Technical Note

Forecasting Energy Consumption Time Series Using Recurrent Neural Network in Tensorflow

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Abstract: The environmental issues we are currently facing require long-term prospective efforts for sustainable growth. Renewable energy sources seem to be one of the most practical and efficient alternatives in this regard. Understanding a nation's pattern of energy use and renewable energy production is crucial for developing strategic plans. No previous study has been performed to explore the dynamics of power consumption with the change in renewable energy production on a country-wide scale. In contrast, a number of deep learning algorithms demonstrated acceptable performance while handling sequential data in the era of data-driven predictions. In this study, we developed a scheme to investigate and predict total power consumption and renewable energy production time series for eleven years of data using a Recurrent Neural Network (RNN). The dynamics of the interaction between the total annual power consumption and renewable energy production are investigated through extensive Exploratory Data Analysis (EDA) and a feature engineering framework. The performance of the model is found satisfactory through the comparison of the predicted data with the observed data, visualization of the distribution of the errors and Root Mean Squared Error (RMSE) value of 0.084. Higher performance is achieved through the increase in the number of epochs and hyperparameter tuning. The proposed framework can be used and transferred to investigate the trend of renewable energy production and power consumption and predict the future scenarios for different communities. Incorporation of the cloud-based platform into the proposed pipeline may lead to real-time forecasting.

Keywords: Recurrent Neural Network; Renewable Energy; Power consumption; Open Power System Data; Multivariate Exploratory; Time series forecasting

1. Introduction

In recent decades, interest in renewable energy has grown significantly [1–4]. These non-polluting, resource-unrestricted energies would provide the perfect electrical source for any activity, whether household or industrial, if it weren't for their unpredictability [5–7]. It is challenging to predict how much power will be gained from renewable sources because their throughput varies greatly depending on the circumstances and qualities of the location where they are found. In many nations today, it is essential to promote the use of renewable energy sources because they provide a wealth of benefits [8–10]. As a result, while main energy resource imports are greatly decreased, the security of the energy supply and the preservation of traditional resources are both guaranteed. Additionally, the use of renewable energy spurs economic growth on a local, regional, and international scale and generates new job possibilities [11–14]. Utilizing renewable energy has the advantage of lessening environmental degradation [15–18].

Solar energy has emerged as one of the most important sources of energy in recent years [19, 20]. In some countries, solar energy uses a significant percentage of the sun's energy

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and has a more predictable behavior than wind-based energy. As a result, it ranks among the most significant renewable energy sources for a variety of nations in south Europe, including Spain, as well as other places along the same latitude, such as Saudi Arabia or India [21–23]. Thermal solar energy, which transforms solar radiation into thermal energy used to heat buildings, desalination plants, homes, and water treatment facilities, among other things, and photovoltaic solar energy, which transforms solar radiation into electrical energy that can be transported for purposes other than heating [24–26]. A plentiful natural resource and sustainable energy source is wind. It is known that wind energy is both clean and pollution-free. In general, the characteristics of wind are its speed, direction, and time of occurrence. The force or speed of the wind is what determines how much energy can be extracted from its natural flow [27, 28]. Generally speaking, the wind speed or force has a nonlinear and variable nature. Despite its natural origins, wind has the capacity to produce the necessary amount of energy for the nation's ongoing needs. It is necessary to forecast wind speed in order to increase the amount of energy produced [29–31]. Wind speed forecasting strikes a balance between the energy generated and the needed demand. An efficient technique for reducing operating costs and enhancing grid system functionality is a wind speed prediction model that is very accurate and dependable [32–35].

The use of Deep Learning (DL) has made it possible to anticipate various physical systems with greater accuracy. There are several different industries where DL is used [36–41]. In the modern world, virtually every power grid incorporates renewable energy-based sources. For successful participation in the electricity market, accurate predictions of renewable energy sources are crucial. Because of how much these sources depend on the weather; it can be difficult to forecast the plant's production. In recent years, there has been a rise in ML research and applications for forecasting plant output from renewable energy sources. Different models, including Feedforward Backpropagation (FFBP), Feedforward Neural Networks (FFNN), Multilayer Feed-Forward with Backpropagation Neural Networks (MFFNNBP), etc., with various learning algorithms, including Bayesian Regularization (BR) and Levenberg-Marquardt (LM), can be found in References under the category of variants of the neural network [42, 43]. Some examples of these techniques include Support Vector Regression (SVR), Random Tree (RT), M5P Decision Tree (M5PDT), Gaussian Process Regression (GPR), and Physical Photovoltaic Forecasting Model (P-PVFM) [44, 45]. Although several approaches for supervised training of RNNs have been investigated over the past decade and there are many various types of training algorithms, none stand out as the ideal model. Backpropagation revisited and through time are common training methods for RNNs as they combine the two qualities listed below. 1- They have a distributed hidden state that enables them to store a significant amount of historical data effectively; 2- They implement the nonlinear dynamics, which enables them to develop sophisticated ways to update their hidden state. These are the main reason that RNN can compute a large data set with enough neurons and time.

The use of RNN models to investigate the dynamics of energy consumption in relation to renewable energy is a relatively recent development [46–50]. This study aimed to evaluate how well the RNN model predicted energy consumption when renewable energy sources were produced. In order to enable researchers, engineers, and decision-makers understand the temporal dynamics of the power consumption and renewable energy production, make informed engineering/managerial decisions, the goal of this study is to build an effective and practical RNN method for forecasting future scenarios in annual power production and consumption. Engineers and managers will be able to evaluate the energy's short- and long-term behavior and trend, allowing them to eventually develop preventative measures using the earlier observational data for a variety of issues in the region. The RNN-based method used in this study only requires observed data, therefore a substantial amount of computational effort is needed. To get the most performance out of the RNN results in this study, a comprehensive exploratory data analysis, feature engineering, and hyperparameter optimization are conducted. The remainder of the essay is structured as follows: Section 2 provides a full explanation of RNN fundamentals as well as data engineering and experimental methodology. The outcomes of the experiment are thoroughly discussed and analyzed in Section 3. The conclusion portion and closing thoughts regarding this article are presented in Section 4.

2. Data and Methods

2.1 Data Source and workflow

The time series of the total energy consumption, wind and solar power production is used in this study to forecast the future trend of the variables in Germany. The time series dataset is retrieved from the Open Power System Data (OPSD) for Germany, which has been rapidly expanding its renewable energy production in recent years [51]. The temporal resolution of the variables used for the RNN -based prediction is daily. The data set's timeframe includes data over a decade, from 2006 to 2017. Electricity usage and generation from wind and solar sources are reported in gigawatt-hours (GWh). In the Table 1, a full description of the variables is presented.

Table 1: Full description of the energy consumption variables used for EDA and predictive analysis with RNN.

