTM), and Convolutional Neural Network (CNN)—for wind speed forecasting across various regions in Saudi Arabia: Al-Jouf, Abha, Al-Ahsa, and Al-Dawadami. The historical wind speed dataset covering the year 2018 was utilized, with data preprocessing conducted using the Exploratory Data Analysis (EDA) method to ensure consistency and quality. The models were assessed based on three primary error metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Square Error (RMSE). Results show that CNN consistently outperforms SARIMA and the other deep learning models, particularly when forecasting stable wind speed patterns. LSTM demonstrates an ability to handle fluctuating wind speeds effectively, while BiLSTM offers advantages in capturing complex bidirectional temporal dependencies. On the other hand, SARIMA generally exhibits lower performance compared to deep learning approaches. The superior performance of CNN is likely attributed to its strength in local feature extraction and handling spatial patterns effectively, which are beneficial for short-term forecasting. These findings provide valuable insights into model selection for wind energy forecasting and can contribute to optimizing renewable energy integration and planning strategies. Future work may explore hybrid model approaches to further enhance forecasting accuracy.

KEYWORDS — SARIMA, CNN, LSTM, BiLSTM, Wind Speed, Forecasting.

INTISARI — Penelitian ini mengevaluasi kinerja metode statistik tradisional, khususnya *Seasonal Autoregressive Integrated Moving Average (SARIMA),* dibandingkan dengan model deep learning lanjutan—*Long Short-Term Memory (LSTM*), *Bidirectional LSTM (BiLSTM),* dan *Convolutional Neural Network (CNN)*—dalam peramalan kecepatan angin di berbagai wilayah di Arab Saudi: Al-Jouf, Abha, Al-Ahsa, dan Al-Dawadami. Dataset historis kecepatan angin sepanjang tahun 2018 digunakan dalam studi ini, dengan data mentah yang telah dibersihkan menggunakan metode *Exploratory Data Analysis (EDA)* untuk memastikan konsistensi dan kualitas. Model dievaluasi menggunakan tiga metrik kesalahan utama: *Mean Absolute Error (MAE), Mean Squared Error (MSE)*, dan *Root Mean Square Error (RMSE).* Hasil menunjukkan bahwa CNN secara konsisten mengungguli *SARIMA* dan *model deep learning* lainnya, terutama dalam meramalkan pola kecepatan angin yang stabil. LSTM menunjukkan kemampuan dalam menangani data angin yang berfluktuasi, sedangkan BiLSTM unggul dalam menangkap ketergantungan temporal dua arah yang kompleks. Di sisi lain, SARIMA umumnya menunjukkan performa prediksi yang lebih rendah dibandingkan pendekatan *deep learning*. Keunggulan CNN kemungkinan besar disebabkan oleh kemampuannya dalam mengekstraksi fitur lokal dan menangani pola spasial dengan lebih efektif, yang sangat bermanfaat untuk peramalan jangka pendek. Temuan ini memberikan wawasan berharga dalam pemilihan model untuk peramalan energi angin dan dapat berkontribusi pada optimalisasi integrasi energi terbarukan. Studi selanjutnya dapat mengeksplorasi pendekatan model hibrida untuk meningkatkan akurasi prediksi.

KATA KUNCI — SARIMA, CNN, LSTM, BiLSTM, Wind Speed, Forecasting.

I. INTRODUCTION

Forecasting has gained significant traction in various domains today, ranging from predicting stock market trends [1], [2], marketing outcomes [3], seasonal decomposition [4], and electric load projections [5], to wind speed [6], [8], [9], [20] and tidal forecasting [7]. A plethora of forecasting methods have been applied, including classical statistical approaches such as ARIMA [10] and seasonal ARIMA for dealing with seasonal data [11]. Nevertheless, the integration of artificial intelligence (AI), machine learning (ML), and deep learning (DL) techniques has not only accelerated the forecasting process but also substantially reduced the likelihood of errors, thanks to iterative training and testing procedures [12]. Precise wind speed prediction plays a vital role in enhancing the efficiency of wind energy systems and safeguarding the public during severe weather conditions [13]. Previous studies have utilized deep learning models such as LSTM and CNN for wind speed forecasting; however, comprehensive comparisons that include BiLSTM alongside CNN, LSTM, and classical SARIMA models across multiple geographically diverse regions remain limited. This study addresses that gap by critically evaluating and comparing the predictive capabilities of SARIMA, LSTM, BiLSTM, and CNN models for wind speed forecasting.

