International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
IJISAE
ISSN:2147-6799 www.ijisae.org Original Research Paper

Wind Speed Prediction for Duhok City Applied Recurrent Neural Network

Zozan Saadallah Hussain[1], Najat Yohana Danha[2], Karwan Muhammed Muheden[2], Shahab Wahhab Kareem[2,3]

Submitted: 07/09/2022 **Accepted**: 20/12/2022

Abstract

The wind has exploded in popularity in recent years, and it is expected to continue to do so in the future. To efficiently schedule and utilize that source of energy, better forecasting methodologies are required. In the recent decade, numerous studies on forecasting wind speed generation on timescales of minutes, days, months, and years have been conducted. According to a comprehensive set of forecasting methodologies, physical approaches, statistical or hybrid methods, such as neural networks, are the most widely used tactics for predicting wind speed day-ahead. The goal of this paper is to keep prediction error to a minimum. Plotting and predicting the speed of wind in Dohuk city, KRG/Iraq, using a recurrent neural network model. The LSTM architecture is the type of artificial recurrent neural network used in deep learning. Based on the dataset, the approach plots the predicted wind speed and forecasts the future dispersion. Data centers were suggested for Dhouk as a way to utilize the electricity generated by wind turbines and integrate it with other sources of renewable energy and the electrical grid. The city accepted the proposal. With future implementations, it is possible to accurately quantify how much energy is being created as well as how much money is spent on operations and maintenance.

General Terms: Computer Engineering**,** Machine learning

Keywords: Artificial neural networks (ANN), artificial recurrent neural networks (RNN), Long Short-Term Memory (LSTM), Regional Meteorological Centre (RMC)

1. Introduction

Climate change and energy security concerns have driven significant changes in how electricity and energy are used. Currently, the energy supply in Kurdistan has mostly based on fossil fuels, with gasoline and natural gas accounting for around 85% of total energy production. Then, the remaining 15% has covered by hydroelectric power facilities and solar energy, which is virtually endless by one percent. Despite the availability of fossil fuels, as a result of a lack of electric generators, electricity demands cannot be met, particularly in the winter and summer when loads are at their peak. The Kurdistan region has employed renewable energy to address the region's long-standing energy shortage. As a result of its geographic location and climate, the study sought to determine whether Kurdistan could replace fossil fuels with renewable energy. According to the findings, the Kurdistan Regional Government (KRG) may save money on fossil fuels by switching to renewable energy sources or pooling their resources KRG will be able to improve the region's power situation. Many publications have been published on this topic [1]. Because of this, the region will need to import electricity from Turkey and Iran in the future. Renewable energy sources have been studied extensively, but the dynamics of social acceptance are still challenging to grasp. Small and big consumers are now being encouraged by the Iraqi government to participate in the generation of electricity from renewable resources to reduce global warming [2].

Renewable energy has become a major problem for many countries and governments throughout the world due to growing worldwide concerns about a nuclear power shortfall, fossil fuel shortages, and climate change. In wealthy countries, there has been a considerable increase in the use of renewable energy supplies and the efficiency of that ecologically friendly power. This is due to the quick rise in regular or fossil fuel prices, which causes pollution and global warming. The most serious challenges to humanity today and in the future are air pollution, global warming, and climate change [3]. Clean energy, combined with the non-polluting generation, has few negative effects on the environment and is currently replacing a portion of fossil-based power generation in many regions of the world. Because of their clear presence in the Kurdistan area climate, two forms of renewable energy sources have been focused on as techniques to be applied: solar power and wind power. Solar and wind energy, which is both clean energies, are available naturally in Iraq and do not produce any pollutants [4]. Since ancient times, man has directly profited from solar energy in a variety of applications, including crop drying, water distillation [5-6], and domestic water heating employing sustainable energy and PLC techniques [7]. This energy has also been used based on PI controller unit

1 Department of Electrical Techniques, Northern Technical University, Mosul, Iraq
2 Department of Information System Engineering, Erbil Technical Engineering, Erbil Polytechnic University, Erbil, Iraq
3 Department of Information Technology, College of Engineering and Computer Science, Lebanese French University, Erbil, Iraq
Correspondence: shahab Wahhab Kareem; Email: shahab.kareem@epu.edu.iq

for home usage and other uses [8-9]. The Duhok Governorate understands the critical need to combat climate change and is working to transform the city into a low-carbon, resilient environment. With financial assistance and help from foreign counterparts, it promised to reduce GHG emissions by at least 40% below 2015 levels by 2030.

