WCRG Global Research

WORLD COMET RESEARCH GROUP

International Journal of Modern Innovations and Emerging Trends
Vol. 4, No. 2, 2021
Doi: 10.67228/30715628/IJMIET-2021PII9N4A
PP. 01-11

Original Article

Renewable Energy Prediction Using Deep Learning Techniques

Dr. Lucas Martin[1], Dr. Chloe Bernard[2]

[1]*Professor, Sorbonne University, France.*

[2]*Associate Professor, University of Paris-Saclay, France.*

Received: 10-05-2021 Revised: 10-24-2021 Accepted: 11-03-2021 Published: 11-05-2021

ABSTRACT

The accurate prediction of renewable energy generation is essential for the efficient operation, planning, and optimization of modern power systems. The increasing integration of renewable sources such as solar photovoltaic (PV) and wind energy introduces uncertainty because their output depends on meteorological conditions. Traditional statistical and physics-based forecasting methods often fail to effectively capture the complex, nonlinear, and stochastic characteristics of renewable energy time-series data. Deep learning models have recently emerged as powerful tools for renewable energy forecasting due to their ability to automatically learn hierarchical representations from large-scale historical and exogenous data. This study presents a comprehensive analysis of renewable energy forecasting using deep learning techniques, focusing on short-term and medium-term prediction horizons. The paper reviews the evolution of forecasting approaches from conventional time-series models to advanced deep learning architectures such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), long short-term memory (LSTM) networks, gated recurrent units (GRUs), and hybrid deep learning models. The proposed forecasting framework integrates meteorological variables, historical power generation data, and temporal features to improve prediction accuracy and robustness. A unified deep learning–based forecasting scheme is presented, including data collection, preprocessing, feature engineering, model training, validation, and deployment. Mathematical formulations of the learning process and loss optimization are also provided to establish a theoretical foundation. Extensive experiments are conducted on real-world renewable energy datasets obtained from publicly available sources to demonstrate the superiority of deep learning models over traditional methods. Model performance is evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). The results show that deep learning models provide significantly better forecasting accuracy, particularly under highly variable weather conditions. The study highlights the importance of model selection, hyperparameter optimization, and data quality in renewable energy forecasting and serves as a useful reference for researchers and practitioners working on intelligent energy management and decision-support systems.

KEYWORDS

Renewable Energy Forecasting, Deep Learning, Solar Power Prediction, Wind Energy Forecasting, Time-Series Analysis, Smart Grid, Energy Analytics.

ISSN: 3071-5628
PP: 01-11.

1. INTRODUCTION

1.1. Background

The international move towards the aspect of sustainable and low-carbon energy systems has enhanced the mass utilization of renewable energy sources specifically solar and wind power as an alternative energy source of the fossil-fuel based energy generation. On the one hand, the international climate obligations, environmental regulations, and increasing popularity of clean energy initiative gives the governments and utility suppliers worldwide a serious reason to invest in the renewable energy infrastructure with the aim to lower greenhouse gas emissions, curb the effects of climate change, and improve energy security in the long term. Despite the enormous impact on both the environment and economy, used renewable energy technologies bring new major issues to the operations of the current power systems since, in addition to an open dependency on weather conditions, they are characterized by their intermittency. Fluctuating sun intensity, wind velocity, temperature and atmosphere may lead to quick change in the totality of power generation and hence renewable generation cannot be controlled or projected in a normal grid functioning model. As the concentration of renewable grows, these uncertainties are very dangerous to the stability, reliability, and the efficient usage of resources in the power system. Proper prediction of renewable energy output has consequently become a very essential demand to the contemporary power system run as well as planning. Valid predictions allow the grid operators to optimally find a balance between supply and demand of electricity, optimize unit commitment and dispatch, decrease the requirement of spinning reserve, and minimize the use of costly and carbon-heavy back up generation. The quality of the forecasts also applies in energy trading as well as congestion management and integration of energy storage system, which enhances efficiency of the system overall. Inaccurate forecasting on the other hand may cause power imbalances, high costs of operation, volatile voltages and frequencies as well as curtailment and blackout risks. These difficulties impound the necessity to develop sophisticated forecasting methods that can focus on the dynamic nature of the intricate, nonlinear, and time-dependent relationship between the output of renewable energy and weather conditions. Inspired by these practical and strategic correlative scenarios, the target of this research is to make use of the deep learning-based forecasting models to improve the accuracy and robustness of prediction to support sustainable and reliable integration of renewable energy into the contemporary power grids.

