

AI-BASED TECHNIQUES TO PREDICT ELECTRICITY CONSUMPTION IN ALGERIA USING RNN AND LSTM APPROACHES

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ABSTRACT:

Artificial Intelligence (AI) has emerged as a game-changer in various industries, and the energy sector is no exception. By leveraging machine learning (ML) and Deep Learning forecasting models, the energy industry is experiencing significant advancements in efficiency, sustainability, and reliability. This article delves into the application of a machine-learning model employing a deep-learning forecasting technique in the realm of energy and its transformative impact on the sector.

The forecasting of daily Electricity power consumption improves the quality, reliability, and stability of the power system. This study aims to develop an LSTM technique for daily forecasting of electricity power consumption. Furthermore, RNN is used to daily perform predictions of electricity power consumption, we will use daily data on Algeria's electricity demand that was collected between January 2000 and December 2022. We run a comparative analysis for all these techniques. We found that the Deep learning technique (RNN) has better forecasting accuracy than other developed techniques in terms of better-performing goodness-of-fit metrics.

Key words: Artificial intelligence, Energy forecasting, Machine learning, Deep learning, RNN-LSTM.

I INTRODUCTION

Ce The growing demand for electricity in Algeria, driven by industrial expansion and population growth, necessitates accurate and reliable forecasting models to ensure efficient energy management and distribution. Traditional methods of predicting electricity consumption have often fallen short in capturing the intricate patterns and variability inherent in energy usage data. With advancements in artificial intelligence and machine learning,

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particularly in Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) networks, there is an unprecedented opportunity to enhance the accuracy of electricity consumption forecasts.

Artificial intelligence (AI) offers a smart way to help society achieve goals in a modern manner by implementing techniques involving predictive analytics, claims analytics, emerging issues detection, etc. AI covers a wide range, but the fields were not formally founded until 1956, at a conference at Dartmouth College, in Hanover; Through the lens of machine learning algorithms, we embark on a journey to analyze historical energy consumption data, by leveraging the power of data, we aim to build models that not only capture the nuances of the past but also pave the way for more informed decision-making.

RNN and LSTM models are designed to handle time series data effectively, making them ideal for applications involving sequential data such as electricity consumption. These models can learn and retain dependencies across time steps, enabling them to predict future values with greater precision. This article explores the application of RNN and LSTM techniques in predicting hourly electricity consumption in Algeria. By leveraging historical consumption data, these AI-based models aim to capture complex temporal dynamics and provide actionable insights for energy planners and policymakers.

Analyses of the pertinent literature show that the significance of Electricity power consumption forecasting approaches has been steadily increasing globally. Recently, academics have put up a number of theories in an attempt to forecast the Electricity power consumption. Two appropriate classification categories based on architectural kinds are the regression model and the time series technique. A review of the pertinent literature reveals that a wide range of forecasting techniques, such as regression models and time series approaches, have been used to address the problem of projecting energy use and future power expenditures. The most likely future demand is estimated by modeling Electricity power consumption, or electricity demand, as a function of past demand using the time-series approach. Two primary approaches have been used to achieve algorithmic Electricity power consumption predictions: classical models and AI-based models. [4]

This study aims to build a machine-learning model employing a deep-learning techniques to predict Algeria's daily electricity demand. To do this, we will use daily data on Algeria's electricity demand that was collected between January 2000 and December 2022. These findings offer a foundation for logical and consistent forecasting. The structure of the paper is as follows: the literature review in the first section, The methodology and data description is covered in the second section. This is the methodological framework presented in section 2. The final section presents a summary of discussing the results after evaluating the best model's prediction potential.

II LITERATURE REVIEW

Electricity consumption forecasting is a critical aspect of energy management and planning. Accurate predictions enable better decision-making for energy generation, distribution, and consumption, ensuring stability and efficiency within the power grid. Traditional forecasting methods, such as statistical techniques and classical time series models, often struggle to capture the nonlinear and complex patterns in electricity consumption data. With the advent of artificial intelligence (AI) and machine learning, more sophisticated models like Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) networks have shown significant promise in improving forecast accuracy.

