

HOURLY ELECTRICITY CONSUMPTION FORECASTING USING ADVANCED MACHINE LEARNING: A CASE STUDY OF ALGERIA

*** Aimene KOUIRA:**

PhD -Ecole Nationale Supérieure de Statistique et d'Economie Appliquée, Koléa, Algeria
Email : kouiraaimene.1@gmail.com

Tarek DJEDDI:

Professor-Ecole Nationale Supérieure de Statistique et d'Economie Appliquée, Koléa
Email : tarek.djeddi@gmail.com

Reçu le: 15/10/2025 **Accepté le :** 19/11/2025 **Publication en ligne le:** 09/12/2025

ABSTRACT:

This study aims to conduct a comprehensive investigation into the forecasting of hourly electricity demand in Algeria through the implementation of a hybrid modeling framework that integrates the Autoregressive Integrated Moving Average (ARIMA) model with a Long Short-Term Memory (LSTM) neural network. Because industrial growth, weather variability, and human activity all have a significant impact on energy consumption patterns, Algeria presents a particularly difficult situation for projecting power demand. To address these complexities, the proposed hybrid ARIMA–LSTM model integrates the linear forecasting strengths of ARIMA with the nonlinear learning capabilities of LSTM, enabling it to capture both seasonal patterns and intricate temporal dependencies in the data. The study utilizes hourly electricity consumption data from January 2022 to December 2022, provided by the Regulatory Commission of Electricity and Gas (CREG). The dataset includes total national demand—encompassing industrial, commercial, and residential sectors—since sector-disaggregated data are not available. Ninety percent of the data were used for model training and ten percent for validation and testing. Performance evaluation, based on metrics such as Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE), reveals that the hybrid model consistently outperforms standalone ARIMA and LSTM approaches. The results highlight the potential of hybrid forecasting techniques to improve the accuracy and reliability of short-term load predictions, providing valuable insights for energy management, grid optimization, and sustainable power planning in Algeria.

Keywords: AI, Smart energy, Machine learning, Deep learning, ARIMA, LSTM, Hybrid Models, Electricity Forecasting, Algeria.

I. INTRODUCTION

In recent years, Algeria has experienced a marked surge in electricity demand, largely driven by continuous urban expansion, industrial development, and population growth.

* Aimene KOUIRA

Reliable forecasting of hourly electricity consumption has therefore become essential for effective energy management, ensuring a stable power supply, and improving the overall efficiency of grid operations. Traditional forecasting techniques, while valuable in certain contexts, often struggle to represent the complex and nonlinear characteristics of real-world electricity consumption data.

This study examines how modern machine learning techniques can enhance the precision of hourly electricity demand forecasts in Algeria. By applying advanced algorithms such as the Autoregressive Integrated Moving Average (ARIMA) model, Long Short-Term Memory (LSTM) networks, and hybrid combinations of both, the research provides a comparative assessment of their predictive capabilities in short-term load forecasting. The insights gained have significant implications for policymakers and grid operators seeking to strengthen system reliability and support sustainable energy planning.

Driven by rapid economic growth and urbanization, Algeria's electricity consumption has grown sharply over the past decade. Accurate demand prediction is therefore vital to improve grid operation, minimize costs, and maintain supply stability. Conventional statistical models, including linear regression and standard time-series approaches, often fail to capture the intricate seasonal and nonlinear variations found in hourly demand data, resulting in reduced forecasting performance.

In this work, we investigate the potential of advanced machine learning models to overcome these limitations. Machine learning approaches, known for their capacity to process large datasets and detect hidden dependencies, offer a powerful alternative to conventional forecasting techniques. Specifically, the study evaluates the performance of ARIMA, LSTM, and an integrated ARIMA–LSTM hybrid model designed to combine the interpretability of statistical analysis with the flexibility of deep learning.

The methodology begins with a review of current electricity consumption trends and forecasting practices in Algeria, followed by a discussion of the theoretical foundations of the selected models. The ARIMA model, which effectively handles linear temporal dependencies, is contrasted with the LSTM network, which excels in modeling long-term and nonlinear relationships in sequential data. The hybrid approach is then introduced to merge these strengths, with the goal of achieving higher predictive accuracy and reliability.