1.2. Importance of Renewable Energy Forecasting

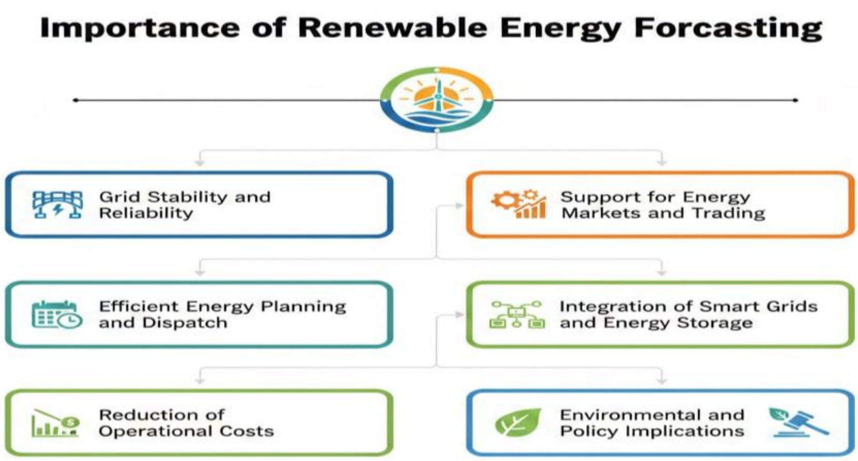

Fig 1 - Importance of Renewable Energy Forecasting

ISSN: 3071-5628
PP: 01-11.

1.2.1. Grid Stability and Reliability

Renewable energy forecasting is very important in ensuring stability and reliability of the modern power systems. Given that the generation of solar and wind energy is very volatile and varies with the weather conditions, correct forecasts enable the grid operators to predict variable power production and proactively respond to the variations in order to sustain the frequency and voltages at constant levels. Predictability minimizes the possibility of unexpected power surges, diminishes grid congestion, and enables safe grid operation, particularly when there is a high ratio of renewable energy in the grid.

1.2.2. Efficient Energy Planning and Dispatch

Proper prediction of renewable energies will allow proper short term and long term energy planning. Forecasting facilitates the process of making optimum unit commitment and economic dispatch decisions, in assistance of the operators to understand how much conventional generation or energy storage capacity would be necessary to supplement renewable sources. This enhances the efficiency of the system as a whole, it consumes less fuel and also does not require the unnecessary appearance and disappearance of the conventional power plants, which results in the reduced costs of operation, and wear of equipment.

1.2.3. Reduction of Operational Costs

The forecasting precision gives a direct influence on the working cost of power systems. The better forecasts of renewable energy will lead to less expensive spinning reserves and backup generation that are normally fossil-based. Reducing the errors in forecasting will enable utilities to reduce reserve levels, reduce fines related to energy imbalance in electricity markets, and enhance profitability in renewable energy generation suppliers and remain a reliable power supplier.

1.2.4. Support for Energy Markets and Trading

In deregulated electricity markets, renewable energy forecasting is needed in bidding and price forecasting. Prediction of the generation allows those in the market to make bids in a more credible way, lower imbalance penalty and enhance market transparency. Forecasting also assist system operators to deal with market uncertainty in an unstable renewable generation which leads to fair pricing and market competency.

1.2.5. Integration of Smart Grids and Energy Storage

This is as a result of smart grid technologies and the good use of energy storage systems, which could only be aided by renewable energy forecasting. Control strategies, based on forecast, enable additional scheduling of battery storage and demand response programmes and electric vehicle charging. This synchronized operation will increase the flexibility of the grid, and maximize the use of renewable energy sources, as well as the shift to an intelligent, resilient, and sustainable grid.