A *Traditional Forecasting Methods*

Classical time series forecasting methods, including ARIMA (AutoRegressive Integrated Moving Average), Exponential Smoothing, and Seasonal Decomposition, have been widely used for electricity consumption prediction. These models, while useful, have limitations in capturing nonlinear dependencies and handling large-scale data with multiple variables. Studies have shown that these traditional models often fail to adequately predict sudden changes in consumption patterns caused by external factors like weather conditions, socio-economic changes, and policy shifts.

B *AI-based Forecasting Models*

The application of AI and machine learning techniques in time series forecasting has gained traction due to their ability to model complex relationships and learn from large datasets. Among these techniques, RNN and LSTM networks have emerged as powerful tools for electricity consumption forecasting.

C *Recurrent Neural Networks (RNN)*

RNNs are designed to handle sequential data by maintaining a hidden state that captures information from previous time steps. This makes them suitable for time series forecasting tasks. However, standard RNNs suffer from the vanishing gradient problem, which limits their ability to learn long-term dependencies. Despite this limitation, several studies have successfully employed RNNs for short-term electricity load forecasting.

D *Long Short-Term Memory (LSTM) Networks*

LSTM networks, a variant of RNNs, address the vanishing gradient problem by introducing memory cells that can maintain and update information over long sequences. This makes LSTMs particularly effective for time series data with long-term dependencies. Numerous studies have demonstrated the superiority of LSTMs over traditional methods and standard RNNs in electricity consumption forecasting. LSTM networks have been shown to capture

intricate patterns and temporal dynamics in electricity usage, leading to more accurate predictions.

E Applications in Electricity Consumption Forecasting

Several researchers have explored the application of RNN and LSTM models in predicting electricity consumption. For instance, Smyl (2016) utilized an LSTM-based model to forecast electricity demand, achieving superior performance compared to conventional methods. Similarly, Marino et al. (2016) applied deep learning techniques, including LSTM networks, to electricity load forecasting, demonstrating significant improvements in accuracy. [12]

In the context of Algerian electricity consumption, few studies have specifically focused on AI-based forecasting techniques. However, the growing availability of electricity consumption data and advancements in AI offer opportunities to apply these models in Algeria. This research aims to fill this gap by leveraging RNN and LSTM approaches to predict hourly electricity consumption in Algeria, providing insights into their effectiveness and potential benefits.

F Comparative Studies

Comparative studies between traditional methods and AI-based models consistently highlight the advantages of the latter. Bontempi et al. (2012) compared machine learning techniques, including LSTM networks, with classical time series models for electricity load forecasting. The results indicated that machine learning models outperformed traditional methods, particularly in capturing nonlinear patterns and adapting to changes in the data.

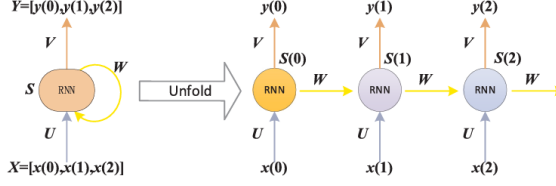
III METHODOLOGY

A Recurrent Neural Networks (RNN)

In order to implement the forecasting technique, traditional ANN attempts to create a direct mapping between input historical data and output forecast data. Unfortunately, the ANN model cannot represent the relationship between data and time since time correlation in the data sequence is not taken into account, which limits its use in time series forecasting techniques. In order to get over this drawback, the Recurrent Neural Network (RNN) is suggested. RNN can create a sequence-to-sequence mapping between input and output data by giving neurons cyclical connections. As a result, the input from the previous time step influences the output of subsequent time step. Consequently, RNN realizes the "memory" property. Fig. 1 illustrates the RNN's structural layout. A single time step's neuron is represented by each node. The input connection weight is W_1 , the output connection weight is W_3 , and each neuron's self-connection weight is W_2 . In accordance with time steps, the

input data sequence enters the network one at a time, and the weight coefficient is recycled. [5].