Furthermore, the study focuses on four distinct regions in Saudi Arabia: Al-Jouf, Abha, Al-Ahsa, and Al-Dawadami. These regions were selected due to their varying geographical and climatic characteristics, which present different wind behavior patterns and forecasting challenges, making them ideal testbeds for evaluating model generalization and robustness. While emphasizing the refinement of the ARIMA model for optimized outcomes [10], this research also explores hybrid methodologies that combine classical techniques with contemporary deep learning strategies [3].

II. METHODOLOGY AND FORMULATION

In the realm of time series forecasting, Conventional ARIMA (Autoregressive Integrated Moving Average) and its extension SARIMA (Seasonal ARIMA) have long stood as cornerstones. These models offer powerful tools to analyze and predict time-dependent data, distinguishing between non-seasonal and seasonal components within a series. However, the emergence of ML methodologies has sparked a paradigm shift, introducing models like CNN, LSTM, and Bidirectional LSTM into the forecasting landscape.

A. ARIMA AND SARIMA METHOD

An ARIMA model helps predict future values by examining patterns in past data. It does this through three main elements: Autoregressive (AR): This part looks at how past values can predict what comes next. It considers a certain number of past values denoted as 'p.' Differencing (I): This step is about making the data more predictable by removing trends or patterns. It does this a number of times indicated as 'd.' Moving Average (MA): Here, past prediction errors are used to forecast future values. It considers a number of past errors marked as 'q.' The general formula for an ARIMA method is:

$$Y(t) = c + \varphi 1Y(t-1) + \varphi 2Y(t-2) + ... + \varphi pY(t-p) - \theta 1e(t-1) - \theta 2e(t-2) - ... - \theta qe(t-q) + e(t) \quad (1)$$

Y(t) represents the time series value at time t, where c is a constant. The coefficients φ1, φ2, ..., φp correspond to the autoregressive terms, while θ1,θ2,...,θq denote the moving average coefficients. The term e(t) represents the white noise error at time t. For seasonal data, the SARIMA model with key variables (p,d,q)×(P,D,Q)s is mathematically defined by the following equations:

$$\Phi p\ (B\ )'PP(B\ L)y(t\ ) = \theta q(B)vQ(B\ L)Et \quad (2)$$

The model's objective is to find the best combination of these elements to make accurate forecasts based on historical data. In this context, c is a constant, y(t) represents the time series value at time t, et denotes the white noise error, yt - p indicates the lagged value of y(t) by p steps. The parameters 'θ' and 'φ' belong to the ARMA method. within the ARMA
at a lag of 'p', and both 'θ' and 'φ' are key variables within the ARMA model. The ARIMA model of level (p,d,q) is mathematically expressed in Equation 3.

$$y'(t)=c+et+\phi 1yt-1+\ldots+\phi pyt-p+\theta 1et-1+\ldots+\theta qet-q \quad (3)$$

Here, y (t) is defined as y′ (t)= y′ (t) - y(t-1). And is represented in equation 4.

$$y'(t)= y(t) - B1(y(t)) \quad (4)$$

where B1 is referred to as the backward shift operator of level 1.The SARIMA model of level (p, d, q)×(P, D, Q)L can be expressed using the following equations :

$$\phi p\ (B\ )\ \varphi P(BL)y(t) = \theta q(B)\upsilon Q(BL)\ \epsilon\ t \quad (5)$$

And the seasonal period is represented by L, then

$$\phi p\ (B\ )=1 - \phi B\ldots - \phi\ pBp, \quad (6)$$

$$\phi p\ (B\ )=1 - \theta 1B\ldots - \theta qBp, \quad (7)$$

$$\phi\ p\ (BL\ )=1 - \varphi 1LBL\ldots - \varphi PLBL, \quad (8)$$

$$\phi\ Q\ (BL\ )=1 - \varphi 1LBL\ldots - \varphi QLBL, \quad (9)$$

Here, ϕ, θ, φ, υ become key variables of the SARIMA model that we have.

B. LONG SHORT TERM MEMORY (LSTM)

Unlike conventional recurrent networks, LSTM introduces cell states, allowing the model to selectively retain or discard information, thereby improving its ability to capture long-term dependencies in sequential data. For LSTM training, we employ three advanced techniques using Keras.