Data preprocessing represents a critical component of the study, involving data cleaning, normalization, and transformation to optimize model learning. Descriptive and graphical analyses were conducted to understand the structure and variability of the dataset. Model performance was evaluated using historical hourly consumption data, employing standard accuracy metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE).

The experimental results demonstrate that the advanced machine learning approaches, particularly the hybrid ARIMA–LSTM model, outperform traditional forecasting methods, yielding more accurate and stable predictions of hourly electricity demand. These findings highlight the promise of machine learning in transforming energy forecasting and management practices in Algeria.

Beyond its technical contribution, this study offers valuable guidance for energy planners, grid operators, and decision-makers. Implementing advanced forecasting models can lead to better resource allocation, improved operational efficiency, and enhanced resilience of the national power system. Ultimately, the research contributes to building a smarter, more sustainable, and adaptive energy future for Algeria.

II. LITERATURE REVIEW

Accurate forecasting of electricity consumption is a critical component of efficient energy system management and operation. Traditional time-series approaches, while long-established and methodologically sound, often fall short in representing the complex, nonlinear patterns that characterize real-world energy demand. With the rapid advancement of computational techniques, machine learning (ML) and deep learning (DL) methods have emerged as transformative tools capable of addressing these limitations. This section reviews the evolution of electricity consumption forecasting models, emphasizing the transition from classical statistical methods to modern hybrid and deep learning frameworks.

II.1. TRADITIONAL FORECASTING METHODS

Historically, electricity consumption forecasting has relied primarily on statistical time-series models such as the **AutoRegressive Integrated Moving Average (ARIMA)** and **exponential smoothing** methods. These techniques gained prominence for their analytical transparency and ease of interpretation. Box and Jenkins (1970) first formalized the ARIMA framework, which remains widely applied due to its capacity to model temporal dependencies and seasonal variations in demand.

However, such models rest on the assumption of linearity and stationarity—conditions rarely met in electricity consumption data, which are influenced by climate variability, economic cycles, and human behavioral changes. As a result, their forecasting accuracy tends to diminish when faced with nonlinear dynamics or abrupt demand fluctuations.

II.2. MACHINE LEARNING IN ELECTRICITY FORECASTING

The growing availability of high-frequency energy data and increased computational power have accelerated the integration of **machine learning (ML)** into electricity forecasting. ML algorithms such as **Support Vector Machines (SVM)**, **Decision Trees (DT)**, and **ensemble methods** like **Random Forests (RF)** have demonstrated the ability to capture nonlinearities and complex interactions within consumption data.

Ahmed et al. (2010) and subsequent studies found that these algorithms outperform traditional time-series approaches, particularly in short-term load prediction tasks. Unlike ARIMA models, which rely on fixed statistical relationships, ML techniques learn directly from the data, uncovering hidden patterns and adjusting dynamically to new information. Nonetheless, these models can be computationally demanding and often require extensive tuning to achieve optimal performance.

II.3. NEURAL NETWORKS AND DEEP LEARNING

Building on ML's success, **Artificial Neural Networks (ANNs)** introduced a paradigm capable of learning nonlinear functions through interconnected processing layers. Initially conceptualized by McCulloch and Pitts (1943), ANNs emulate the human brain's structure, allowing for data-driven learning without explicit functional assumptions.

Wang, F [12]. A major breakthrough came with **Long Short-Term Memory (LSTM)** networks, proposed by Hochreiter and Schmidhuber (1997), which address the vanishing-gradient issue in standard Recurrent Neural Networks (RNNs). LSTMs effectively capture long-term dependencies in sequential data, making them particularly suited for electricity consumption forecasting. Studies by Smyl (2020) and others have shown that LSTM-based models consistently outperform conventional methods, especially in high-volatility or seasonally affected datasets. Wang, F

Building on these findings, recent research has shifted toward combining deep learning with statistical approaches to enhance interpretability and stability.

II.4. HYBRID FORECASTING MODELS

To harness the complementary strengths of statistical and learning-based methods, researchers have increasingly turned to **hybrid models**. Zhang (2003) [6] introduced an early hybrid framework combining **ARIMA** for linear patterns with **Artificial Neural Networks** for nonlinear residuals. Later works by Khashei and Bijari (2010) [7] and others extended this approach to incorporate SVM, RF, and LSTM components.