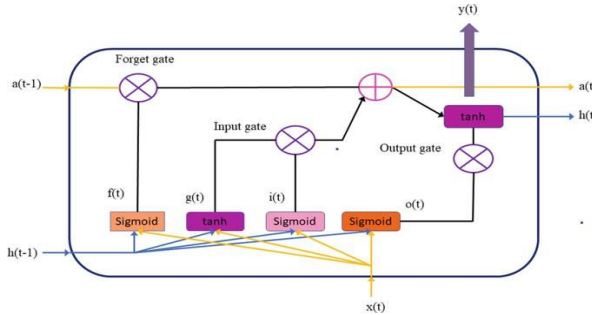
Fig.1 Recurrent Neural Network Structure



B Long short-term memory (LSTM)

Both forward and backward passes are used in RNN training. Backpropagation over time, or backward pass, is how RNN weights are changed (BPPT). The chain rule is frequently applied in BPPT, much like in conventional backpropagation. Using relevant mapping information between input and output is a key element of the RNN. However, standard RNN architectures have a limited context range. The accuracy of the basic RNN model is increased by the LSTM. Fig. 2 depicts the basic LSTM neuron. In LSTM-RNN, the subnets are referred to as memory blocks. Every memory block has three gates: the input, output, and forget gates. For memory cells, these gates handle the write, read, and reset functions. When the input gate is activated, data is saved and sent to the output. After the output gate is activated, the data is then moved to the subsequent neuron. When the forget gate is activated, the data stored in the memory cell is erased. Consequently, these gates' activation realizes the input data sequence's lengthy short-term memory. Additionally, LSTM neurons are trained through forward and backward passes. The neuron weight is updated using the BPTT approach. [1].

Fig.2 Long short-term memory



C Performance Parameters to Measure Forecasting Accuracy

The parameters used for the evaluation of the prediction model are given as follows:

The mean absolute error (MAE), root-mean-square error (RMSE), and correlation coefficient (R²) are used to evaluate the predicting performance of the proposed model. Equations 01–03 express the relevant formulas: [4]

$$MAE = \frac{1}{n} \sum_{i=1}^n |\widehat{y}_i - y_i| \tag{01}$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n |\widehat{y}_i - y_i|^2} \tag{02}$$

$$R^2 = \left(1 - \frac{\sum_{i=1}^n (\widehat{y}_i - y_i)^2}{\sum_{i=1}^n (\widehat{y}_i - \bar{y})^2}\right)^{\frac{1}{2}} \tag{03}$$

Where $\widehat{y}_i$ depicts the predicted value, y_i is the observed value, and $\bar{y}$ is the mean value

IV DATA DESCRIPTION

The Regulatory Commission of Electricity and Gas (CREG) provided the sample for this study, which consists of Megawatt-level data on electricity consumption for Algeria's northern interconnected grid (RIN), which includes coastal areas, highlands, and some southern regions. The data was collected between January 2000 and December 2022. Residential, commercial, and industrial sectors are all covered. The load data that were utilized included hourly data intervals for every day of the sample's year. Daily electricity demand is defined as the total of the 24 hourly electrical load values recorded for each day. This gives us a total of 8401 observations throughout the duration of the study (2000 - 2022).[3]

A Descriptive analysis:

In this part, we will try to take a preliminary look at the nature of Electricity Consumption Data in the study sample, by using statistical methods to analyze the different parameters during the study period.

Table No. (01): Summary statistics

Statistic	AEP_MW
count	8401.000000
mean	7013.929056
std	2329.497635
min	3258.000000
25%	4979.000000
50%	6910.000000
75%	8605.000000
max	15656.000000

Source: output of python program. (Authors calculation)

The descriptive statistics presented in Table (01) provide insights on the distribution of Electricity Consumption Data. The average Electricity consumption is 7013.92 TWh, with a variation of 2329.49 TWh. Notably, The highest level of Electricity consumption recorded is 15656.00 TWh and the lowest was 3258.00 TWh, while more than half of the observations surpass 6910.00 TWh.