1.2.6. Environmental and Policy Implications

Environmentally and politically, precise renewable energy forecasting improves the country and international climate objectives by promoting more integration of renewable energy and less reliance on intensive carbon generation production. Consistent predictions can allow policymakers and planners to shape a realistic response to energy-related policies, evaluate potential of renewable energy and guarantee that the goals of sustainability are attained without jeopardizing the performance of grids.

ISSN: 3071-5628
PP: 01-11.

1.3. Emergence of Deep Learning for Energy Forecasting

The development pace of deep learning methods has dramatically altered the energy forecasting arena as it has now become possible to model further the nonlinear and time-dependent and complex patterns inherent to renewable energy generation more accurately and with greater strength. In contrast to simple and classical statistical and shallow machine learning techniques, deep learning models can automatically extract high-level features of raw data, thus eliminating the process of manual engineering of features and assumptions requiring domain knowledge. Recurrent neural network-based architectures, specifically the Long Short-Term Memory (LSTM) and the gated recurrent unit (GRU) models have been shown to be very effective in long-term temporal dependencies and sequential dynamics in solar and wind power generation data. Conventional neural networks have also been implemented effectively to take advantage of the spatial relationships in meteorological conditions and satellite images, which increases the level of forecasting. The availability of large-scale historical data including this progress through the rise of advanced sensing instruments and smart meters as well as the expanding number of high-performance computing resources and cloud-based computing systems has enhanced the implementation of deep learning in energy forecasting of renewable energy. These technologies enable the possible training of complex models when using large data volumes to provide enhanced generalization and scalability to other geographic locations and evenalterations in climatic conditions. The empirical literature and studies continue to have consistent results that the deep learning models perform better than conventional forecasting techniques, especially in the conditions of strongly varying and uncertain weather, and are, therefore, well suited to contemporary power systems with high renewable energy penetration. It is inspired by those advancements that this paper is structured into a systematic and detailed study of deep learning based renewable energy forecasting solutions, specifically, the model design, training, and performance evaluation. More so, the paper investigates the practical use of the deep learning forecasting models in smart grid settings and how they contribute to improving the reliability of the grid, aiding in making real-time decisions, and the effective inclusion of renewable energy sources into intelligent power systems in the future.

2. LITERATURE SURVEY

2.1. Statistical and Machine Learning Approaches

The emergent studies on renewable energy forecasting were largely based on the classical statistical approaches of the time series, and the basis of short term prediction models of wind speed, solar irradiance and power output have been dominated by Autoregressive Integrated Moving Average (ARIMA) and its derivatives. The models were popular due to their mathematical clarity, low computationalism, and good ontological grounds, which resulted in their application when the temporal dynamics are steady, and the data variability is not high. Renewable energy generation, however, is a stochastic phenomenon subject to the inherent stochastic meteorological variation of cloud cover, wind turbulence, and temperature variations which make linearity and stationarity, which is assumed in classical statistical models, invalid. Consequently, accuracy of the forecasts greatly decreased when the weather conditions changed quickly and it was not seasonal. In order to overcome these drawbacks, machine learning algorithms such as supportvector machine (SVMs) and decision trees, random forests and artificial neural networks (ANNs) were introduced. These methods were found to be better performers with nonlinear gains in historical power production and the use of exogenous weather variables. However, they were super sensitive to manual feature extraction, sensitive parameters tuning and knowledge of the domain, so the scalability and generalization to different geographic and climatic regions were constrained.