Wind energy is one of the fastest-growing sustainable energy technologies on the worldwide market. Iraq has a significant electricity leakage as a result of rising population and electrical consumption, and the old power infrastructure is unable to meet this need. Solar and wind energy sources, which also provide a significant source of revenue for the Iraqi government, have become critical in addressing the energy shortfall. The most important technical issue affecting the economic viability of a wind project is the availability of wind. For investors to decide if a project is economical in a certain location, a thorough understanding of available wind resources is essential [10]. In the last two decades, global installed wind-generation capacity has increased by around (75) times, growing from (7.5 gigawatts (GW)) in 1997 to (564 GW) by 2020, according to the latest IRENA data. Approximately 20% of all renewable electricity generation was provided by wind energy. Even though wind speeds are high in many parts of the world, it's difficult to find sites where they can be harnessed for power generation. There is a lot of potential in offshore wind power [11]. Designing a wind energy application using ArcGIS has been completed in the Kurdistan area, with the application being used to look for wind energy resources in each governorate in the Kurdistan region of Iraq. This program assists a designer in locating information about wind resources and archaeological sites, as well as their geographic locations. The (30km) proposed substation and the (132kv) proposed substation in Kurdistan's three governorates (Erbil, Duhok, and Sulaymaniyah) have been identified [12].

The wind is created by the movement of air from a high-pressure zone to a low-pressure zone with equal elevation and densities. In the atmospheric boundary layer, the wind is always turbulent and is represented by a mean velocity component and a fluctuating turbulence component. With increasing height, there is a modest influence of surface roughness on regional wind velocity, which causes the wind velocity to increase proportionally [13]. Wind power is generated by harnessing the kinetic energy of moving air. Electricity can be generated from this by wind turbines or other wind energy equipment. To begin with, the wind strikes the turbine blades and causes them to spin, in turn, the associated turbine to turn. Kinetic energy is transferred to rotational energy by rotating a shaft coupled to an electromagnetic power generator, which generates electrical energy. Wind speed changes from minute to minute and from location to location. Wind resources should be analyzed in a variety of sites for optimal selection before wind farms may be built. To manage wind turbines constantly, optimal locations must have a good wind speed and frequency [14].

Wind turbines, which are used to generate electricity, feature two or three blades mounted on a horizontal axis, which generate power based on wind speed. The capacity of wind turbines has grown over time. New wind power projects typically use turbines with a capacity of about two megawatts (MW) and three to five (MW) off the coast. Commercially accessible wind turbines with rotor diameters up to 164 meters and outputs of up to 8 MW are presently on the market. The MATLAB Graphical User Interface can assess wind speed, handle missing data, and calculate correlation coefficients, in addition to plotting the results of this analysis (wind and Rose). In addition, the software provided detailed information on the parameters of the Weibull distribution using two alternative ways (Standard Deviation Method and Energy Pattern Factor) to help users understand the distribution [15]. Wind speed and turbine blade diameter influence the amount of energy produced by wind turbines, with wind speed increasing as the turbine rises from the ground. A big number of windmills are clustered together to produce the maximum electricity. The size of the turbine and the length of its blades determine the quantity of power that can be gathered from the wind. The output is related to the size of the rotor and the cube of the wind speed [16]. Wind power potential increases by a factor of eight when wind speed doubles, according to theory. The use of small wind turbines to generate electricity under Iraqi meteorological conditions has been studied. The appropriate regions for the production of electricity using wind turbines may not be within cities, and you may be in rural areas and locations that are not connected to the power system [17].