Energy Consumption Variables	**Unit**	**Descriptions**
Total consumption	GWh	Daily total energy consumption
Wind power production	GWh	Daily wind power production
Solar power production	GWh	Daily solar power production

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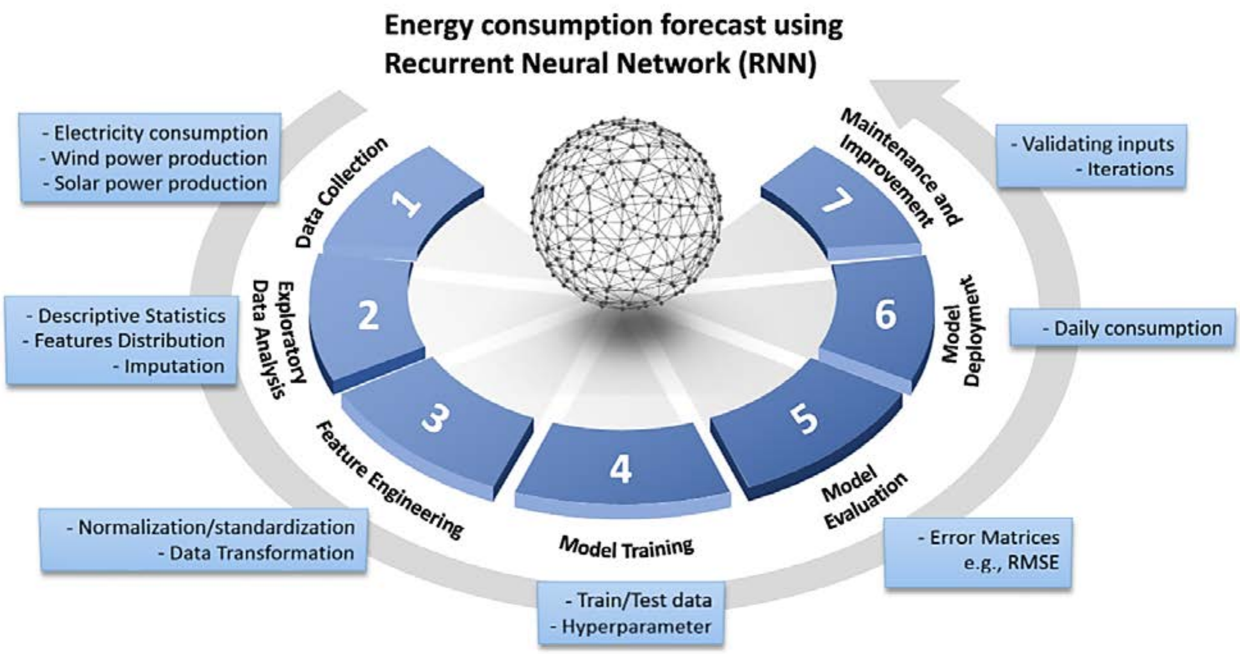

Figure 1: Entire pipeline of RNN-based prediction.

The shift and fluctuation in electricity usage and generation over time in Germany scrutinized in this paper. Time series tools used to examine both seasonal variations and long-term trends in wind and solar power production as well as their consumption. Furthermore, these tools compared the wind and solar power production with electricity usage. Using an RNN model anticipated each day's consumption based on historical and observed data.

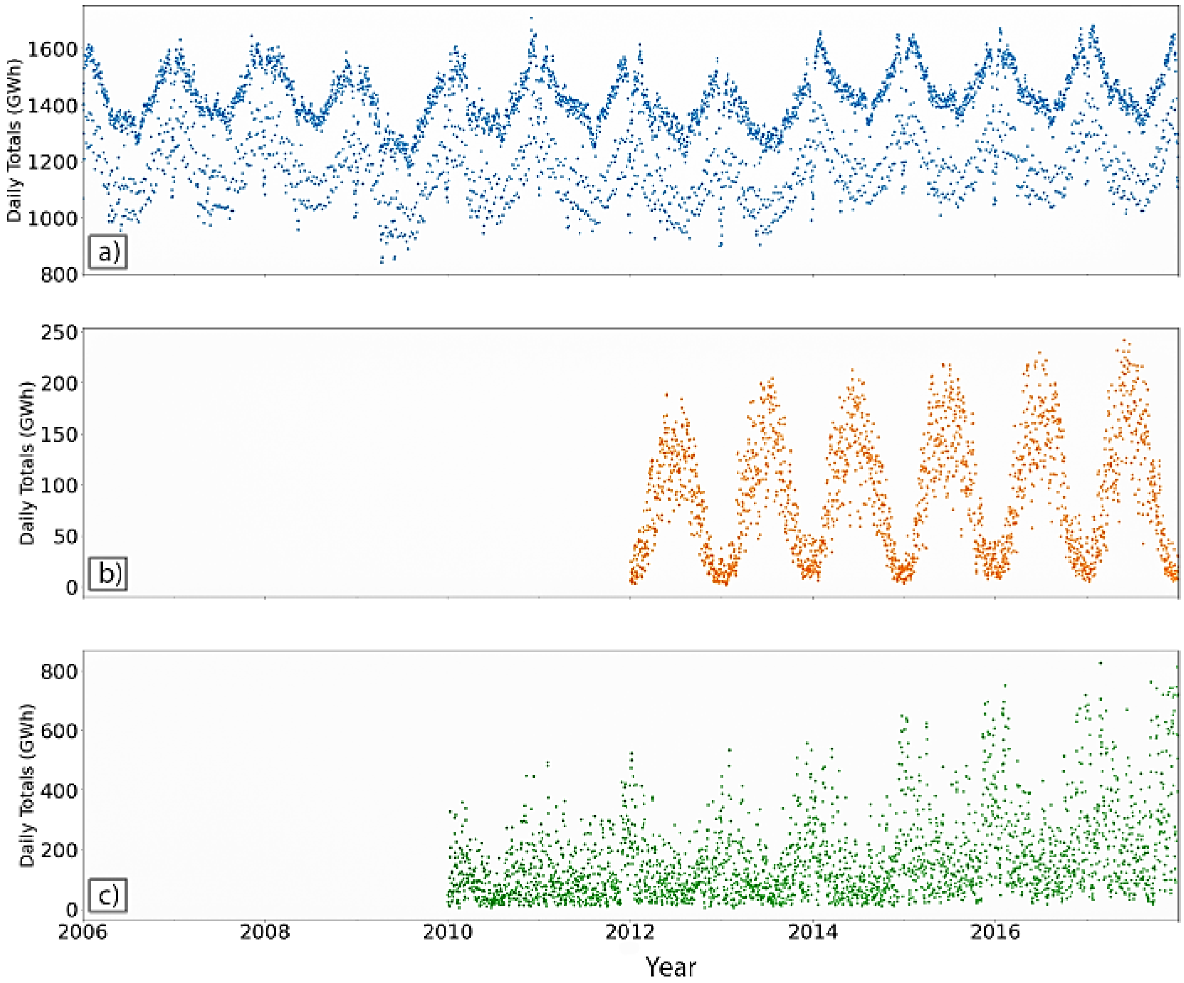

Figure 2: Line plots showing the temporal dynamics of the variables, total energy consumption (a) wind production (b) and electricity production (c) from 2006 to 2017.