2.2. Deep Learning Models for Renewable Energy Forecasting

Deep learning architecture development was a paradigm shift in prediction of renewable energy, as it was capable of automatically extracting features, and it could learn using large, high-dimensional datasets. Convolutional neural networks (CNNs) were first used to use spatial correlation in grid representation of meteorological data and satellite images to predict solar power. These models efficiently represented local weather trends and local spatial dependencies that could not easily be represented with conventional models. Afterwards Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, rose to popularity as a consequence of their capacity to capture long-term temporal interactions and sequence dynamics of energy generation instantaneous data. The models based on LSTM had a profound advantage in being more accurate in short-time and medium-time forecasting compared to the standard RNNs that face the problem of vanishing gradient. Another more recent type of study has suggested hybrid CNN-LSTM networks that combine spatial feature maps with temporal sequence learning, and with more significant improvements in predictive performance. Also the mechanisms of attention and transformer based models have been investigated to perform dynamic attention of the relevant input features and time steps, allowing more adaptive and context-dependent predictions, especially in unstable weather conditions.

2.3. Research Gaps and Challenges

Although significant progress has been made in the field of forecast accuracy using deep learning, a number of research gaps and practical issues are still to be addressed. Among them, one can single out insufficient data and its inconsistency particularly in areas with poor sensor coverage or missing history, which negatively impacts model training and transfer. Another issue is computational complexity, which is typically large and requires a great deal of processing ability and memory to implement deep learning models, making them unsuitable to use in real-time or edge-based energy management systems. Moreover, since most deep learning models could be interpreted as black-box, there are questions about their interpretability and reliability, which is highly demanded by the grid operators, who need the clear decision-support mechanisms. Resilience during extreme and uncommon weather conditions, e.g., a storm or extended cloudiness, also is something that can be problematic, and such outliers are not present in the training data. Also, no standard benchmarking data and assessment have been standardized which makes it hard to do a true comparison between studies and find out what actual performance improvement has been made. The above issues need to be tackled in order to have the sustainable implementation of advanced forecasting models in working renewable energy systems and strategic energy planning systems.

3. METHODOLOGY

3.1. System Architecture Overview

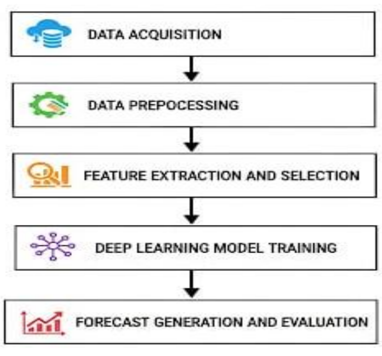

Fig 2 - System Architecture Overview

ISSN: 3071-5628
PP: 01-11.

3.1.1. Data Acquisition

The data acquisition stage will collect the heterogeneous type of data that are sourced by more than one source needed to forecast the renewable energy. This usually contains past power generation data of solar farms, wind farms, weather station or numeric weather prediction models, and meteorological data (solar irradiance, wind speed, temperature, humidity and pressure), and auxiliary data (calendar effects and geographical positioning). Constant and consistent data gathering operates to maintain the trend of the forecasting system to capture the temporal and the ambient factors on energy production.

3.1.2. Data Preprocessing

Preprocessing of data is meant to enhance quality and consistency of data prior to the training of the model. This step is to deal with the missing values, noise reduction, outliers and without normalization or standardization, data would be volatile indicating numerical stability and hence stable learning. Meteorological and power generation data are also synchronized in time so that they stay synchronized at rates of different sampling rates. Proper preprocessing will also increase the strength of the model, and will give less chances of biased or unreliable predictions.

3.1.3. Feature Extraction and Selection

Raw input data is converted into relevant features in this stage that play a big role in increasing the accuracy of the forecast. To describe inherent patterns of energy generation, statistical characteristics, time fixed indicators, and modified meteorological variables are inferred. The methods used to select features are used to help filter out redundant or irrelevant inputs, hence reduced dimensionality and complexity in calculations. This will assist the learning model in prioritising on the most instructive variables affecting the production of renewable energy.

3.1.4. Deep Learning Model Training

Deep learning models are trained with the processed and selected features that can capture complex nonlinear and temporal aspects between two or more features. The neural networks like CNNs, LSTMs, or CNN-LSTM models are trained on historical data by means of iterative optimization. In training, a process of adjusting model parameters is undertaken to ensure that the forecasting error is minimized and validation schemes are used to avoid overfitting as well as deter generalization to unseen data.