The unit cost of power generated by ten different wind turbines has been calculated using two different methodologies. To show the project's financial viability near AL Shihabi, a wind farm with a capacity of (5.0) MW and ten identical wind turbines (EWT DW54-500kw-50m height) was designed using RETScreen software [18]. Wind potential has been calculated in three Iraqi cities: Baghdad, the capital, and Basra, (550 km) south of Baghdad, and Mosul, (450 km) north of Baghdad. Researchers looking into the potential of wind power in Iraq can use the study as a starting point [19]. Computational fluid dynamic (CFD) was used in ANSYS CFX 14.0 to investigate the wind flow and pressures at the Duhok Rixos Hotel in Duhok, Iraq. In addition, the optimum code of analysis was chosen based on the numerical analysis outputs [20, 21]. For the preliminary design assessment of wind devices for wind sites where trustworthy data is not easily available, an artificial neural network (ANN) technique has been given for predicting WS in Duhok city, Iraq. Without a doubt, the findings have been valuable to local wind farm designers, planners, and manufacturers in the examined regions in Iraq's north [22].

In the present work, the authors applied Recurrent Neural Network (RNN) for predicting wind speed and direction for Duhok Governorate using the data set collected from Meteorological Directory in Dohuk Governorate. This paper also includes an up-to-date annotated bibliography of wind forecasting literature, as well as an overview of integrated forecasting methodologies. In addition, the paper highlights potential future research topics for combination strategies to assist researchers in the field in developing more effective wind speed forecasting tools.

2. Wind Energy

While annual mean wind speed variation is difficult to forecast from year to year, wind speed fluctuations throughout the year can be well described in terms of a probability distribution. At many common sites, the Weibull distribution has been proven to be a suitable description of the variance in hourly mean wind speed over a year [23]. The wind vector has been regarded to be consisting of a steady wind plus oscillations regarding the steady wind for wind energy use and wind turbine design; however, the power and energy obtained from wind can only be based on the steady wind speed. The well-known statement [15] gives the power output, P, of a wind turbine:

$$P_T = \frac{1}{2}\rho A c_p U^3 \quad (1)$$

Where A is the area swept by the rotor in m^2, U is the wind velocity (m/s) and ρ is the density of air in (kg/m^3), c_p is the power coefficient which measures how much of the wind's energy can be transformed into mechanical work by a turbine. In theory, it can reach a maximum value of 0.593 (the Betz limit), but in practice, it tends to peak at lower values. Under typical circumstances, (sea-level, $18c^{\circ}$) the density of air is 1.225 kg/m^3. Wind speed data is usually available at a height of (10 meters) above the ground in most places, and wind speed tends to increase with height. Because the hub in energy production systems is higher than (10 meters), wind speed at various elevations must be calculated to determine which wind turbine may be installed at the specified location [17].

3. Dohuk City's Wind Characteristics

A thorough understanding of statistical wind data is essential for both geographical and temporal analysis of the wind's speed and direction in addition to its frequency distribution across time. As you move south from the north, Iraq's wind power potential increases in value. This is because the air temperature increases on this route. Weibull's model is a good tool for wind power analysis and might be utilized to provide electricity to many sections of Iraq [4]. In Dohuk city's central district, the highest monthly mean wind speed in 2020 was 2.0 m/sec in June, followed by 1.84 m/sec in March and 1.69 m/sec in April. When examining the average wind speed values, it is clear that the wind speed is highest in June. Therefore, these months are considered the best among others months. Data centers play an essential role in arranging the functionality of wind turbines because the generated power is dependent on the speed of the wind, which varies from time to time. As the wind speed increases, the cost of wind power reduces considerably. The wind speed in Dhouk is concentrated in the city center, notably during February and June.

The variable and intermittent natures of renewable sources need a large amount of backup generation or energy storage and the ability to delete them from the energy mix. Home appliances, lighting fixtures, and electric cars have been considered potential sources of supply-following loads. Electric vehicles could be charged only when enough wind and solar power is available, for example, by using this strategy to schedule or sculpt the electric load to match power availability from renewable sources. Power generated varies from one time to another depending on the power source, location of power generators, and weather conditions. The power requirement is mostly calculated by the data center's power management rules and the data center's time-varying workloads [24]. With wind speed and direction forecasts, power management plans can be improved. Because of this, wind forecasting systems should be installed in the data centers. To assess wind speed, direction, and available electricity generated by each turbine, data centers must be connected via a network and located near wind turbines so that information can be exchanged. Then they're in charge of managing the power distribution plan based on the generated power and scheduling the electrical load based on the available generated power [20].