An LSTM network consists of an input layer, hidden layers, and an output layer [3]. The input layer contains neurons corresponding to the number of input features, while the output layer represents the target output, such as two neurons indicating wind speed at t + 1 relative to the cross-sectional median. The core functionality of LSTM lies in its hidden layers, which contain memory cells controlled by three key gates: the forget gate (f_t), input gate (i_t), and output gate (o_t). These gates regulate the cell state (s_t), allowing the network to effectively retain and update information over time.

At each time step t, the three gates receive inputs: x_t (a single element of the input sequence) and the previous timestep's memory cell output, h_t−1. These gates operate as filters, serving distinct roles: The forget gate decides what information should be discarded from the cell state. The input gate determines the information to be added to the cell state. The output gate regulates the selection of information from the cell state for output purposes.

A. BIDIRECTIONAL LONG SHORT TERM MEMORY (BI-LSTM)

BiLSTM network, a configuration integrating both backward and forward LSTMs, demonstrates robustness in processing time series data. Illustrated in the diagram is the architectural structure of the BiLSTM [15]. This integration of forward and backward LSTMs enhances feature extraction while capturing temporal dependencies [16]. The computations of U*1 in the forward pass and I_U in the backward pass jointly contribute to the network's output, y.

B. CONVOLUTIONAL NEURAL NETWORKS (CNN)

CNNs originated from Fukushima's work in 1980 but were significantly refined by Yann LeCun in 1998, making them powerful tools in areas like object detection, medical imaging, and image classification [17]. As deep multilayer perceptrons (MLPs), CNNs extract local features at higher layers and combine them into more complex patterns at lower layers. While primarily designed for visual data, CNNs can process non-visual data by encoding it to resemble visual structures [17].

III. DATASET AND BENCHMARK

To evaluate the effectiveness of the forecasting methods, wind speed time series data from the Saudi Arabia Hourly Climate Integrated Surface Data [18] was used. This dataset, provided by the National Oceanic and Atmospheric Administration, covers regions such as Abha, Al Ahsa, Al-Jouf, and Al-Dawadami for the year 2018. This dataset consists of 365 daily measurements of wind speed recorded at a height of 30 meters. Figure 1 visually depicts the specific wind speed time series of these distinct Saudi Arabian locations.