3.1.5. Forecast Generation and Evaluation

The trained model produces short term or medium term forecasts of the renewable energy depending on the input data in the final stage. To measure the standard performance metrics (mean absolute error, root mean square error, and mean absolute percentage error) are used to determine the predicted results. It has been evaluated to offer a quantitative view into the predictive capability and reliability that can be used in decision making regarding grid management, energy trading, and operational planning.

3.2. Data Acquisition and Preprocessing

Past power generation data and the respective weather conditions data such as temperature, wind speed, solar irradiance, humidity, etc is widely accessible in publicly availed energy repositories, national grid operators and meteorological weather stations. Such datasets are generally measured at high temporal rates (e.g. 5-minute, 15-minute or hourly intervals) and can be heterogeneous sources having different formats, sampling rates and quality of data. All datasets are brought to a common time interval to achieve consistency. Preprocessing of data is very crucial to

ISSN: 3071-5628
PP: 01-11.

increase the performance and reliability of the models. Missing values, often returned by sensor failures, communication failures, maintenance failures, and so forth, are filled in with interpolation methods like linear interpolation, spline interpolation or forward-backward filling to maintain a sense of time continuity. Statistical thresholds or z-score techniques are used to identify the outliers due to sensor noise or abnormal weather and correct or remove them to avoid bias in the model. Besides, to scale input variables to similar numerical ranges to enhance numerical stability and faster convergence in deep learning model training, input data is normalized and scaled using min-max normalization or z-score standardization. Time of day, day of week, seasonal or other time-related features can also be coded to reflect periodic patterns in the renewable energy production. The raw heterogeneous data is converted into structured, clean and machine readable inputs via these preprocessing steps and this will ensure that the forecasting model learns meaningful trends and not noise hence enhancing prediction accuracy and generalization potential.

3.3. Deep Learning Model Design

The proposed framework uses an LSTM-based deep learning framework because it has demonstrated effectiveness in revealing nonlinear, long-term time-related interdependences in time series data, which are features of renewable energy generation patterns. In contrast to the classical recurrent neural networks, the LSTM networks have a blocked memory which allows the selective retention and forgetting of information with time which overcomes the problem of the vanishing gradient. On every time step, the model is fed an input of an input vector of the extracted features, including historical power output and meteorological variables, and the model provides an update on its internal states by a sequence of gate operations. The forget gate indicates what information needs to be forgotten in the previous cell state by the use of a sigmoid activation operation on the combination of the previous hidden state and the present input. The input gate then controls the amount of new information to be stored in the cell state by integrating a sigmoid function to gate and a hyperbolic tangent function to produce candidate values. The revised cell state is obtained as a weighted average between the past trapped information and the candidate information that has been learned. Lastly, the output gate is a factor that determines what flowing information is passed to the hidden state through the application of a sigmoid activation and then a hyperbolic tangent transformation of the updated cell state. The resultant hidden state is an output of the present time step and input of the succeeding time step. The LSTM model is capable of modeling time-correlations and delayed impacts of a renewable energy system through a series of successive data points through the process of iterative learning. This type of architecture allows the correct prediction by the architecture in all weather conditions and provides the architecture with strong performance in diverse forecasting horizons.

4. RESULTS AND DISCUSSION

4.1. Model Training and Optimization

The defined deep learning architecture will be trained with the help of the backpropagation through time (BPTT) algorithm which is tailored to optimization of recurrent neural networks by laying out the time lateralities through sequential data. The model takes the input sequences in multi-time steps during training and backward propagation of the prediction errors in the network corrects the model parameters. Adam optimizer is used to optimize the parameters as it has an adaptive learning rate system and efficient in computation which is suitable when dealing with large systems of time-based data. Adam hybridizes both momentum-based optimization and adaptive gradient algorithms by keeping both exponential moving averages of both the training gradient and its squared forms, allowing it to converge faster and be more stable in training. The mean squared error (MSE) loss function is taken as the objective function to measure the difference between the

ISSN: 3071-5628
PP: 01-11.