4. Recurrent Neural Neywork

One of the numerous machine learning models is an ANN. The earliest ideas for ANN were proposed in 1943 as a way to imitate the human brain [25]. Neural networks (NN) are formed by connecting neurons; the most basic ANN is comprised of one input layer, one hidden layer, and one output layer. The buried layer of a NN makes a decision using a non-linear activation function. For each link between individual neurons, the activation function receives a weight and bias. The non-linear activation function, as well as these input weights and biases, characterize the signal that a neuron produces. To produce the most accurate outputs at the output layer, these weights and biases are modified frequently during the model's training. The model achieves this by minimizing a difference function between model predictions and observations in a validation set of data, such as the mean squared error. Deep learning is an extension of ANN models and a Machine Learning technique that made use of the deep NN. A multi-layer NN with two or more hidden layers is used between the input and output layers known as a deep NN, also is the essence of Deep Learning even though it appears to be simple. Figure 1 depicts the concept of Deep Learning and how it relates to Machine Learning. Deep learning models include convolutional NN are built with a grid-like architecture in mind to analyze data, and they are widely used for image categorization [26].

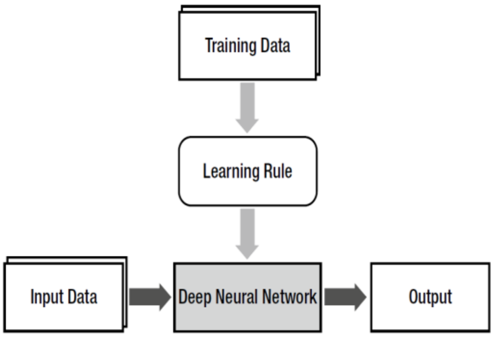

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Figure 1: Concept of Deep Learning and its relationship to machine learning

The challenge of multilayer NN training was finally overcome when the back-propagation method was discovered in 1986. Once again, the NN was in the spotlight. It was quickly met, however, with a new problem. It fell short of expectations when it comes to real-world problems. The use of hidden layers and hidden layer nodes has been used to get around the restrictions. None of them, on the other hand, were able to succeed. Many of them received even lower grades. Because the design and concept of the NN are so simple, there wasn't much that could be done to improve it. Finally, NN was written off as unimprovable and forgotten. It has been mostly ignored for about 20 years. The emergence of Deep Learning in the mid-2000s opened up a new avenue [27].

The deep-hidden layer takes a long time to achieve satisfactory results due to the difficulty in training the deep NN. In any event, modern Deep Learning technologies produce remarkable results, beating both traditional Machine Learning approaches and other NNs, and dominating Artificial Intelligence research. Finally, the lack of a learning rule took the multi-layer neural network 30 years to overcome the limitations of the single-layer NN, which were eventually solved by the back-propagation method. However, it took another 20 years for deep NN-based Deep Learning to be introduced due to its poor performance.

4.1 Long Short-Term Memory Networks (LSTM)

In 1997, they invented LSTM networks to overcome the difficulty of RNNs maintaining information over extended periods [28]. RNNs have proven to be the only way to solve sequence classification issues while retaining information from earlier input data and adjusting output at each time step. The backpropagation gradients computed during the RNN model's training phase either vanish (due to the cumulative multiplication effect of values between 0 and 1) or explode (due to the cumulative multiplication effect of high values) if the sequence is long enough, causing the model to train slowly. In this scenario, an LSTM network comes to the rescue. It's a form of RNN architecture that helps with model training and memory retention from previous input time steps over long sequences. It solves the gradient vanishing or gradient explosion problem by including input and forgets gates, which allow for better gradient management by letting the user choose which information to keep and which to discard, thereby controlling the information's access to the current cell's state and thus allowing for better preservation of "long-range dependencies." As a result of the RNN's flaws, LSTM networks have gained prominence as a method of quickly solving the problem. The repeating module of LSTM networks has a distinct structure from the chainlike structure; there are four NN layers instead of one, each of which interacts uniquely. Figure 2 depicts the structure of an LSTM cell [29].