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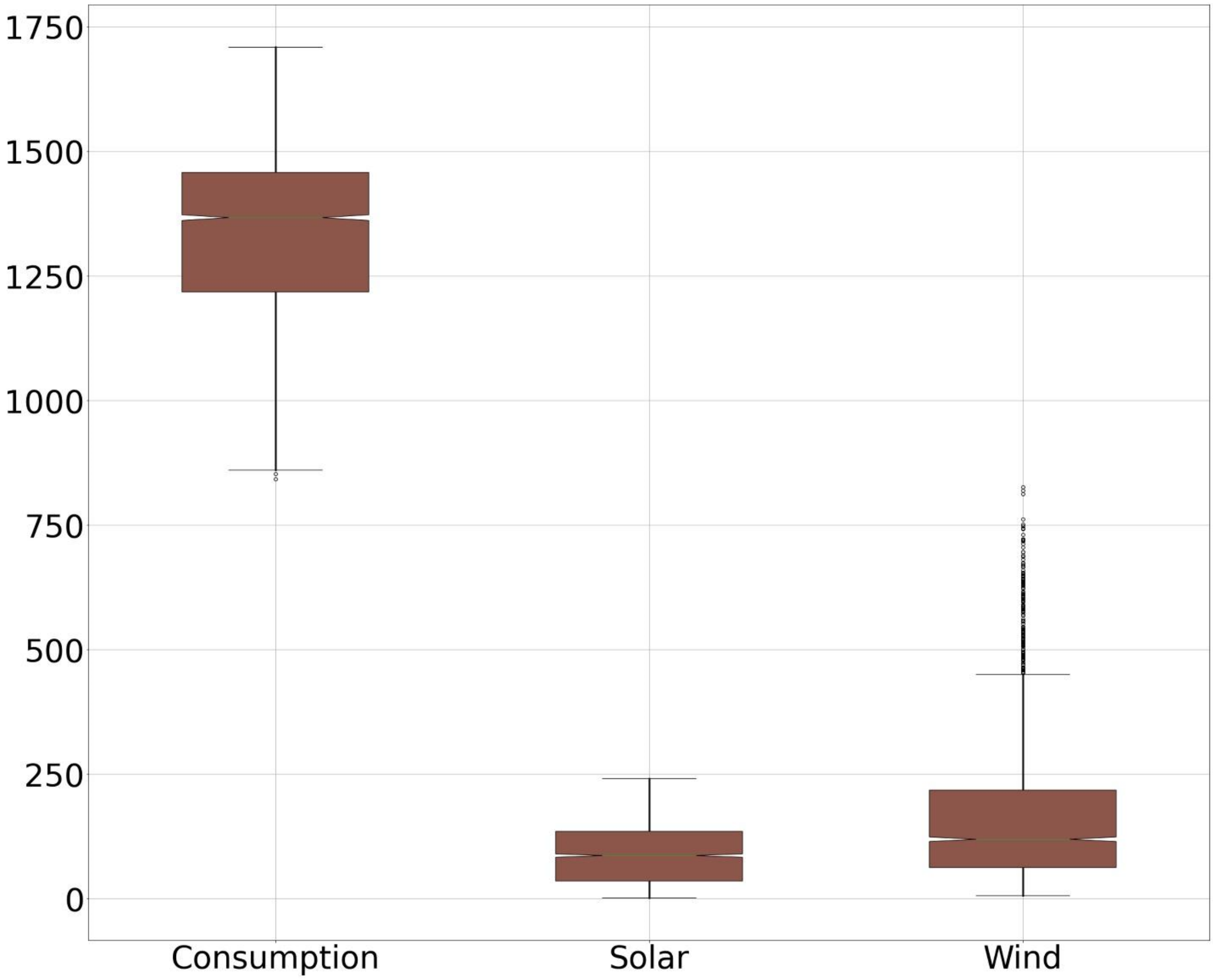
2.2 *Multivariate Exploratory Data Analysis*

Multivariate exploratory data analysis (EDA) is performed to understand the internal distribution of the attributes of the variables [62]. Temporal distribution of all the variables is explored using several visual and numerical representation. EDA includes an important process of conducting initial exploration of the variables to investigate the hidden pattern in the dataset. EDA is grouped into multiple activities in this study. They are presented as the descriptive statistics of the variables, probability distribution with histogram to determine the normality (skewness) of the variables. Descriptive statistics provides a great way to demonstrate the basic distribution of the values of the variables with the number of data points, mean, standard deviation, percentiles, interquartile range, and range (max/min). Full multivariate descriptive statistic of the all the variables is shown in Table 2. To show the normality, histograms with line of probability distribution is used as a visual representation and Pearson's coefficient of skewness (PCS) is used as an indicator of skewness to analyze the distribution.

Table 1: Descriptive Statistics of the variables

Variable	Count	Mean	Std	Min	25%	50%	75%	Max
Consumption	4383	1338.67	165.77	842.39	1217.85	1367.12	1457.76	1709.56
Wind	2920	164.81	143.69	5.75	62.35	119.09	217.90	826.27
Solar	2188	89.25	58.55	1.96	35.17	86.40	135.07	241.58