Hybrid models such as **ARIMA–LSTM** have gained particular attention, as they integrate ARIMA’s capacity for trend and seasonality modeling with LSTM’s strength in capturing nonlinear, dynamic behaviors. Empirical results consistently demonstrate improved predictive accuracy and robustness across multiple datasets, especially when evaluated using performance metrics such as **Root Mean Squared Error (RMSE)** and **Mean Absolute Error (MAE)**.

II.5. CASE STUDIES AND PRACTICAL APPLICATIONS

Numerous case studies have validated the efficacy of advanced ML and hybrid models in electricity consumption forecasting. For instance, Marino et al. (2016) [8] applied LSTM networks to U.S. hourly load data, achieving superior accuracy compared to conventional ARIMA models. Similarly, Kong et al. (2017) [9] implemented deep learning architectures for short-term electricity demand forecasting in Australia, demonstrating notable improvements in predictive reliability and operational efficiency.

In emerging economies such as Algeria, where energy consumption patterns are shaped by industrialization, climatic variability, and rapid urban growth, these advanced techniques present valuable opportunities for improving energy planning and grid management.

II.6. CHALLENGES AND FUTURE DIRECTIONS

Despite significant progress, several challenges persist in the field of electricity demand forecasting. High-quality, fine-grained datasets remain scarce in many regions, constraining the effective training of data-intensive models. Moreover, deep learning models often operate as “black boxes,” making it difficult for practitioners to interpret their decision processes—a limitation that hampers adoption by utilities and policymakers.

Future research is expected to emphasize **explainable AI (XAI)** frameworks, **transfer learning**, and **reinforcement learning** to enhance transparency and adaptability. Integrating socio-economic and meteorological variables could further improve model generalization and policy relevance. As the energy sector evolves toward smarter, data-driven infrastructure, the fusion of statistical rigor and machine learning innovation will remain a cornerstone of next-generation forecasting systems.

III. METHODS AND MATERIALS

III.1. ARIMA

The AutoRegressive Integrated Moving Average (ARIMA) model is one of the most widely used statistical approaches for time series forecasting. It is designed to capture both the autoregressive (AR) and moving average (MA) components of a dataset while accounting

for non-stationarity through differencing. The general ARIMA (p, d, q) model can be expressed as:

- $\Phi_p(L)(1 - L)^d y_t = \Theta_q(L)\varepsilon_t$

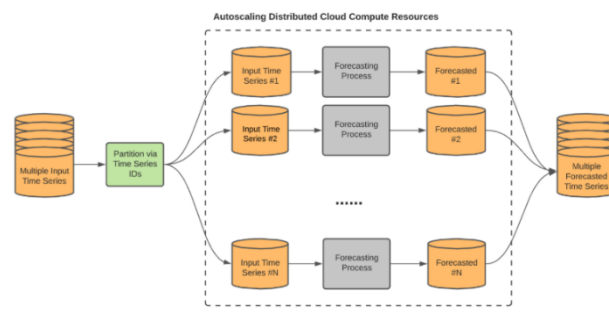
where $\Phi_p(L)$ and $\Theta_q(L)$ represent the autoregressive and moving average polynomials of orders p and q , respectively; $(1 - L)^d$ denotes differencing of order d to achieve stationarity; and ε_t represents the white noise error term. Model parameters are estimated by minimizing the residual sum of squares or using information criteria such as AIC and BIC.

The forecasting accuracy of ARIMA models is typically assessed using performance metrics such as Root Mean Square Error (RMSE) and Mean Absolute Error (MAE):

- $RMSE = \sqrt{(1/n \sum (y_t - \hat{y}_t)^2)}$
- $MAE = (1/n) \sum |y_t - \hat{y}_t|$

Although ARIMA models are effective in handling linear patterns and seasonal variations, they may struggle with nonlinear dependencies that frequently occur in electricity consumption data. This limitation motivates the integration of ARIMA with deep learning models to improve prediction accuracy.