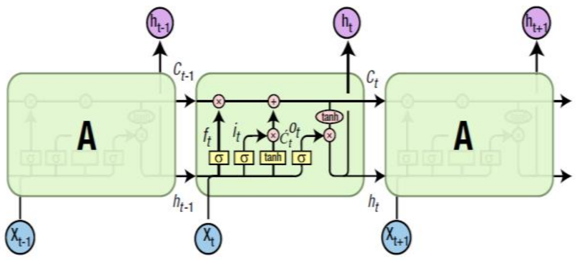

Figure 2: LSTM module with four interacting layers.

An LSTM is a collection of gates that may be used to control the flow of information via them. They weigh the component's passing limit using a point-wise multiplication operation and a sigmoid neural net layer with an output range [0, 1]. Ci denotes the cell state in the accompanying diagram, which remains constant during all time steps and is modified by interactions. In [30], they suggested utilizing ANN; a soft computing method is a positive step toward developing an intuitive system capable of interpreting nonlinear weather conditions and making forecasts. The suggested research aims to provide a user-friendly weather forecasting system with the lowest feasible error rate and a more acceptable design. They start research to predict weather using ANN and the Back-propagation algorithm by acquiring meteorological data from the Indian Meteorological Department's Regional Centre (RMC) for the previous three years (2009, 2010, and 2011).

A simplified LSTM technique was suggested based on Machine Learning architecture to predict solar power generation with a one-day lead time. The proposed simplified LSTM model outperforms the MLP model in mask learning tasks such as data handling, model fitting, cross-validation, measurement assessment, and hyper-parameter modification [31]. In [32], the paper has examined the capacity to recreate long-term seasonal plumage patterns of linear and nonlinear modeling approaches. For the production of linear and non-linear models multiple linear regressions (MLR) and ANN. The El Nio South Oscillation (ENSO) and Dipole (IOD) oceanic climate drivers have been recognized as reliable predictions based on the lag (past) data for seasonal rainfall. MLR models have been evaluated that were statistically significant and did not have multi-linearity problems.

The study's probabilistic forecasting technique for wind power generation has included an adaptive neuro-fuzzy inference system (ANFIS) training model, a fuzzy c-means clustering approach, and predicted interval post-processing [33]. The suggested probabilistic forecasting model utilized ensemble wind speeds from numerical weather prediction (NWP), NWP spot wind speed forecasts, and historical wind power measurements as input data. A two-part artificial intelligence approach has been proposed for forecasting wind speed time series based on a well-thought-out architectural plan. An autoencoder is utilized to reduce the dimensionality of the wind speed input. A deep NN called an autoencoder is employed to reduce DE noise. The Elman NN is a form of RNN that is particularly sensitive to a root mean square error (RMSE), mean absolute bias error (MABE), mean absolute percentage error (MAPE), and coefficient of determination when evaluating the method [34].

A wind power forecasting system based on NN has been created. In addition, the efficiency analysis of Kinmen farm and the anticipated wind power forecasting system have been evaluated. Finally, the suggested wind power forecasting system can forecast up to 48 hours ahead of time using MATLAB. The input layer, hidden layer, and output layer are the three main components of the backpropagation (BP) NN used external data and represent it in the network in this study [35]. It has been demonstrated that a Group Method of Data Handling (GMDH)-NN technique anticipates wind speed (Ws) and wind power output (WPO) in the short term. Wavelet de-noising was employed to filter away high-frequency outliers in the Ws data, allowing NN to train smoothly on Ws. Using historical Ws and WPO, the performance of the wavelet denoising-GMDH-NN was studied. The findings suggest that GMDH-NN is effective for Win prediction, and that integrating wavelet de-noising with GMDH-NN increases prediction accuracy by increasing precision and decreasing errors [36].