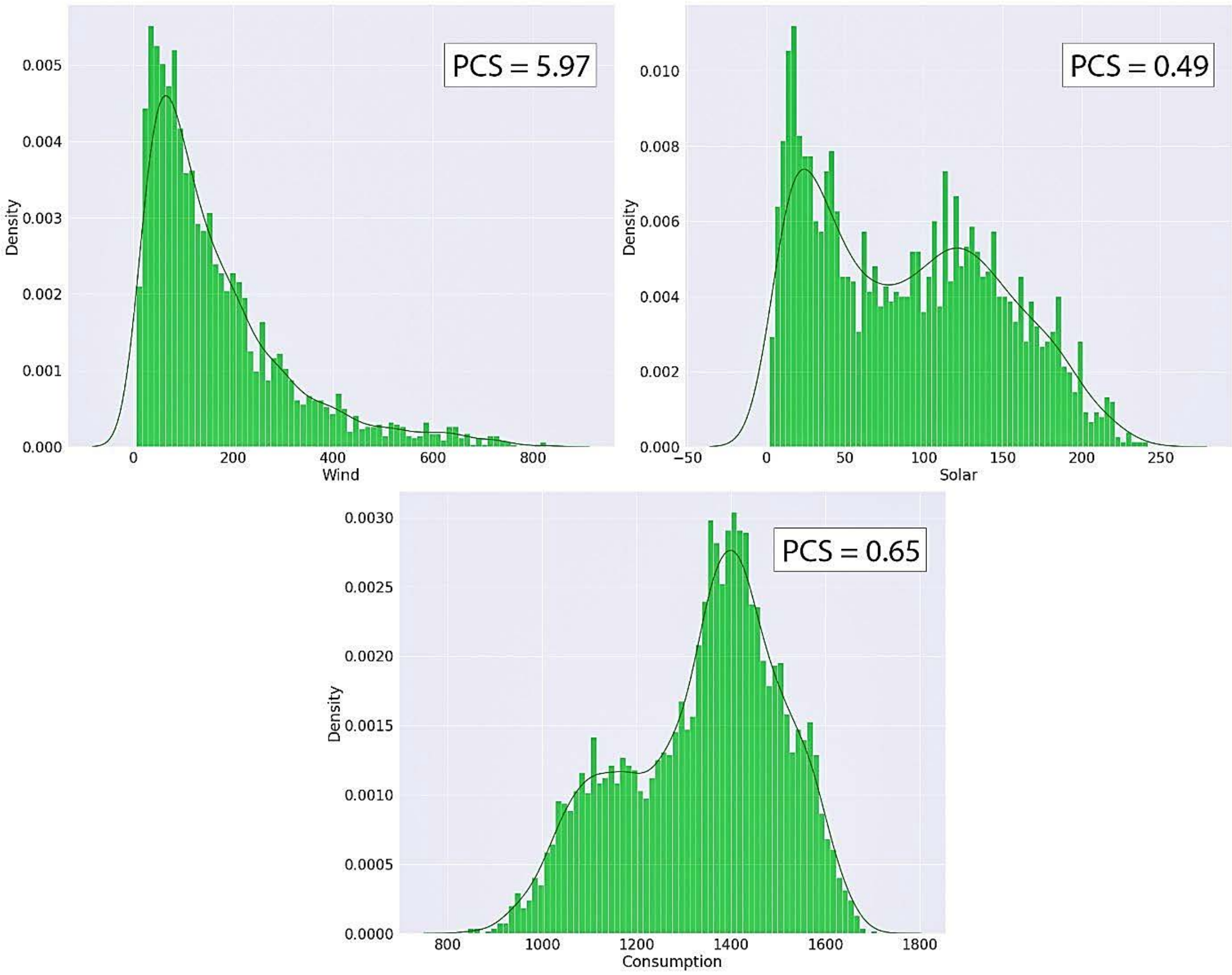


Figure 3: Distribution of the variables using box plot (a), histogram and density plot (b). Pearson's Correlation Coefficient (PCS) values shows the measure of skewness.

A visual representation of the distribution and the normality of the variables is showed in the Figure 3. Overall non-linearity of the wind production is high with left skewness. The values of the Pearson Correlation of Skewness (PCS) are attached with figures to the numeric measurement of the skewness. PCS values for the wind and solar power production and total energy consumption are 5.97, 0.49 and 0.65. Wind power production show the highest non-normality among all other variables. Normal distribution is a very crucial part in the RNN model performance as it is directly linked to the error minimization through the back propagation. Normal distribution is the most crucial factor in the field of data-driven predictive analysis e.g., deep neural network regression. As the distribution of the values of wind power production is highly skewed to the left showing a significant non-normally, the neural network regression algorithms without appropriate data transformation does not contribute to satisfactory outcomes with good optimization. As the distribution of the Renewable energy production series is found to be highly skewed, data transformation is performed to decrease the non-normality of the series in the feature engineering section. The linear linkage is found to be low among variables. The values of the linear correlation coefficients are showed in the bivariate correlation plot in Figure 4. The direction of the linear relationship is found to be both positive and negative.

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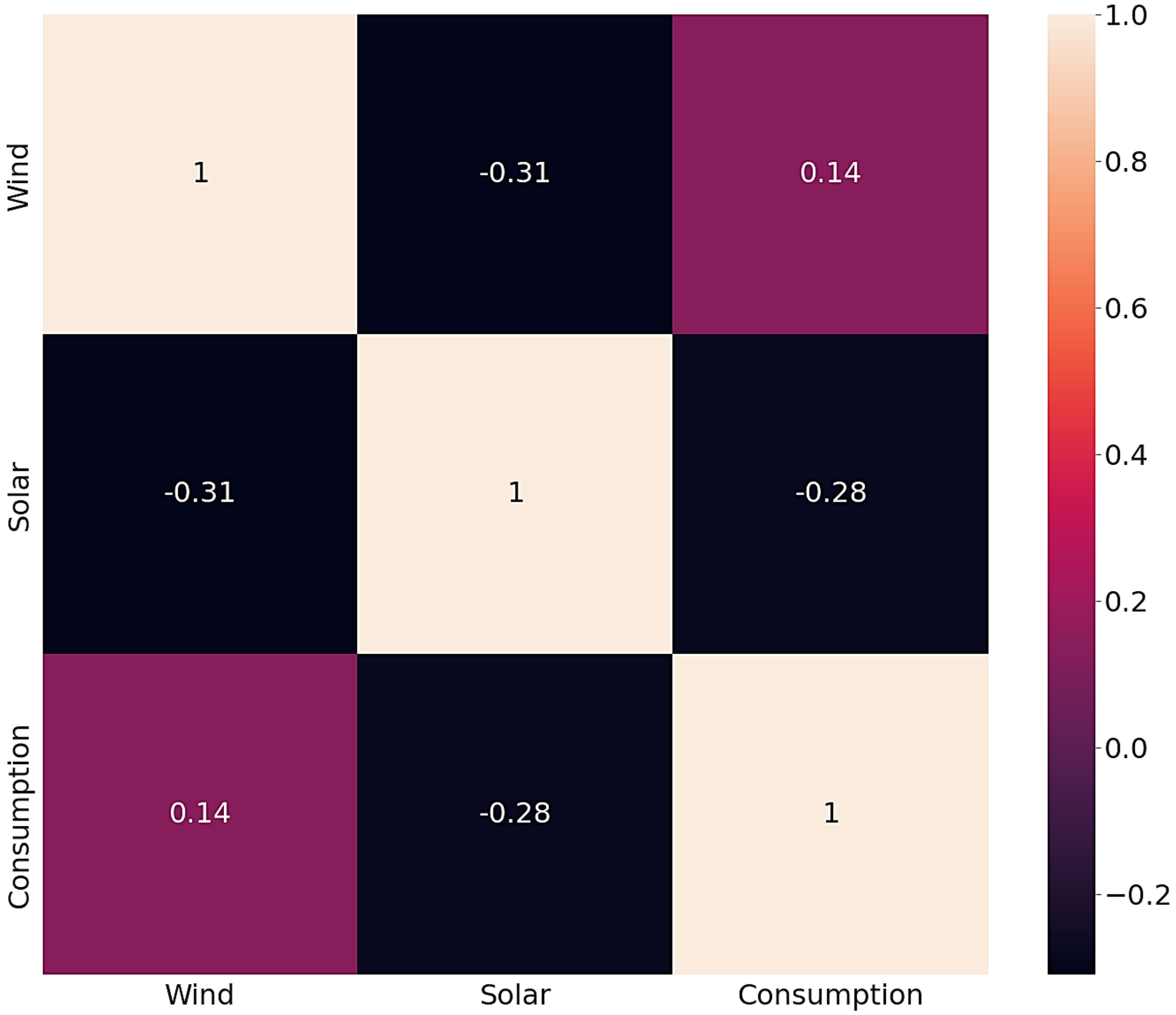