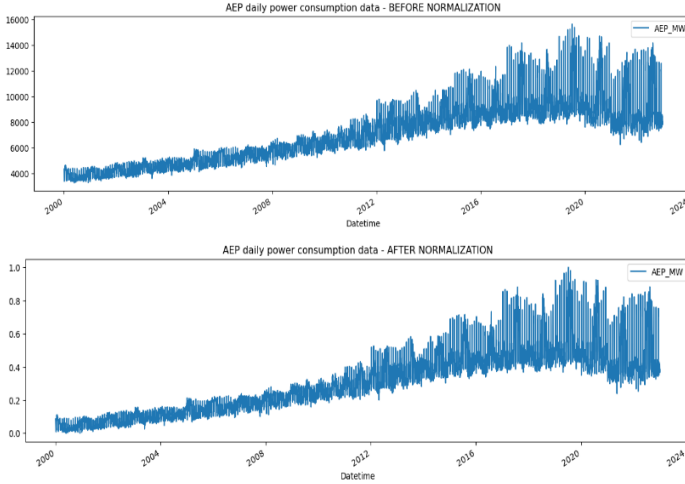
B Normalize data

Before proceeding with further data analysis we must ensure that the data is normalized.

Visualize data after normalization

- After normalization the range of power consumption values changes which we can observe on the y-axis of the graph. In the earlier graph that was displayed it was in the range 0 - 15656
- Now after normalization we can observe that the data range on y-axis is 0.0 - 1.0

Fig.3. Electricity consumption Data: before, and after normalization

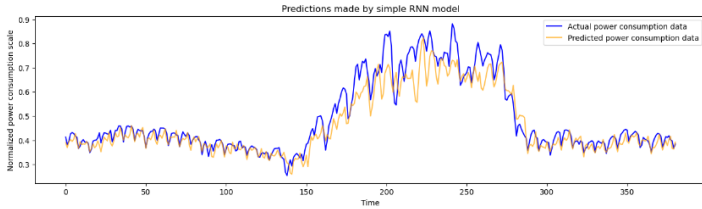


V RESULTS AND DISCUSSION

A RNN Model Results

The hyperparameters of the RNN model include one RNN layer, 50 model nodes, trained for 20 epochs with a batch size of 1000, ReLU activation function, and the Adam optimizer. The code was implemented using the Keras library, which is integrated into the TensorFlow deep learning framework. The model was created using the Python programming language.

Fig.4. The prediction results of the time series models on the actual values. RNN model.

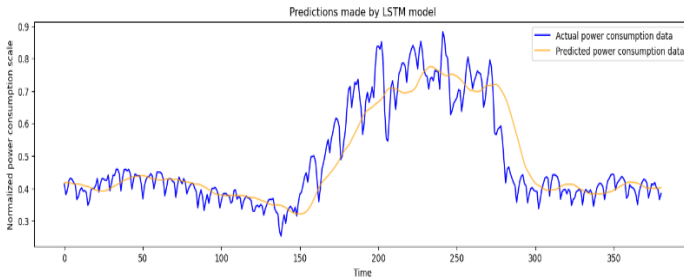


We see that the predicted values are close to the actual values meaning the RNN model performs well in predicting the sequence.

B LSTM Model Results

The hyperparameters of the LSTM model include one LSTM layer, 40 model nodes, trained for 20 epochs with a batch size of 1000, ReLU activation function, and the Adam optimizer. The code was implemented using the Keras library, which is integrated into the TensorFlow deep learning framework. The model was created using the Python programming language.

Fig.5. The prediction results of the time series model on the actual values. LSTM model.

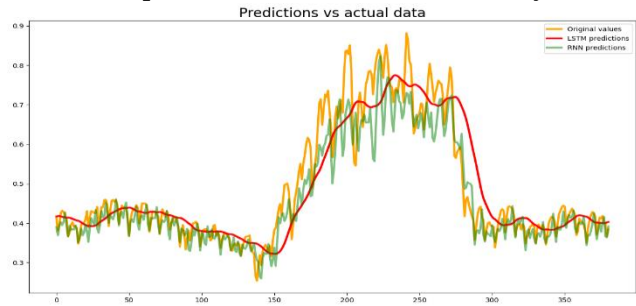


We see that the predicted values are less close to the actual values meaning the LSTM model performs well in predicting the sequence.