4.2 Result and analysis

A multipurpose system, an LSTM is made up of a repeating network with feedback linkages. To predict the values of succeeding time steps in a sequence, designate answers as training sequences with values that change with each time step. The LSTM network can anticipate the value of the following stage at every step of the input series. Predictors are sequences of training excluding the last step. Use AndUpdateState to anticipate many future time phase values one by one, changing the network state in each forecast. For each forecast, use the preceding prediction as to the job entry. Experiment data should be standardized using the same criteria as preparatory data. Sign XTrain Training Data [3] before configuring network status. Create your first forecast using the last stage of the YTrain training response phase (end). Repeat the remaining forecast and combine it with the forecast and status of the preceding prediction. The procedure for applying LSTM to the mentioned dataset is as follows: -

1. Open the dataset, it is made up of a single time series in which the years represent time steps and the values represent the number of monthly wind speeds. A cell array is created as a result, with each element representing a single time step. Make a row vector out of the data. Separate the data into two groups: training and testing. Before testing for the last 15%, train for the first 85 percent of the sequence.
2. Standardize the training data to a zero mean and unit variance to improve the fitness and keep the training from diverging. You must use the same settings to equalize the test and training data at prediction time.
3. Respond to training sequences with one-time step shifted values to forecast the values of future time steps in a sequence.
4. Open the dataset, it is made up of a single time series in which the years represent time steps and the values represent the number of monthly wind speeds. A cell array is created as a result, with each element representing a single time step. Make a row vector out of the data. Separate the data into two groups: training and testing. Before testing for the last 15%, train for the first 85 percent of the sequence.
5. Standardize the training data to a zero mean and unit variance to improve the fitness and keep the training from diverging. You must use the same settings to equalize the test and training data at prediction time.
6. Respond to training sequences with one-time step shifted values to forecast the values of future time steps in a sequence. In other words, for each time step in the input sequence, the LSTM network learns to predict the value of the following time step. Predictors are training sequences in which the last time step is not included. Create a regression network using the LSTM method. Allow 100 hidden units in the LSTM layer.

7. Choose from a variety of training methods. Set the gradient threshold to 1 to prevent the gradients from exploding. Maximum Epochs: 1000; initial learn rate: 0.055; drop learn rate after 100 epochs by multiplying by a factor of 0.12; maximum Epochs: 1000; initial learn rate: 0.055; initial learn rate: 0.12.
8. Train the LSTM network using the train network training options.
9. With the predict AndUpdateState method, you may predict the values of numerous future time steps one at a time while updating the network state. Each prediction should be based on the prior forecast.
10. Using the same training data parameters, standardize the test data.
11. Make a prediction using the training data. First, use XTrain to set the network state. Make your initial prediction based on the YTrain training response's final time step (end). After looping over the remaining predictions, send the previous prediction to predictAndUpdateState. The root-mean-square error (RMSE) generated from standardized data is displayed on the training progress plot. Using the unstandardized forecasts, calculate the RMSE.
12. Plot the projected values against the training time series.
13. Compare the predicted values to the actual data.
14. Use observed values to update the network state.
    a) You may modify the network state if you have access to the actual time step values between predictions rather than the predicted ones by utilizing the observed values.
    b) Set up the network state first. Use reset State to reset the network state before making predictions on a new sequence. The network state is reset to avoid previous forecasts from influencing predictions on new data. Reset the network state and then predict the training data to initialize the network state.

The results for April months (as an example) are presented in figure 3, and 4.

Table 1. shows some other comparisons between the algorithms, also the GMDH is better than other applied algorithms. Table 1presents the comparison between the proposed methods and ARIMA (J. W. Taylor and R. Buizza, 2002), Back Propagation Algorithm (BP) (G. K. Rahul, S. Singh and S. Dubey, 2020, pp. 21-26,), and wavelet-deniosing-GMDH-NN (S. Makhloufi and G. G. Pillai, 2017) based RMSE. Based on the result shown in the table 1, the LSTM is better than other presented methods.