Figure 4: Bivariate correlation coefficients among the variables represented by the correlation heatmap.

2.3 *Feature Engineering*

Feature Engineering (FE) is performed after a successful EDA. FE is an important step before the training/testing phase of the RNN algorithm. Without a successful FE, any data-driven method may not yield to a satisfactory performance with minimum error. An adequate optimization through the iterative gradient descent cannot be reached without a successful scrutiny of the dataset. Therefore, a comprehensive feature engineering is performed to transform the dataset most suitable for the learning algorithm of RNN. FE is performed to prepare the dataset for the predictive analysis. FE involves imputation, data transformation, data standardization and splitting the dataset into training, testing, and validation sets. Imputation in preformed to fill the null values so that the entire dataset becomes consistent. In this research, null values or null observation were found in every variable. These cells in the dataset are imputed with the median of the entire series. In this study, three methods of data transformation are considered e.g., logarithmic, power, cubic transformation to transform the distribution of the features more to the normal distribution. Pearson's coefficient is used as an indicator of normality.

Through the data standardization process, the values of a variable are rescaled so that the variable has the mean 0 and variance 1 (or Z-score normalization) which is identical to the bell-shaped normal distribution curve. As the variable considered in this study is the continuous independent variable, the standardization of the variable is crucial for training/testing the neural network algorithm. Standardization is an important step for the optimization problem. The RNN recurrent neural network model uses the gradient descent technique where the feature value (Renewable energy production) affects the step size of the technique. Smooth progress towards minima in gradient descent requires the update of the steps at the same rate for all the feature values. A standardized variable is a prerequisite of reaching the minima in the gradient descends process.

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

All the values in the Renewable energy production series are standardized to prepare the training dataset for the RNN model.

Equation 1 shows the formula of standardization of the Renewable energy production series. The difference between the Renewable energy production value and the minimum of the entire Renewable energy production series is divided by the range of the series provides the standardized data which is further used in the training/testing process of the RNN. The entire standardized Renewable energy production series is split into two portions i.e., a training set that is used to train the model and a testing set that is used to test/evaluate the model. Eighty (70) percent of the dataset is used for training and twenty (30) percent is used for testing. In a nutshell, EDA, and feature engineering are pivotal steps for the satisfactory performance of the predictive model.

2.4 Recurrent Neural Network (RNN)

Recurrent neural networks (RNNs) are a type of neural systems that can reveal dynamic temporal behavior by enabling the use of hidden states and previous outputs as inputs. RNNs, which are derived from feedforward neural networks, process input sequences of various lengths via using their internal state (memory) and connect the outputs of all neurons to their inputs. The main structure concept of NN is the replication of connection weights configurations to zero to imitate the lack of connections between particular neurons.

For each timestep t, the activation $a^{<t>}$ and the output $y^{<t>}$ are expressed as follows:

$$a^{<t>} = g_1(W_{aa}a^{<t-1>} + W_{ax}x^{<t>} + b_a) \quad \textbf{(2)}, \text{ and}$$

$$y^{<t>} = g_2\left(W_{ya}a^{<t>} + b_y\right) \quad \textbf{(3)}$$

Where W_{ax}, W_{aa}, W_{ya}, b_a, and b_y are coefficients that are shared temporally and g_1, g_2 are activation functions.

In the case of a recurrent neural network, the loss function Ꞩ of all time steps is defined based on the loss at every time steps as follows:

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$$\mathfrak{L}(\hat{\boldsymbol{y}}, \boldsymbol{y}) = \sum_{t=1}^{T_y} \mathfrak{L}(\hat{\boldsymbol{y}}^{<t>}, \boldsymbol{y}^{<t>}) \quad \textbf{(4)}$$

Backpropagation is done at each point in time. At timestep T, the derivative of the loss $\mathfrak{L}$ with respect to weight matric W is expressed as follows:

$$\frac{\partial \mathfrak{L}^{(T)}}{\partial W} = \sum_{t=1}^{T} \left. \frac{\partial \mathfrak{L}^{(T)}}{\partial W} \right|_{(t)} \quad (5)$$