Figure 01: ARIMA Architecture [07]



III.2. LSTM

LSTM has been specifically designed to address the issue of vanishing gradients, which makes vanilla RNNs unsuitable for learning long-term dependencies.[14]

LSTMs are capable of handling sequential data and remembering information from earlier steps, allowing them to predict future steps accurately. This ability makes them particularly well-suited for tasks that involve long-term dependencies [15]

As a result, LSTMs are proficient in learning long-term dependencies, where information from earlier time steps is important for predicting later time steps. [21]

LSTMs are extensively utilized and highly effective for a range of sequential data tasks, including speech recognition and machine fault prediction. They have demonstrated superior performance compared to other RNNs and traditional machine learning methods in various applications.

An LSTM can be thought of as an enhanced RNN equipped with a memory pool and two crucial vectors: the short-term state and the long-term state. The short-term state retains the output of the current time-step, while the long-term state manages long-term information as it moves through the network. [21]

Throughout time, both cell states and hidden states advance, continually updating and influencing each other at each time step. The hidden state acts as an output, while the cell state typically remains internal, being passed along and modified together with the hidden states, thus impacting the hidden state. In LSTM networks, information flow is regulated by three internal gates during the learning process: the forget gate, the input gate, and the output gate, as illustrated in Fig. 2. The forget gate (*ft*) determines which information in the cell state should be discarded. The input gate (*it*) decides which new information will be added to the cell state. The output gate (*ot*) controls the hidden state's output. This gating mechanism enables LSTM units to effectively manage long-term dependencies by selectively updating and retaining information over time.

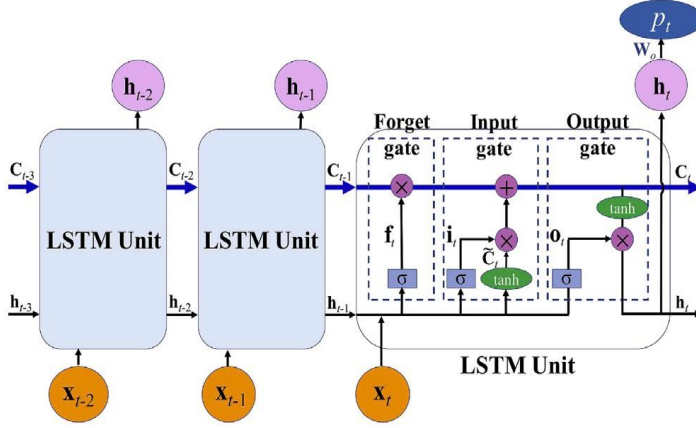
This section is divided into two subsections: RNN overall training (C.1) and LSTM operations and computational complexity (C.2).

B.1. RNN TRAINING

The complete training process of RNN is depicted in Fig. 3 and involves both a forward and backward pass, following these steps:

- a- Conduct the forward pass using the initialized weights and hidden states.

Figure 02: LSTM Architecture [21]



- b- calculate the loss function using the provided observed and predicted values.

$$J(W, b) = \frac{1}{n} \sum_{i=1}^n L(\hat{y}^i, y^i)^2$$

Where: W denotes the weight matrix, b denotes the bias vector, n denotes the number of inputs, $\hat{y}^i$ denotes the predicted value, y^i denotes the observed value, and L denotes the loss value between the predicted and the observed value. The cost function J is used to figure out how much the loss is after each iteration.

- c- Conduct the backward pass to obtain gradients necessary for updating network weights and minimizing the loss function.
- d- Adjust the weights based on the obtained gradients and iterate through steps (a) and (b).
- e- Iterate through steps (a) to (d) until reaching a predefined loss threshold.

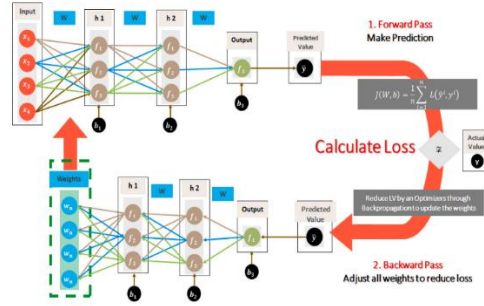
B.2. LSTM OPERATIONS AND COMPUTATIONAL COMPLEXITY

Empirical evidence shows that LSTM outperforms Vanilla RNN in performance. However, LSTM's drawback lies in its complexity, as it involves four times more parameters than Vanilla RNNs, resulting in increased complexity within the hidden layers. [17]