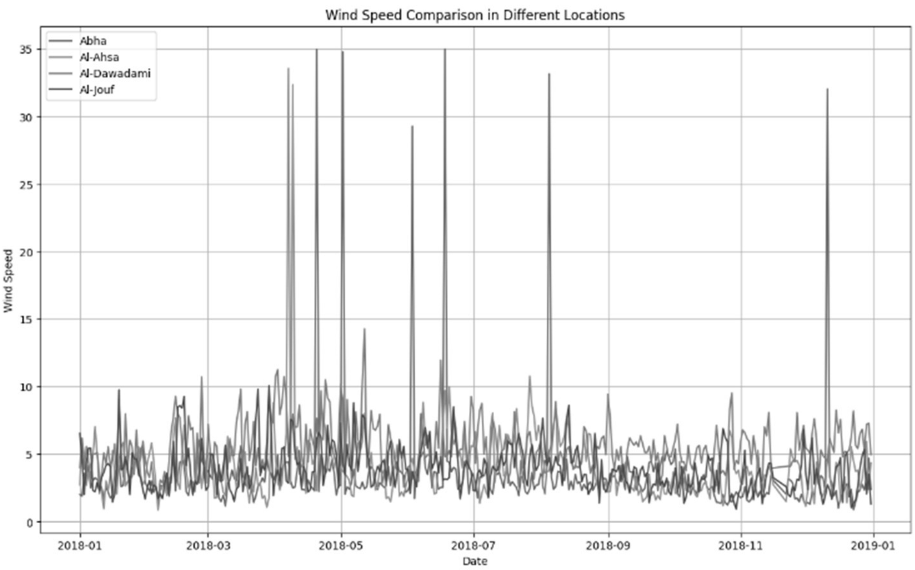

Figure 1. Wind Speed is Measured in Knots Across Four Regions in Saudi Arabia

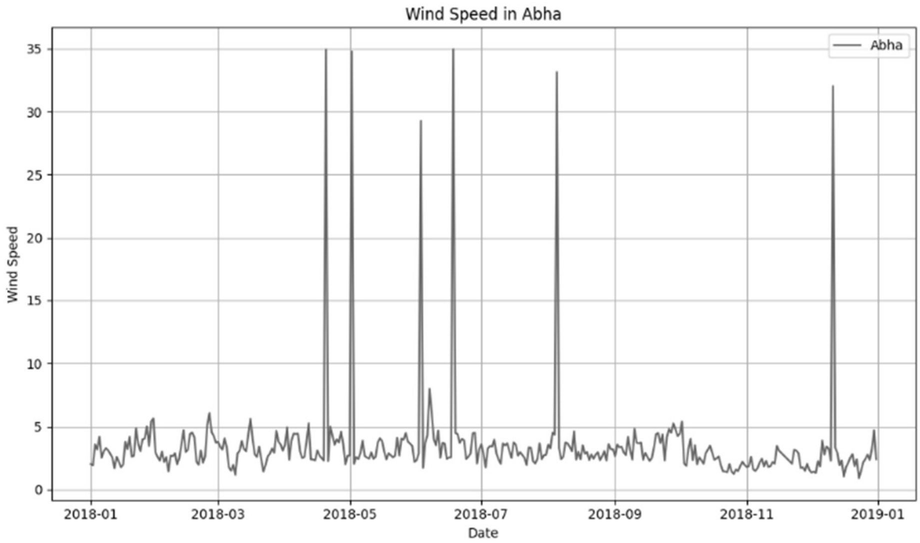

Figure 2. Wind Speed in Knots at the Abha Area

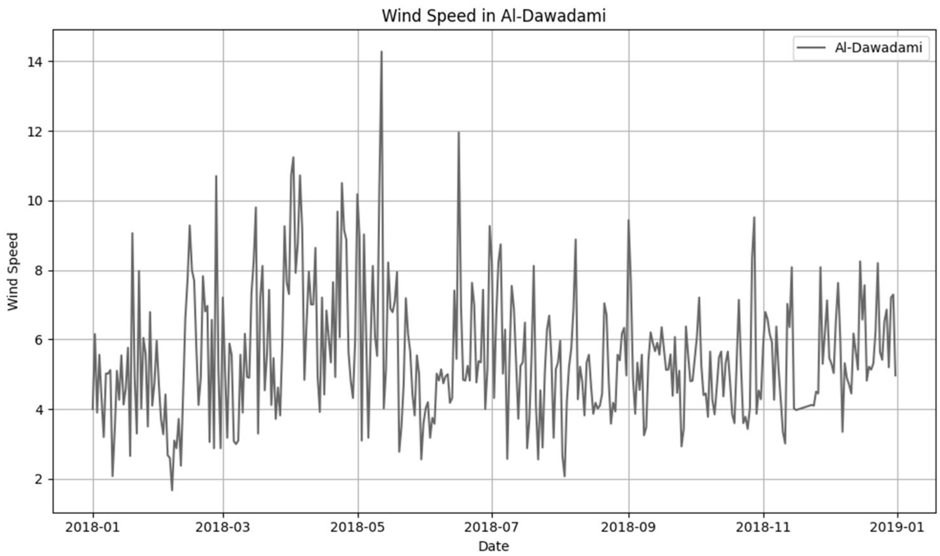

Figure 3. Wind Speed in Knots at the Al-Dawadami Area

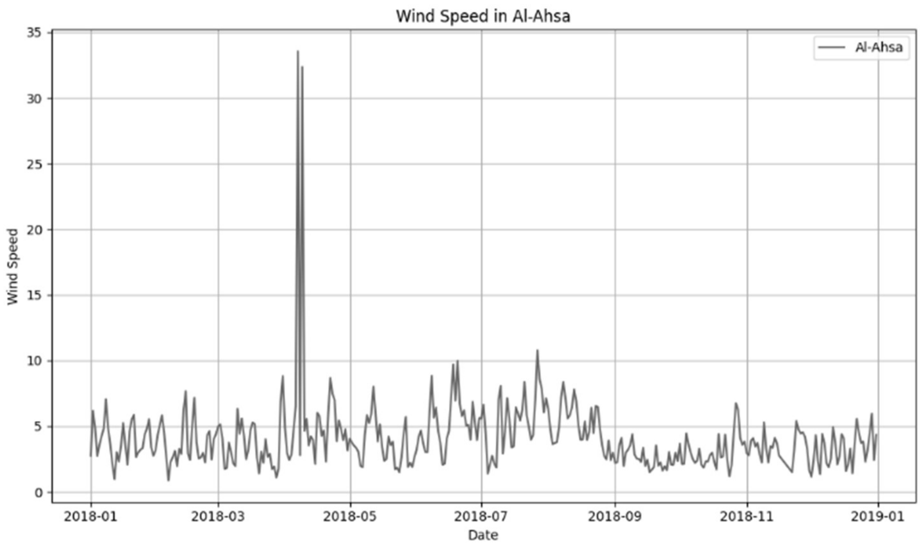

Figure 4. Wind Speed in Knots at the Al-Ahsa Area

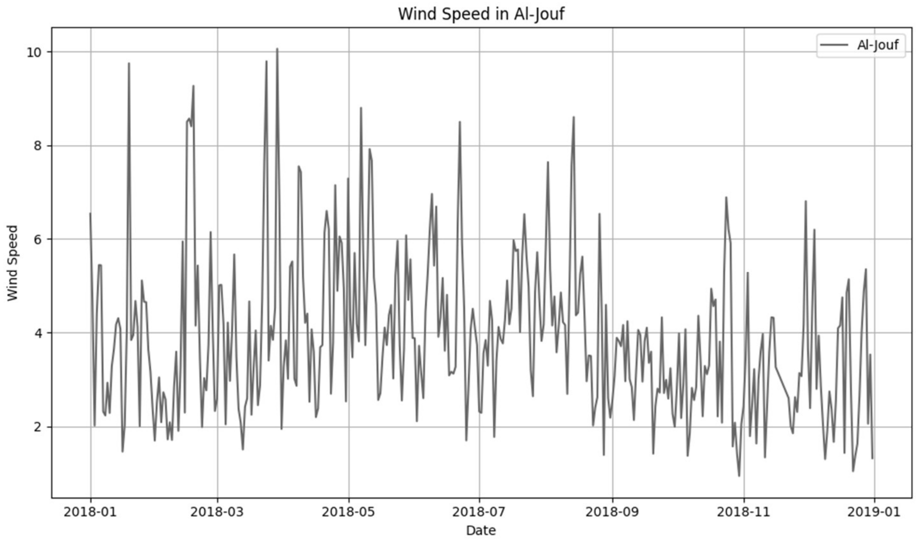

Figure 5. Wind Speed in Knots at Al-Jouf Area

The process commences with the meticulous collection, cleansing, and structuring of wind speed data, followed by partitioning it into training and testing sets. Subsequently, normalization of the data ensures uniformity in scale for effective analysis. The data is utilized to develop predictive models by employing sophisticated modeling methods, like machine learning algorithms. These models generate forecasts that are evaluated against real-world wind speed observations, enabling a comprehensive assessment of their accuracy and reliability.

Our evaluation framework utilizes three key metrics: Root Mean Squared Error (RMSE), Mean Squared Error (MSE), and Mean Absolute Error (MAE). These metrics provide valuable insights into the forecasting models' performance and accuracy, ensuring a thorough assessment of their predictive capabilities.

IV. SIMULATION AND RESULTS

In this phase of the study, the wind speed will be analyzed using SARIMA, LSTM, BiLSTM, and CNN models, as detailed in the preceding sections. The historical wind speed dataset, sourced from [18], covers the entirety of 2018. Before modeling, the raw data were cleaned and preprocessed using the Exploratory Data Analysis (EDA) method [19] to ensure data quality and consistency. For modeling purposes, the historical data from January 1st to December 15th will be used, with the results presented in Figures 6–10 based on the data from November 2018, while forecasting will be conducted for the subsequent 15 days, from December 16th to December 30th, 2018.

Tables I to III showcase the hyper key variables employed in the forecasting techniques investigated in this study, detailing the spectrum of values examined during the optimization phase.

TABLE I

KEY VARIABLES OF THE SARIMA MODEL

KEY VARIABLES	Value
Autoregressive level (p)	1
Differencing level (d)	1
Periodic autoregressive Stage (P)	2
Periodic differencing Stage (D)	1
Periodic Moving Average Stage (Q)	2
Seasonal period (s)	12
Forecast Horizon	12 - 15

a. For the SARIMA method, we use the same key variables of 4 cities (Al-ahsa, Abha, Al-jouf,and Al-dawadami).