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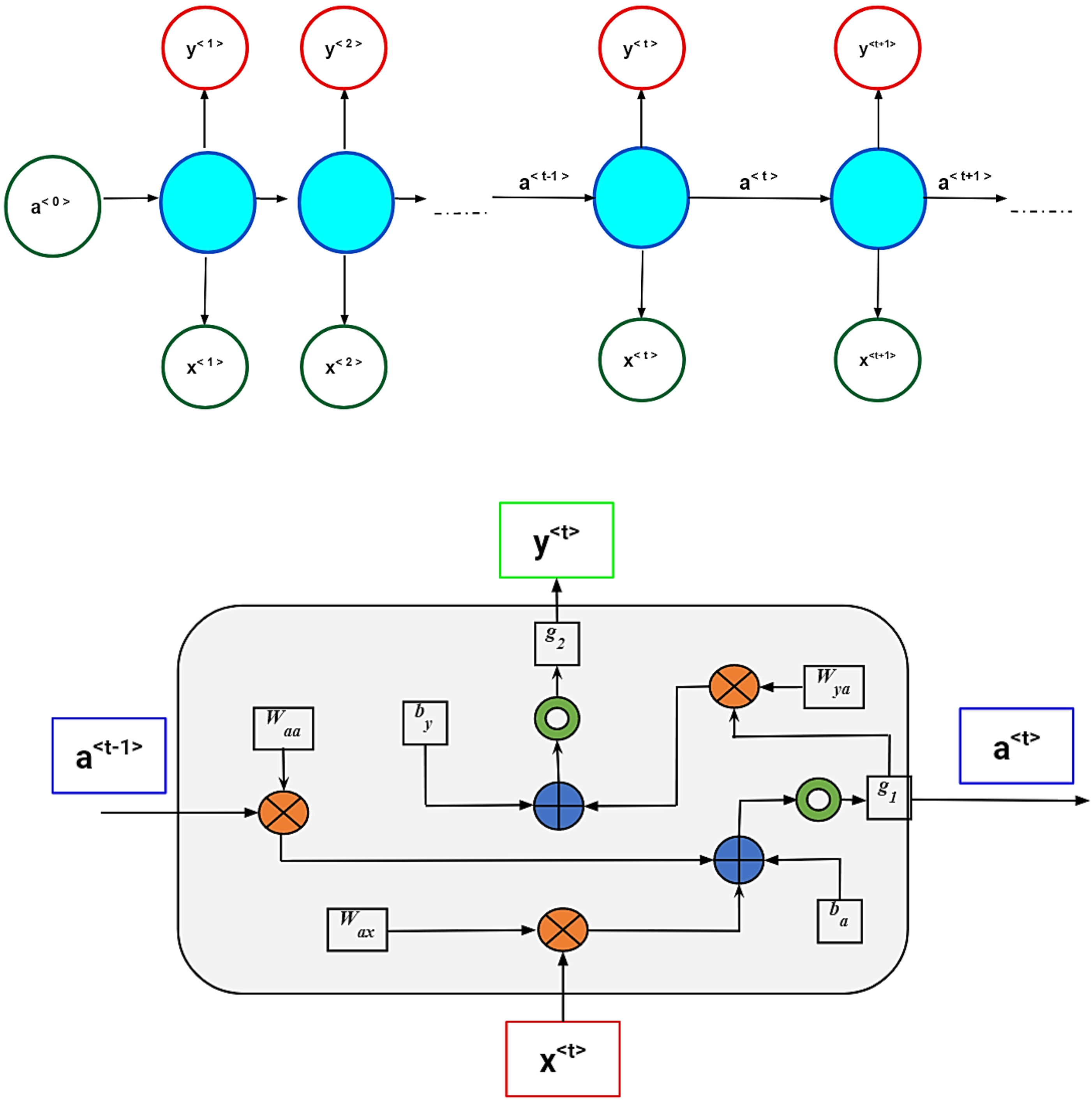

Figure 5: Schematic of the Recurrent Neural Network (RNN)

2.5 Model Evaluation using Loss Functions

Root Mean Square Error (RMSE), correlation coefficient (R), relative error, and consensus were the top four techniques of standard performance assessment (RE). In fact, more than one error metric, which can also accurately capture the high streamflow time series values, should be used to evaluate model correctness. The most popular evaluation metric is the Root Mean Square Error (MSE) as the function is more sensitive about significant errors. That's because the squared term multiplies greater errors exponentially more than smaller ones. MSE is the mean of the absolute value of the errors and is normalized by the number of data points, N:

$$\boldsymbol{RMSE} = \frac{1}{N}\sum_{t=1}^{N}\left|\boldsymbol{Q}_{t(obs)} - \boldsymbol{Q}_{t(com)}\right|^2 \qquad (6)$$

where $Q_{t(obs)}$ = observed Renewable energy production , $Q_{t(com)}$ = computed Renewable energy production , so $(Q_{t(obs)} - Q_{t(com)})$ represents the error term between the real and measured value for each data point which is normalized by dividing by the total number of observations after summation of all terms. The lowest MSE score corresponds to the best predictive accuracy.

The coefficient of determination (R^2) is a popular error metric for the accuracy of the model and the model fitness to the data points' values depicted by this metric. The better the model fits the data, the higher the R^2 is. The square root of coefficient of determination represented as correlation coefficient (R) which is the second error function implemented in this study.

$$\boldsymbol{R} = \frac{\sum_{t=1}^{N}(\boldsymbol{Q}_{t(com)} - \bar{\boldsymbol{Q}}_{(com)})(\boldsymbol{Q}_{t(obs)} - \bar{\boldsymbol{Q}}_{(obs)})}{\sqrt{\left[\sum_{t=1}^{N}(\boldsymbol{Q}_{t(com)} - \bar{\boldsymbol{Q}}_{(com)})^2\right]\left[\sum_{t=1}^{N}(\boldsymbol{Q}_{t(obs)} - \bar{\boldsymbol{Q}}_{(obs)})^2\right]}} \qquad (7)$$

Where $\bar{Q}_{(com)}$ = average of computed Renewable energy production, $\bar{Q}_{(obs)}$ = average of observed Renewable energy production. The R^2 range is 0 to 1, with 0 indicating no correlation and 1 signifying perfect correlation between observed and computed values.

The third evaluation metric utilized in the dataset is Relative Error (RE) which is calculated by dividing the computed Renewable energy production as a measured value by the observed Renewable energy production having a real value, then decreasing the numerator by diving the absolute value of that it by the observed Renewable energy production value.

$$\boldsymbol{RE} = \frac{1}{N}\sum_{t=1}^{N}\frac{\left|\boldsymbol{Q}_{t(com)} - \boldsymbol{Q}_{t(obs)}\right|}{\boldsymbol{Q}_{t(obs)}} \qquad (8)$$

Where the smallest value for RE, the same as MSE, correlates to the best model performance.

3. Results and Discussion

The output from the RNN algorithm is compared to the observed Renewable energy production data from USGS database through visualization in the Figure 7. Both observed and predicted Renewable energy production time series is plotted against the

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number of datapoints. The overall distribution of the predicted Renewable energy production values is approximately identical to the observed data providing a satisfactory performance of the RNN algorithm. After the RNN model is trained with the training portion of the dataset, the entire observed dataset is fed to predict the outcome. The entire dataset is divided into training and testing sets with the proportion of 70% and 30%. Training dataset is used to train the model and testing dataset is used to evaluate the model performance. Observed data is showed in the Figure 6 (a) with green color. In the Figure 6 (b), deep cyan portion of the plot illustrate training portion of the dataset whereas deep blue portion shows the testing portion. The RMSE values of the training and testing portion are 0.097 and 0.045 respectively. Lower RMSE values shows the satisfactory performance of RNN algorithm.