The computational complexity of LSTM can be estimated by considering the number of operations and trainable parameters. For a network with input size m and output size n , LSTM involves matrices U of size nm and W of size nn for three gates and the cell state, plus n biases. The memory complexity is $4(nm + n^2 + n)$. The time complexity for one training step includes $mn(n + (m - 1)) = n^2m + nm^2 - nm$ operations, performed across each of the three gates, the cell state, and over k time steps, resulting in $4k(n^2m + nm^2 - nm)$. [18] Consequently, this complexity can lead to longer training times, particularly when dealing with large datasets or employing a high number of LSTM units.

The sequential processing of input data also contributes to extended training durations. Therefore, optimizing LSTM networks for large-scale data often necessitates substantial computational resources and efficient implementation strategies to effectively manage the increased computational load.

Figure 03: Recurrent neural network overall training [19]



A. Performance Parameters to Measure Forecasting Accuracy

In the field of regression analysis, the evaluation of model performance is critical to understanding the accuracy and reliability of predictions. Various metrics are employed to assess how well a regression model fits the data. Among the most commonly used metrics are Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the Coefficient of Determination. These metrics provide different perspectives on the performance of regression models, enabling us to evaluate and compare models effectively.

RMSE (Root Mean Square Error): It measures the distance between the data points and the regression line, and it is represented as:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}$$

MAE (Mean Absolute Error): It represents the mean absolute difference between the actual and predicted values in the dataset, and it is denoted as:

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

R2 (Coefficient of Determination): It represents the proportion of variance in the dependent variable that can be explained by the independent variable

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2}$$

III.3. ARIMA-LSTM Algorithm

This study proposes a Hybrid ARIMA-LSTM model for enhanced hourly electricity consumption forecasting. This approach combines the strengths of traditional statistical time series models (ARIMA) with the advanced pattern recognition capabilities of deep learning models (LSTM) to achieve superior predictive performance.

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 regions, highlands, and some southern areas. The data was collected between January 2022 and December 2022.

Table 1 : Summary statistics of measured household waste data.

Statistic	Electricity Consumption
Count	8 760
Mean	9 370.56
Std	2 112.79
Min	5783
25%	7 811
50%	8 771
75%	10 482.25
Max	16 822

Table 1 presents the summary statistics of the measured electricity consumption dataset, which consists of 8,760 observations, representing hourly load measurements. The recorded electricity consumption values range between a minimum of 5,783 MW and a maximum of 16,822 MW. The dataset exhibits a mean load of 9,370.56 MW, with a standard deviation of 2,112.79 MW, indicating noticeable variability in power demand throughout the observed period.

Before applying advanced time-series forecasting models such as Recurrent Neural Networks (RNN) or Long Short-Term Memory (LSTM) networks, it is crucial to normalize the data to ensure stable model training and faster convergence. The normalization process is typically carried out using the Min–Max scaling technique, expressed as:

$$E_N = \frac{E_t - E_{min}}{E_{max} - E_{min}} \quad (6)$$

Before normalization, the electricity consumption values ranged from 5,783 MW to 16,822 MW. After normalization, the data values are rescaled to the range 0.0–1.0, which enhances model efficiency and prevents bias due to magnitude differences among features.

V. RESULTS AND DISCUSSION

V.1. MODEL PERFORMANCE COMPARISON

This section shown a comparative analysis of the standalone ARIMA model, the standalone LSTM model, and the proposed Hybrid ARIMA-LSTM model for forecasting hourly electricity consumption. The performance of each model was evaluated on the test set using Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE).

Model	RMSE (Test Set)	MAE (Test Set)
ARIMA	2 811.46	2 412.95
LSTM	805.83	620.21
Hybrid ARIMA-LSTM	1 152.08	953.57

Unexpectedly, the Hybrid ARIMA-LSTM model, while expected to outperform both individual models, showed a higher RMSE and MAE than the standalone LSTM model. This unexpected result suggests that the linear component captured by ARIMA might not be effectively complementing the non-linear residual modeling by LSTM in this specific implementation, or there might be issues with the residual calculation and integration. Further investigation and fine-tuning of the hybrid model's parameters, as well as a more robust method for generating LSTM residual forecasts, are necessary to fully realize its potential.