TABLE II

KEY VARIABLES OF THE BiLSTM AND LSTM MODEL

KEY VARIABLES	Value			
	Al-Ahsa	Abha	Al-Jouf	Al-Dawadami
Units	160	160	180	150
Compact Layer, units	1	1	1	1

Activation function	'relu' (Rectified Linear Activation Function)			
Optimizer	'adam' (Adaptive Moment Estimation)			
Training epochs	250	150	180	150

TABLE III

KEY VARIABLES OF THE CNN METHOD

KEY VARIABLES	Value			
	Al-Ahsa	**Abha**	**Al-Jouf**	**Al-Dawadami**
Filters	54	54	54	54
Kernel Size	4	4	4	4
Max Polling Layer	2	2	2	2
Compact Layer, Units	1	1	1	1
Activation function	'relu' (Rectified Linear Activation Function)			
Compiler optimizer	'adam' (Adaptive Moment Estimation)			
Batch size	32	50	32	32
Epochs of training	250	300	150	150

Based on the key variables from Tables I to III, we used the Python program to find the value of the forecast from the data, and we got the results in Figures 6-10.

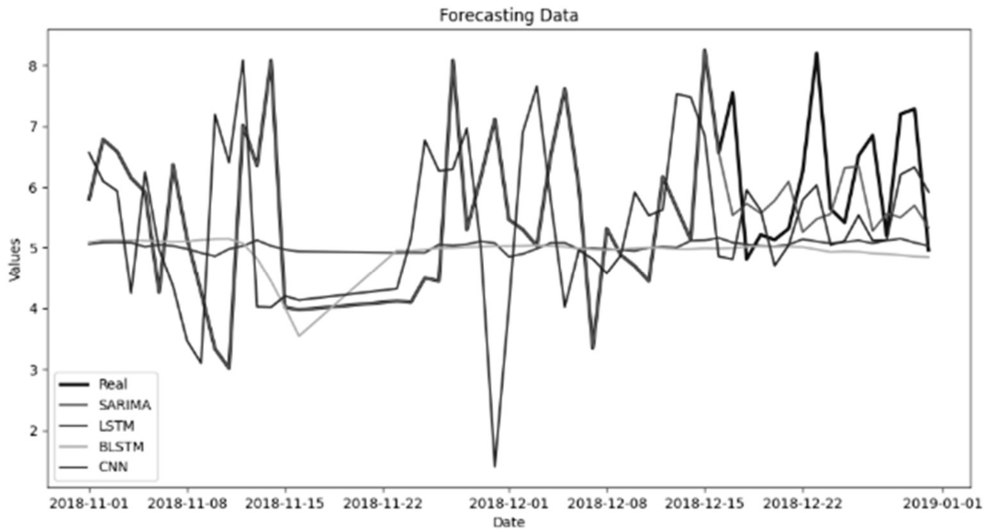

Figure 6. Wind Speed in Knots at Area Al-Dawadami

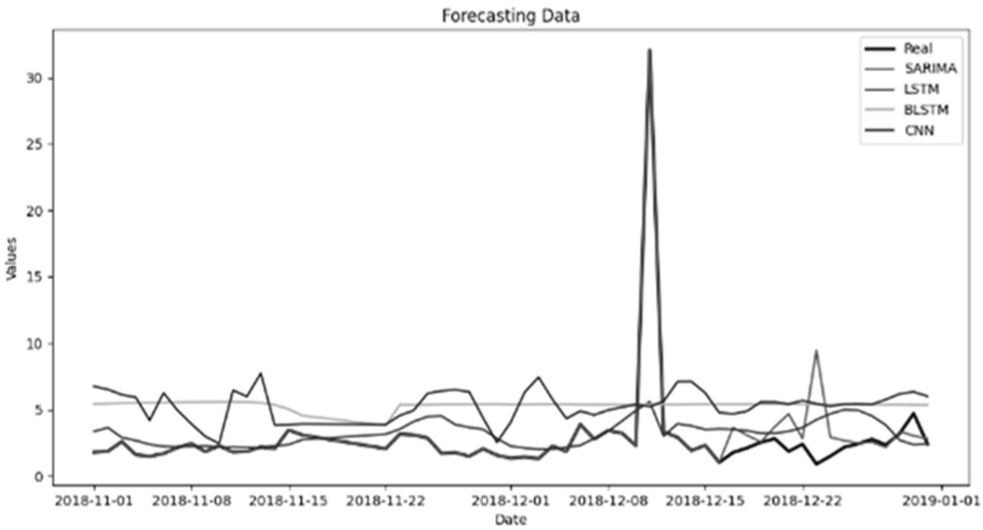

Figure 7. Wind Speed in Knots at Abha

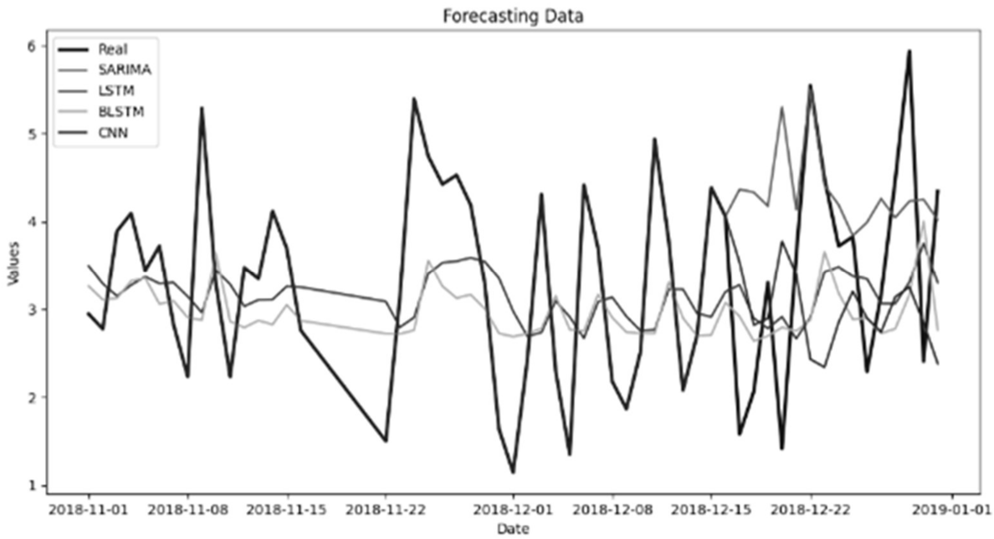

Figure 8. Wind Speed in Knots at Al-Ahsa

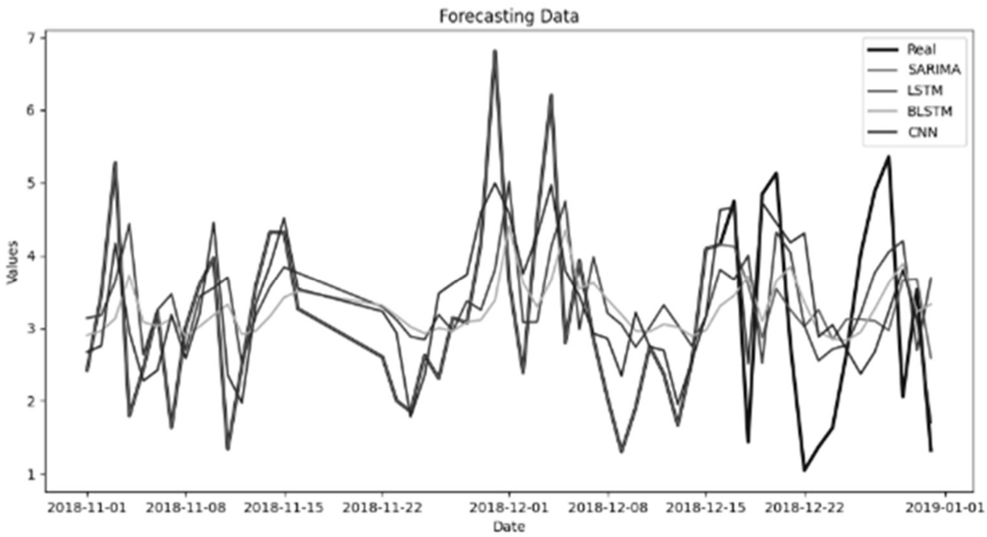

Figure 9. Wind Speed in Knots at Al-Jouf

From four samples of wind speed data in knots taken from different locations using the key variables in Tables 1-4, the results of the MAE, MSE, and RMSE formulations from equations (10 - 12) are presented in Table IV.