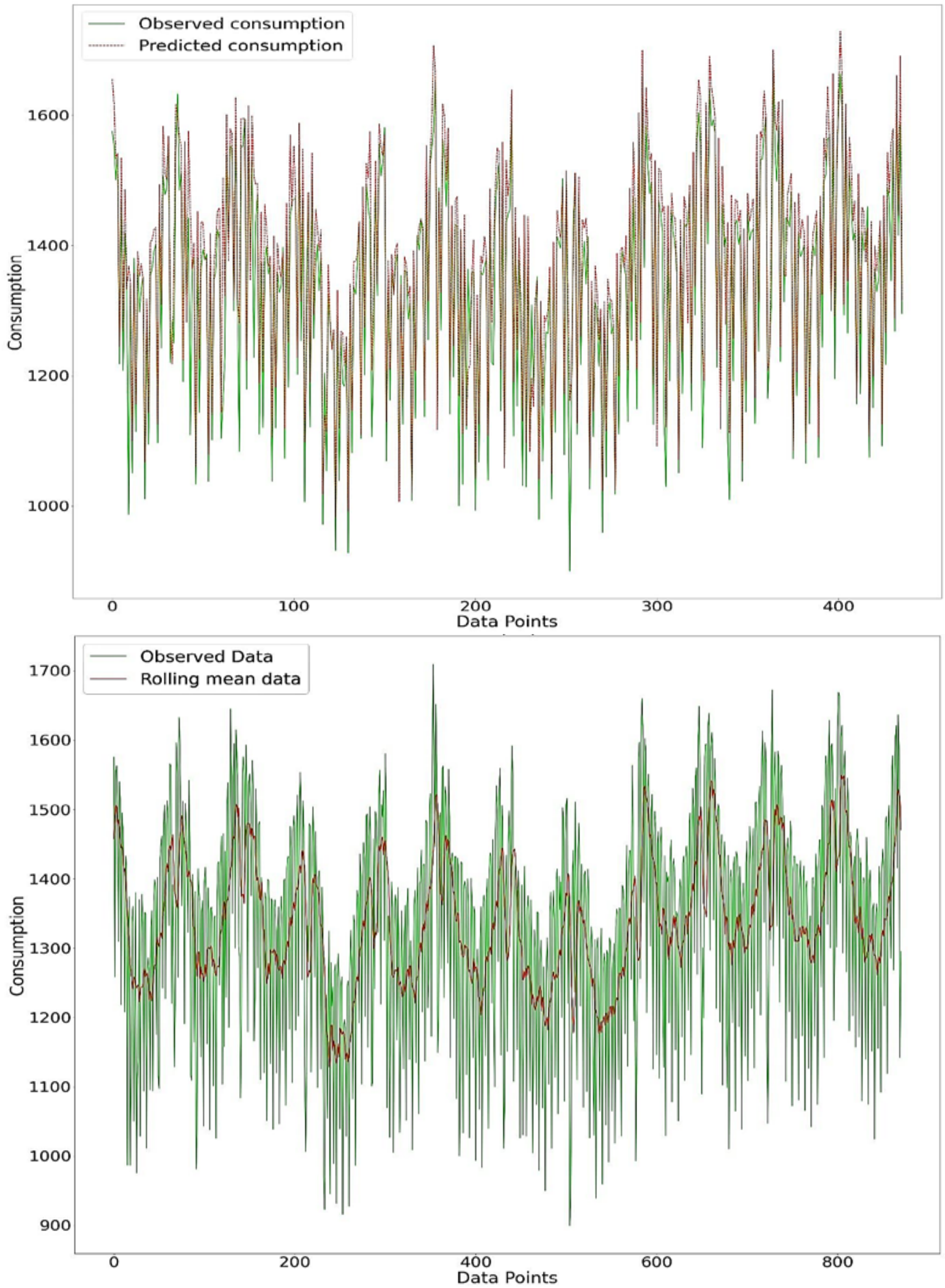

Figure 6: Rolling mean

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3.1 Model Evaluation Matrices and Improvement

The performance of the RNN neural network is evaluated using three error matrices e.g., Root Mean Square Error (RMSE), the coefficient of determination (R^2) and Nash Sutcliffe model efficiency coefficient (E) [63]. Further, the performance of the model also evaluated and improved through increasing the number of iterations i.e., epoch in the neural network. The value of R2 is observed with the increase in the number of epochs in the Figure 7. The number of epochs is increased up to 100 to increase the performance. The RMSE value is found to decrease from 0.01 to 0.0025 which indicates satisfactory performance in the RNN algorithm. The model performance increases significantly from the very beginning of the iteration for both the train and test scenarios. The trend of change in the decrease in the RMSE values reaches a near-steady state after 20 epochs. Local decease in the performance i.e., increase in the RMSE value can be seen after 20 epochs.

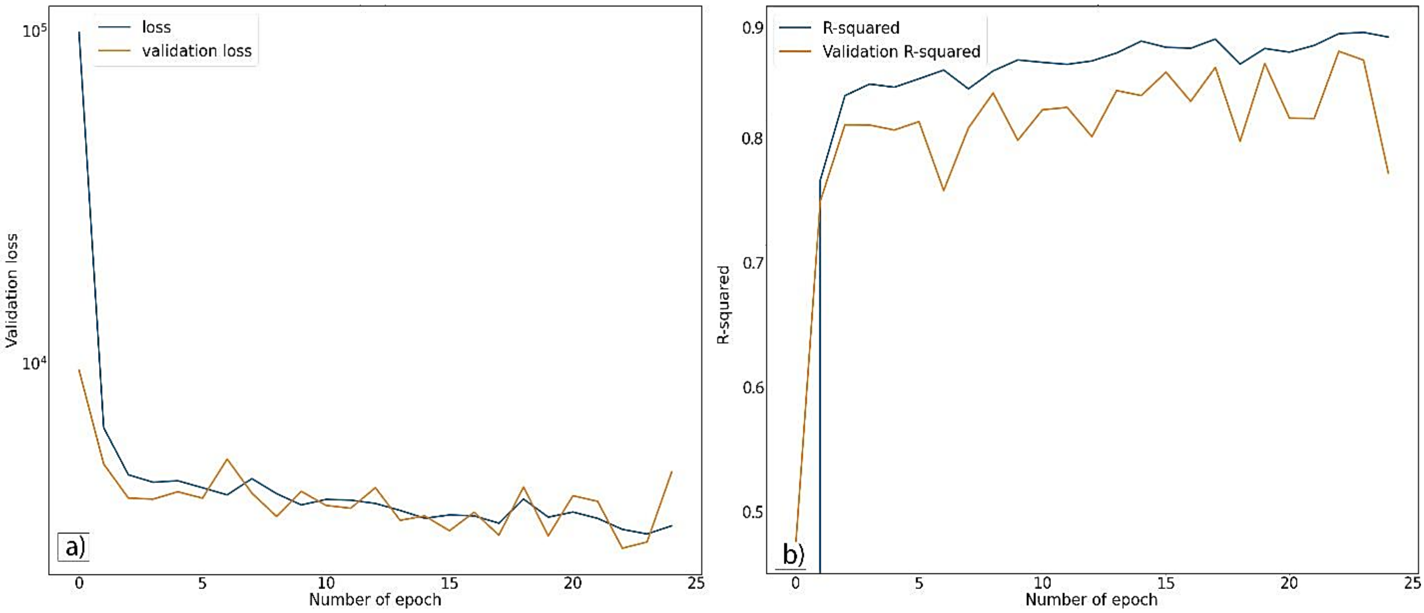

Figure 7: Improvement of the model prediction capability with the increase in the number of iterations i.e., epoch for the train and test set. R2 value is the indicator of the model performance.