anticipated and observed renewable energy production. Colloquially, the MSE is calculated as the average squared difference between actual observed values and the model prediction of the identified samples (all samples make up the training dataset). The error is squared, so that, the large deviations are penalized more strongly thus motivating the model to give accurate and consistent forecasts. This loss function is minimised in an iterative way by updating network weights and biases until the convergence criteria is achieved or the performance on a validation set has stable values. Regularization modes like early termination and drop out can be added to avoid overfitting and enhance generalization to unseen data. Validation loss trends are continuously used to monitor model execution, so that the trained model is balanced in terms of both accuracy and robustness. With such a systematic training and optimization approach the forecasting model is attained into reliable predictive performance but is also computationally efficient, so as to be used in real practice in renewable energy management systems.

4.2. Performance Evaluation Metrics

A collection of commonly accepted statistical error measures, that is, Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) are used to measure the performance of the proposed renewable energy forecasting model to have a definitive and effective measure of the accuracy of the forecasting. Mean Absolute Error is a measure that displays the overall size of the errors in prediction by calculating direct dissimilarity between how a value is predicted and how it actually is. The measure is easy and straightforward to interpret model performance, since it indicates the average deviation of forecast against observed energy outputs expressed in the same units as the variable of interest. Root Mean Square Error on the other hand, lays more emphasis on the bigger errors since it squares the differences between the prediction and obtains the square root of the mean squared error. Consequently, RMSE is especially commonly applied to model identification of models that generate the random but important forecasting errors, which can be of great importance in the work of energy systems where the large deviation can lead to the instability of the grid and affect scheduling steps. Mean Absolute Percentage Error measures forecasting performance relative to the actual performance by dividing the absolute error by the value which allows comparison of different data sets as well as energy scales. It is particularly useful in cases where a performance of models should be evaluated with reference to various sources of renewable energy or irregular sites with different generating potential. Through the combined analysis of MAE, RMSE and MAPE, the assessment system would not only identify absolute and relative forecasting error but also the susceptibility to severe anomalies. A multi-metric evaluation approach is a critical and an objective way of measuring the effectiveness of the proposed model and contributes to evidence-based decisions on the planning and management of renewable energy.

4.3. Comparative Analysis

Table 1: Importance of Renewable Energy Forecasting

Model	MAE (%)	RMSE (%)	MAPE (%)
ARIMA	21.5	29.8	12.6
ANN	16.8	24.1	9.4
LSTM	11.2	17.6	6.1

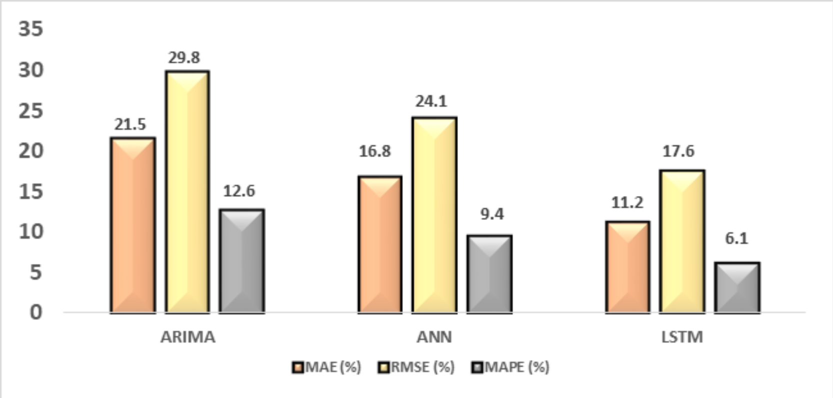

Fig 3 - Importance of Renewable Energy Forecasting

4.3.1. ARIMA

ARIMA model has the largest error values in all the evaluation criteria with a mean absolute error of 21.5 percent, a root mean square error of 29.8 percent, and a mean absolute percentage error of 12.6 percent. These findings suggest low accuracy levels of forecasting, mainly because of the linear assumptions and stationarity limits of time-servers models of ARIMA. Though ARIMA works fairly well in the environment that is stable and predictable, its deficiency in capturing nonlinear relationships and the ability to provide quick weather-related variations in the renewable energy generation is what contributes to an increase in the amount of deviation in forecasts.