TABLE IV

FORECASTING RESULTS

Location	Error	SARIMA	LSTM	BLSTM	CNN	BEST
Al-Ahsa	MSE	0.311	1.182	3.579	0.280	CNN
	MAE	0. 142	0.887	1.159	0.050	
	RMSE	0.529	1.087	1.896	0.333	
Abha	MSE	0.329	1.933	1.909	0.254	CNN
	MAE	0.262	1.060	1.047	0. 056	
	RMSE	0. 573	1.390	1.381	0.504	
Al-Jouf	MSE	0.640	1.882	2.057	0. 096	CNN
	MAE	0. 606	1.059	1.092	0.056	
	RMSE	0.800	1.372	1.434	0. 310	
Al-Dawadami	MSE	0.397	1.997	2.003	0.065	CNN
	MAE	0.306	1.071	1.058	0. 042	
	RMSE	0.630	1.413	1.415	0.255	

This study provides a comparative analysis between deep learning models (LSTM, BiLSTM, and CNN) and the traditional SARIMA model for wind speed forecasting across four locations in Saudi Arabia: Al-Ahsa, Abha, Al-Jouf, and Al-Dawadami. Across all locations, deep learning models generally outperform SARIMA, with CNN achieving the most notable improvements. For example, in Al-Ahsa, CNN reduced the MAE by approximately 65% compared to SARIMA (from 0.142 to 0.050) and lowered the RMSE by about 37% (from 0.529 to 0.333). Similar trends are observed in Abha and Al-Jouf, where CNN consistently records lower MSE, MAE, and RMSE values than SARIMA.

Among the deep learning models, CNN significantly outperforms both LSTM and BiLSTM. In Al-Ahsa, CNN reduces the MAE by around 94% compared to LSTM and RMSE by approximately 82% compared to BiLSTM. LSTM and BiLSTM occasionally show competitive performance but still exhibit higher errors than CNN, and in some cases, their errors approach or exceed those of SARIMA. This indicates that while deep learning provides a clear advantage over traditional methods, model selection within deep learning architectures remains critical. CNN's superior performance can be attributed to its strength in capturing local temporal patterns through convolutional operations, allowing it to better manage the short-term variability and noise typical of wind speed data. Compared to SARIMA, which assumes linearity and stationary behavior, CNN can model complex, nonlinear relationships inherent in meteorological time series.

Moreover, CNNs generally require fewer parameters and training time than LSTM or BiLSTM, enhancing both efficiency and generalization, particularly when the dataset size is moderate. These findings confirm that deep learning, especially CNN, offers a more robust and accurate solution for wind speed forecasting compared to traditional statistical models.

V. CONCLUSION

The comparative evaluation of wind speed forecasting models—SARIMA, LSTM, BLSTM, and CNN—across Al-Ahsa, Abha, Al-Jouf, and Al-Dawadami demonstrates that CNN consistently achieves the best performance. For instance, in Al-Ahsa, CNN reduces the MAE by approximately 65% compared to SARIMA (from 0.142 to 0.050) and achieves a 37% reduction in RMSE (from 0.529 to 0.333). In Abha, CNN also lowers the MAE by nearly 79% compared to SARIMA (from 0.262 to 0.056). While SARIMA occasionally performs competitively, especially in locations with more linear wind patterns, it generally lags behind CNN. LSTM and BLSTM models, although promising, show consistently higher error rates compared to CNN and sometimes even compared to SARIMA, indicating a need for further optimization.

These findings suggest that CNN's superior accuracy can significantly enhance the reliability of wind speed forecasting, with potential practical benefits for optimizing wind energy generation and improving grid stability in regions like Saudi Arabia, where wind resources are increasingly important. Future work could explore hybrid architectures combining CNN with recurrent layers or attention mechanisms to capture both local and long-term temporal patterns more effectively. Additionally, evaluating model robustness across seasonal variations and extreme weather events would further strengthen real-world applicability.

CONFLICT OF INTEREST

The authors declare no conflict of interest with any parties regarding the data published in this research manuscript. Should any conflict of interest be identified in the future, the authors take full responsibility for it.

ACKNOWLEDGMENT

Special thanks to the faculty and colleagues of Intelligent Control 556 and EE 467 (KFUPM): Power Systems Planning and Operations for their invaluable guidance and insights, which were instrumental in shaping this work.

p-ISSN 2830–523X | e-ISSN 2622–6588

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