Table 1: Comparison of the Methods with Related Work for RMSE

LSTM	ARIMA (J. W. Taylor and R. Buizza, 2002)	BP (G. K. Rahul, S. Singh and S. Dubey, 2020, pp. 21-26,)	wavelet-deniosing-GMDH-NN (S. Makhloufi and G. G. Pillai, 2017)
0.1713	0.3235	0.2942	0.3709

5. Conclusion

Using a data science technique to generate machine learning methods and test their appropriateness for wind speed prediction for Duhok governor in this paper. The prediction concept might be significantly different when employing an ANN for long-term data prediction versus just short-term data prediction. Long-term wind speed prediction necessitates the employment of a more advanced ANN tool. Short-term prediction produces better results (better results imply that the error is reduced to to an acceptable level), but it can only be employed for a limited time frame. There is no direct sizing option in the ANN tool (for example which training functions to use or the number of the neurons inside the hidden layers). It is based on the goal of the NN and the experience of the creator. Understanding the relationship between the various data sources, developing the helping function for long-term prediction, and laying a firm foundation for expecting the ANN tool's findings can all be aided by a correlation study of the input data. Even though some of the results were completely undesirable, they helped to reduce the options and make the most use of the data available. The data can then be pre-treated to improve the prediction tool's accuracy. This is especially relevant when using data to make long-term forecasts (keep in mind that the ANN should have all the available cases in the training data in order to be able to predict all the possible coming situations).

The LSTM model, the autoregressive NN prediction model, GMDH, and the weather prediction Adaline NN are all used in this study. Various related systems collect data depending on a given region, however in this study; the scientists used data from the Erbil weather station. An RNN model was constructed after the meteorological data were examined with a NN. The purpose of this paper was to evaluate the performance of numerous prediction algorithms in time series applications employing NN architectures such as ADALINE, NARX NN, LSTM RNN, and the GMHD. To meteorological datasets from the KRG Meteorological Organization and Seismology from 1992 to 2019, the acquired findings suggest that NN techniques decrease error better than statistical approaches.

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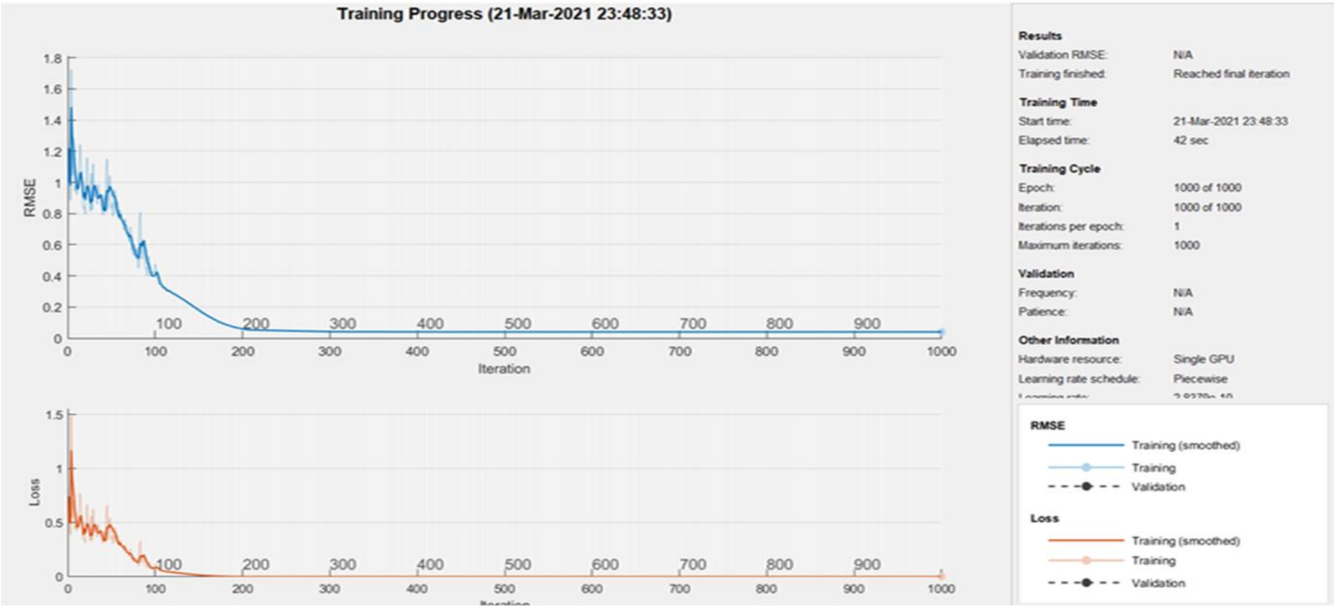