4.3.2. ANN

The artificial neural network model shows that there is a visible enhancement of the ARIMA model as it has low error values with an MAE of 16.8%, an RMSE of 24.1, and a MAPE of 9.4. This enhancement shows the ANN capability to capture nonlinear relationships between meteorological factors and power output. Nevertheless, the relatively larger error values than the deep learning models indicate that it has limitations in terms of long-temporal dependence and successive trends especially when handling the highly volatile re-energizing information.

4.3.3. LSTM

LSTM model has the highest forecasting performance of the approaches considered, lowest MAE of 11.2, RMSE of 17.6 and the lowest MAPE of 6.1. These findings affirm that LSTM networks are efficient in the acquisition of long-term correlation in time and adaptation to dynamic weather conditions. Very short term LSTM LSTM has a gated memory structure, therefore, allowing selection of the ingrained historical data, leading to more accurate and reliable predictions, which makes it a strong tool in predicting renewable energy applications.

4.4. Discussion

The experimental findings strongly indicate that deep learning forecasting models are far superior compared to the traditional statistical methods, as well as the shallow machine learning methods in forecasting tasks of renewable energy. Models that are based on a linear assumption and stationarity like ARIMA have a hard time adapting to the highly dynamic and stochastic nature of renewable energy generation based on quickly varying meteorological conditions. Although the artificial neural networks enhance the predictive accuracy through the nonlinear relationships of the input variables and the energy output, they have a low ability to predict long-term trends, which limits their performance when working with sequential data with seasonal and delayed effects. Conversely, LSTM-based models are always more effective in all the measures of evaluation, which is

ISSN: 3071-5628
PP: 01-11.

its ability to cope with the variability of time and the intricate dependency networks. The gated memory effect of LSTM nets means that memory networks can naturally choose to remember only the information related to history as well as exclude the noise, which makes the forecasts more steady and precise under high variability assumptions such as abrupt changes in wind velocity or the amount of solar energy. Also, LSTM models are more robust during extreme weather as they experience time-related patterns over long periods of time. These benefits make the LSTM architectures especially competitive in operational renewable energy forecasting, in which it is essential to perform precise predictive capabilities over the short and long term to achieve grid stability, energy trading, resource allocation, etc. The findings also indicate that introduction of deep learning models in energy management systems can optimize the decision support and also uncertainty in integrating renewable energy. In general, the results confirm that deep learning models and especially LSTM models are effective and reliable tools of the renewable energy forecasting problems of the modern world.

5. CONCLUSION

The current paper has displayed an in-depth exploration of the topic of renewable energy forecasting with a focus on the state-of-the-art methods of deep learning, and discussed one of the most pressing issues of the present-day power systems the variability and uncertainty of renewable energy in its nature. The study reported the drawbacks of the traditional statistical models, conventional machine learning methods, and the state-of-the-art deep learning architectures in the representation of the complex, nonlinear and time variations that are evident in renewable energy generation data. Based on this reading, a coherent forecasting system was suggested, which does not only combine methodical data gaining, preparing, feature design, and profound learning modeled forecasts but also offers dependable and precise energy prefigurings. The experimental analysis showed that deep learning networks, especially LSTM-based models, are always at the forefront over the conventional techniques, such as ARIMA and artificial neural networks in various performance indices, including MAE, RMSE, and MAPE. These findings support the higher ability of deep learning models to train the long-term temporal dependencies, adapt to fast-evoking meteorological changes, and be resistant to high variability processes. The results demonstrate the engineering value of deep learning in the process of integrating renewable energy because the higher the accuracy of forecasting, the greater the stability of the grid, the optimal energy dispatch, the less required reserves, and wise decision-making in the energy market. As much as these developments have taken place, the research also identifies existing issues that need further research. The research which is proposed to be carried out in the future should focus on creating explainable deep learning models, so that grid operators and policy makers can find it more transparent and trustworthy. Moreover, using transfer learning methods has potential impact whereby leading knowledge can be used across alternate geographic locations and renewed energy locations with minimal historic data available. Lastly, real-time implementation of deep learning-based predictions systems into smart grid and edge computing systems is an important area of direction towards research-to-practice translation. All in all, the present research supports the position of deep learning, as a revolutionary technology in renewable energy prediction, and sets a good basis to continue the exploration and implementation by industries.