Observed and predicted values of the energy from RNN model and the distribution of the RMSE values are illustrated in the Figure 8 using a scatter plot (a) and histo gram (b). The scatterplot shows that the points follow an approximately 45° trend line originated at zero. Some points are found to locate outside of the main cluster of the points which shows the error in the prediction process. The r^2 value of the best fitted straight line is +0.862 which gives a good indication of the performance.

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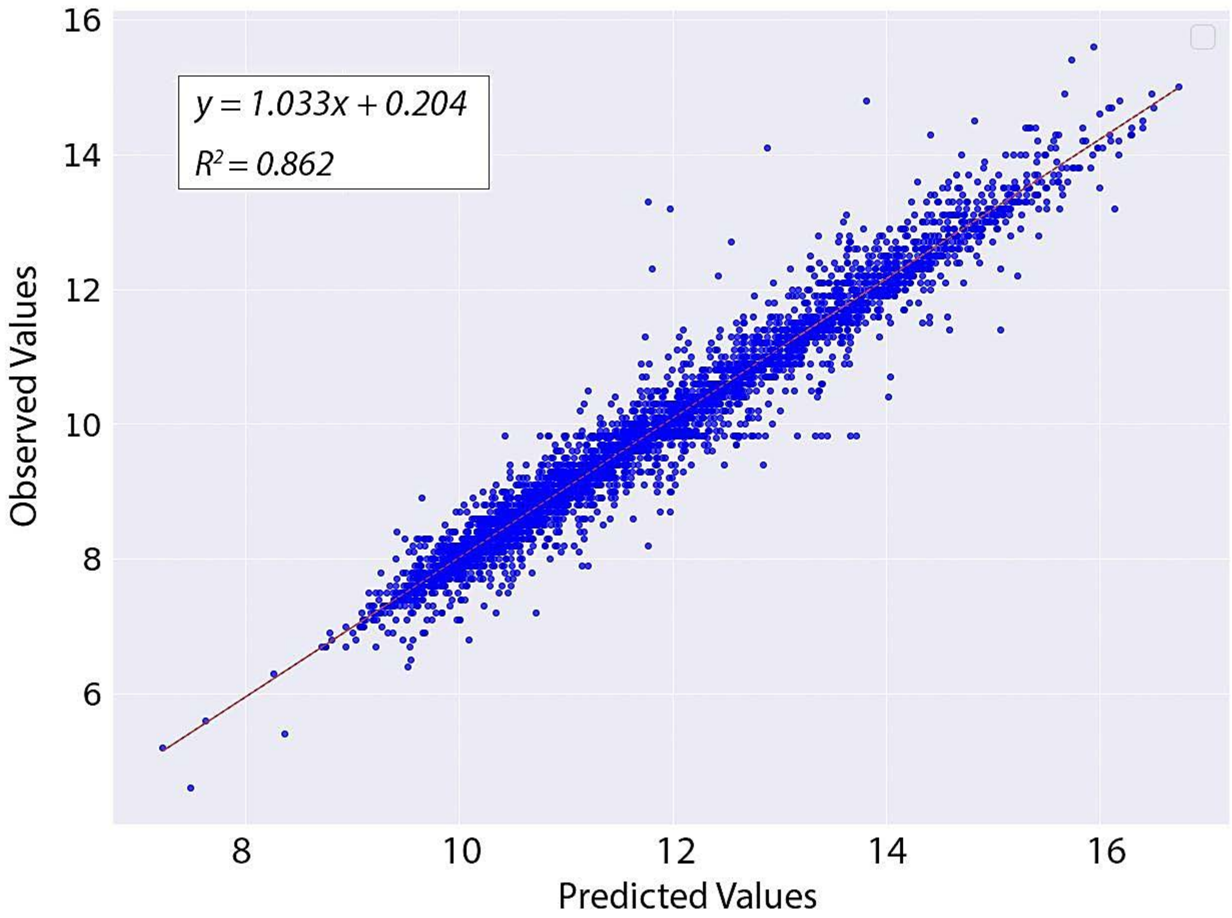

Figure 8: Model performance are presented using the scatterplot of the observed and predicted Renewable energy production values from RNN model.

Time series prediction for renewable energy production and consumption is a pivotal task in the field of power management. The application of the data-driven prediction models is highly efficacious in predicting various energy variables without taking complicated equations and assumptions into consideration. In this study, annual power consumption and renewable energy production is predicted using the most powerful neural network in predicting sequential data i.e., RNN recurrent neural network. RNN algorithm is capable of recalling both the short- and long-term pattern of the time series to forecast. The range of the energy time series considered in this research is quite large containing multiple seasonal dynamics. Traditional physics-based numerical modelling tool requires assumptions, other correlated variables, and expensive calibration of the parameters. Compared to the other neural network regression models, RNN are proved to show good performance especially the time series prediction. As the energy consumption and production provides a sequential data which has high temporal dynamics, RNN is used to quantify future values based on the past data. As the shape of the energy dataset is comparatively large eleven years of daily data, RNN algorithms showed highly satisfactory performance.

4. Conclusions

This study adds to the development of a reproducible template for analyzing large amounts of exploratory data in order to understand the distinctive temporal dynamics of energy consumption and renewable energy production. Various modern data exploration technologies are used to uncover a hidden pattern in the distribution of energy values throughout more than eleven years of data, which is a necessary condition for the successful training of the RNN algorithm. Following a successful training phase, an explicit iterative performance record is used to tweak and optimize the RNN. This performance record can then be used to anticipate the value of the energy in a similar geographic area. The effectiveness of the RNN algorithm in predicting river energy shows how well-suited the algorithm is to the time series of energy. Many error matrices exhibit positive performance with little error.

Along with the benefits, there are a few disadvantages of adopting RNN, including the following: 1) the amount of time necessary to train the model, with RNN analysis taking more time, and the length of time it can take to run the model over a big dataset compared to other conceptual models. The computing effort/time needed for the RNN algorithm in this investigation was discovered to be extremely high. 2) The slow process also made it necessary to use more of the system's memory and storage capacity, which can make it difficult to train on a large dataset, as was the case in our study. 3) A challenging aspect of RNN for time series data processing is overfitting, which can lead to incorrect extremely low error measurements. 4) Despite the fact that the essential to implementing RNN is the capacity to compare the different time lags throughout the whole time series dataset, we were unable to obtain sufficient performance for this dataset for periods longer than three days. Any time lapses that occur during a three-day period are flawless and produce low error measurements that are satisfactory. To achieve the greatest results, future research projects should be done incorporating high performance computing and cloud-based processes. To test the model's transferability, RNN models with various configurations should be used in various geographic and climatic regions.

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