Figure 3 LSTM Training Progress

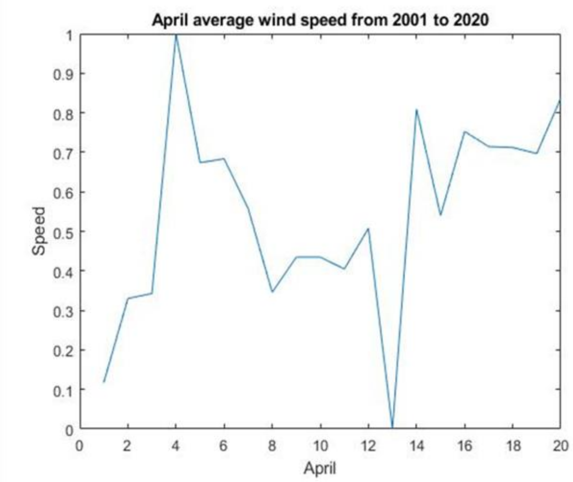

Figure 4 a.Presented wind speed

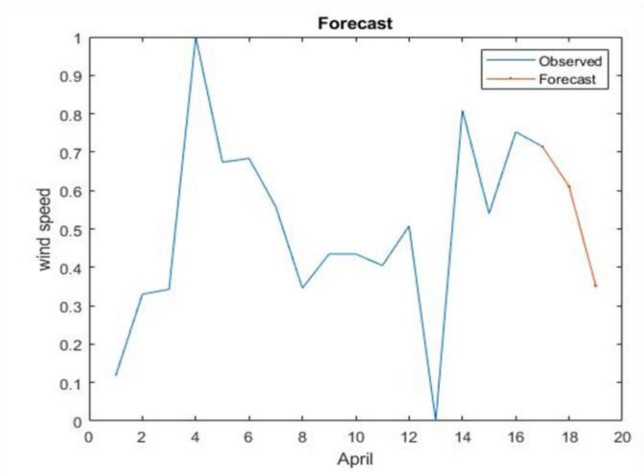

Figure 4 b.Forecasting wind speed

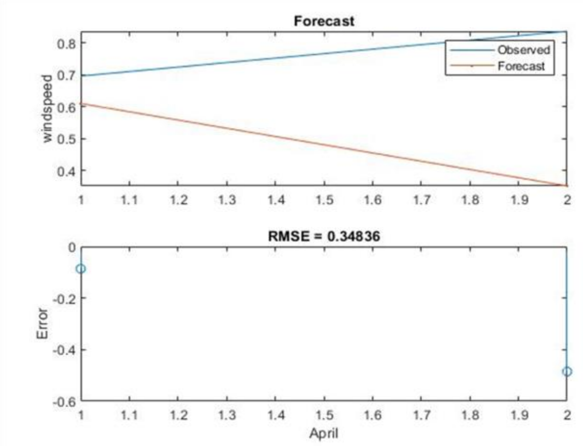

Figure 4 c. RMSE before update

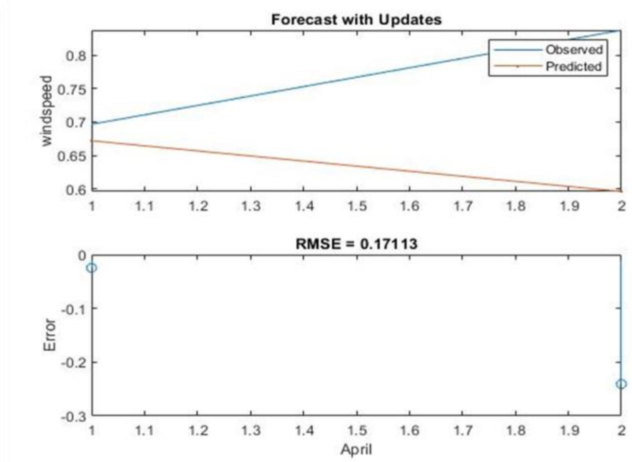

Figure 4 d. RMSE after update

Figure 4: Wind Speed Prediction for April