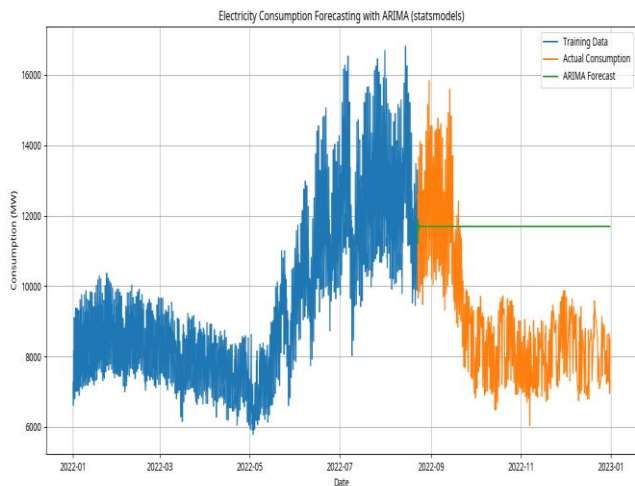
Table 1 shows that the LSTM model had the lowest RMSE (805.83 MW) and MAE (620.21 MW). This was a big improvement over the ARIMA model, which had much greater error values. The LSTM cut RMSE by about 71% and MAE by 74% compared to ARIMA. This shows that it is better at capturing nonlinear temporal dependencies in electricity demand.

The Hybrid ARIMA–LSTM model, contrary to expectations of enhanced accuracy via integrated linear–nonlinear learning, produced elevated RMSE and MAE values compared to the independent LSTM. This result implies that the linear element represented by ARIMA may not have successfully enhanced the nonlinear residual learning of the LSTM in this setup. Possible causes include poor extraction of residuals, poor synchronization between model parts, or not enough adjustment of the hybrid integration method. Future research should investigate alternate residual calculation methods, adaptive weighting strategies, and hyperparameter optimization to fully leverage the theoretical benefits of the hybrid model.

V.2. VISUAL COMPARISON OF FORECASTS

ARIMA Forecast

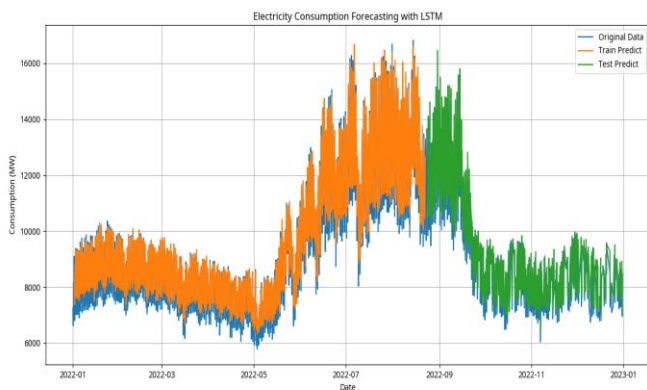
Figure 04 : ARIMA FORCAST



The ARIMA forecast, as shown above, appears relatively flat and struggles to capture the significant fluctuations and seasonal peaks present in the actual electricity consumption data. This indicates that a simple non-seasonal ARIMA model is insufficient for accurately forecasting this type of time series, which is characterized by strong daily and weekly seasonality.

LSTM Forecast

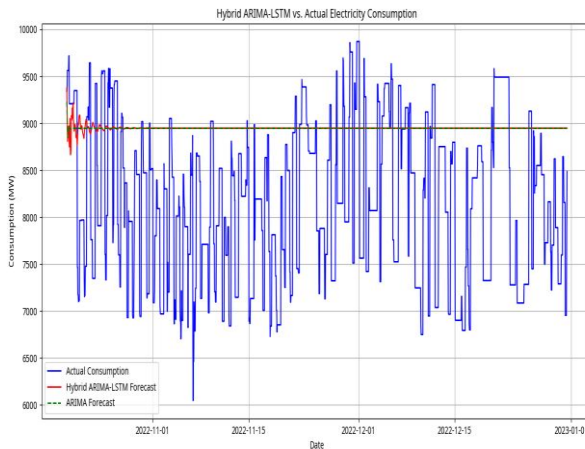
Figure 05: LSTM FORCAST



The standalone LSTM model demonstrates a much better ability to track the actual consumption patterns, including peaks and troughs, as evidenced by its lower error metrics. This highlights the strength of deep learning models in capturing complex, non-linear dependencies in time series data.