REFERENCES

[1] G. E. P. Box and G. M. Jenkins, *Time Series Analysis: Forecasting and Control*, 4th ed. Hoboken, NJ, USA: Wiley, 2008.
[2] J. W. Taylor and R. Buizza, “Neural network load forecasting with weather ensemble predictions,” *IEEE Trans. Power Syst.*, vol. 17, no. 3, pp. 626–632, Aug. 2002.

[3] H. Liu, H. Q. Tian, Y. F. Li, and L. Zhang, “Comparison of two new ARIMA–ANN and ARIMA–Kalman hybrid methods for wind speed prediction,” *Appl. Energy*, vol. 98, pp. 415–424, Oct. 2012.

[4] M. Kusiak, H. Zheng, and Z. Song, “Wind farm power prediction: A data-mining approach,” *Renew. Energy*, vol. 35, no. 7, pp. 1367–1374, Jul. 2010.

[5] S. Salcedo-Sanz, A. M. Pérez-Bellido, E. G. Ortiz-García, A. Portilla-Figueras, L. Prieto, and D. Paredes, “Hybridizing the fifth generation mesoscale model with artificial neural networks for short-term wind speed prediction,” *Renew. Energy*, vol. 34, no. 6, pp. 1451–1457, Jun. 2009.

[6] Y. Bengio, A. Courville, and P. Vincent, “Representation learning: A review and new perspectives,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 35, no. 8, pp. 1798–1828, Aug. 2013.

[7] S. Hochreiter and J. Schmidhuber, “Long short-term memory,” *Neural Comput.*, vol. 9, no. 8, pp. 1735–1780, Nov. 1997.

[8] J. Qin, Q. Liu, J. Wang, and Y. Liu, “A hybrid CNN–LSTM model for short-term wind power forecasting,” *Energy*, vol. 217, pp. 119–132, Feb. 2021.

[9] R. Karim, C. Zhang, S. Yin, and J. J. Zhang, “Deep learning-based solar power forecasting using attention-enabled LSTM,” *IEEE Access*, vol. 7, pp. 191–203, 2019.

[10] A. Sagheer and M. Kotb, “Unsupervised pre-training of a deep LSTM-based stacked autoencoder for multivariate time series forecasting problems,” *Sci. Rep.*, vol. 9, no. 1, pp. 1–16, 2019s.

[11] A. Vaswani *et al.*, “Attention is all you need,” in *Proc. Adv. Neural Inf. Process. Syst. (NeurIPS)*, Long Beach, CA, USA, 2017, pp. 5998–6008.

[12] H. T. Phan, J. D. McCalley, and V. Vittal, “Robust short-term wind power forecasting using deep neural networks,” *IEEE Trans. Sustain. Energy*, vol. 11, no. 4, pp. 2139–2149, Oct. 2020.

[13] M. Lago, F. De Ridder, and B. De Schutter, “Forecasting spot electricity prices: Deep learning approaches and empirical comparison of traditional algorithms,” *Appl. Energy*, vol. 221, pp. 386–405, Jul. 2018.

[14] Z. Q. Chen, K. Q. Zhou, and J. Q. Wu, “Short-term wind power forecasting using an ensemble learning approach,” *Renew. Energy*, vol. 109, pp. 293–305, Aug. 2017.

[15] A. Ahmad, N. Javaid, M. Imran, Z. A. Khan, U. Qasim, and M. Alnuem, “Short-term load forecasting using support vector regression and K-nearest neighbor,” *IEEE Access*, vol. 6, pp. 230–242, 2018.