C Comparison of the two models

Compare predictions made by simple RNN, LSTM model by plotting data in a single graph

Fig.6. The prediction Comparison of the models for electricity consumption forecast.



The time series data on electricity consumption that was gathered between 2000 and 2022 was divided into two sets: a training set and a validation set. This was done in order to use the parameters that were specified in the model's configuration to regulate the prediction performance of the models that were produced. Using the first 8000 of the 8401 daily data sets as training data, the model was applied to forecast the following periods of 2023. To be more precise, the fitted model was assessed for usage in the validation stage after the time series model was adjusted utilizing solely the training data. The degree to which the time series model was able to predict the future was ascertained by comparing its predictions with the facts that actually happened. As demonstrated by Fig. 06.

Table No. (01): The performance evaluation criteria results for the RNN and LSTM models.

Model	MAE	RMSE	R ²
LSTM	0.04636	0.06641	0.8076
RNN	0.03684	0.05305	0.8772

Fig.7. The RNN and LSTM Performance under different goodness-of-fit metrics

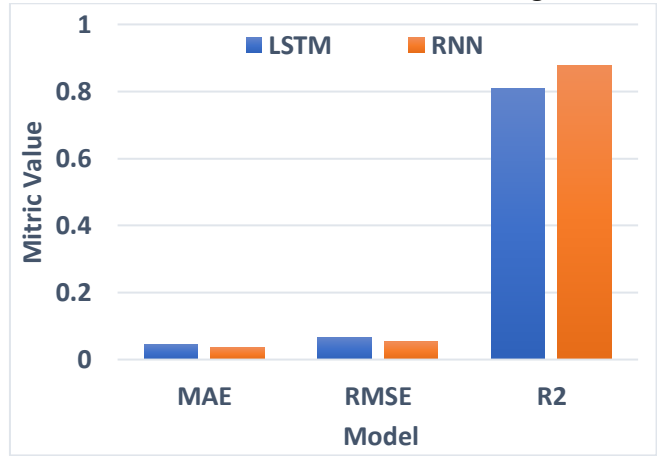


Figure 05 illustrates the prediction performance of RNN, with rolling prediction, and LSTM models, whereas Figure 06 shows the goodness-of-fit quantification of the prediction performance of RNN, both simultaneous horizon and rolling predictions, and LSTM. Both figures reveal that the RNN model exhibits superior convergence, characterized by minimal RMSE and MAE values compared to the LSTM model. Figures 03 states that RNN predictions are closely following the actual values of the test set. Moreover, Figure 04 showcases that introducing RNN has significantly reduced RMSE and MAE as compared to the values listed in Table 02, which became 0.06641, MWh for RMSE and 0.03684, MWh for MAE. This demonstrates the suitability of the RNN model for precise and accurate Electricity Consumption in Algeria.

VI CONCLUSIONS

In conclusion, the application of Deep Learning forecasting models represents a transformative approach to energy management, enabling the energy sector to overcome traditional limitations and embrace a more dynamic, data-driven future. By harnessing the power of AI, energy providers can optimize operations, enhance grid reliability, and accelerate the transition towards a sustainable energy ecosystem. As AI technologies continue to evolve, the potential for innovation and impact in the energy sector is boundless, promising a brighter and more resilient energy future for generations to come.

This research proposed a machine-learning model employing deep-learning techniques (RNN-LSTM) for the forecast of electricity consumption in Algeria, in comparison with other regression techniques. The data used for the study (2000 – 2022) to compare the forecasting results of these techniques. The considered performance parameters are RMSE, MEA, and R2.

It is found that the Deep Learning (RNN) model has better prediction performance in terms of lowest (RMSE and MEA) and highest R2 for forecast electricity consumption compared with LSTM predicting model.

Therefore, it is concluded that the Deep Learning technique (RNN) is the best technique for the prediction of Algerian electricity consumption.

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