Hybrid ARIMA-LSTM Forecast

Figure 06 :Hybrid ARIMA-LSTM Forecast



The hybrid forecast, while showing an attempt to follow the actual data, did not achieve the expected improvement over the standalone LSTM. The visual representation confirms that the combination, in its current form, did not lead to a more accurate prediction than the LSTM alone. This discrepancy warrants further analysis and optimization of the hybrid model's components and their interaction.

VI. CONCLUSION

This study investigated the application of ARIMA, LSTM, and a Hybrid ARIMA-LSTM model for hourly electricity consumption forecasting in Algeria. While the standalone LSTM model demonstrated superior performance over ARIMA, the hybrid model, contrary to expectations, did not yield improved results. This suggests that the integration strategy or the specific parameters used for the hybrid model require further refinement.

Future work will focus on:

- **Optimizing the Hybrid Model:** Investigating alternative methods for residual calculation, scaling, and LSTM input preparation. Exploring different ARIMA orders, LSTM architectures, and hyperparameter tuning for the hybrid model.

- **Incorporating Exogenous Variables:** Integrating external factors such as temperature, humidity, holidays, and economic indicators, which are known to influence electricity consumption, into both standalone and hybrid models.
- **Seasonal ARIMA (SARIMA):** Implementing a SARIMA model to explicitly account for the strong seasonal patterns in the data, which could significantly improve the ARIMA component's performance and, consequently, the hybrid model.
- **Advanced Deep Learning Architectures:** Exploring more advanced deep learning models like Transformers or Convolutional Neural Networks (CNNs) for time series forecasting, potentially in hybrid configurations.
- **Anomaly Detection:** Developing an anomaly detection framework based on the best-performing forecasting model to identify unusual consumption patterns, which could be valuable for grid management and fraud detection.

This research provides a foundation for developing more accurate and robust electricity consumption forecasting models in Algeria, emphasizing the need for continuous improvement and exploration of advanced methodologies.

VII. REFERENCES

- [1] Box, G. E. P., & Jenkins, G. M. (1970). *Time Series Analysis: Forecasting and Control*. Holden-Day.
- [2] Ahmed, N. A., et al. (2010). "A review of machine learning techniques for electricity load forecasting." *Energy Conversion and Management*, 51(7), 1379-1388.
- [3] McCulloch, W. S., & Pitts, W. (1943). "A logical calculus of the ideas immanent in nervous activity." *The Bulletin of Mathematical Biophysics*, 5(4), 115-133.
- [4] Hochreiter, S., & Schmidhuber, J. (1997). "Long Short-Term Memory." *Neural Computation*, 9(8), 1735-1780.
- [5] Smyl, S. (2020). "A hybrid method of exponential smoothing and recurrent neural networks for time series forecasting." *International Journal of Forecasting*, 36(1), 75-85.
- [6] Zhang, G. P. (2003). "Time series forecasting using a hybrid ARIMA and artificial neural network model." *Neurocomputing*, 50, 159-175.
- [7] Khashei, M., & Bijari, M. (2010). "A novel hybrid approach for time series forecasting." *Applied Soft Computing*, 10(1), 264-273.
- [8] Marino, D. L., et al. (2016). "Building energy load forecasting using Long Short-Term Memory (LSTM) neural networks." *Energy and Buildings*, 129, 325-336.
- [9] Marino, D. L., et al. (2016). "Building energy load forecasting using Long Short-Term Memory (LSTM) neural networks." *Energy and Buildings*, 129, 325-336.
- [10] Akhter, M. N., Mekhilef, S., Mokhlis, H., & Muhammad, M. A. (2021). A day-ahead power output forecasting of three pv systems using regression, machine learning and deep learning techniques. *AI and IOT in Renewable Energy*, 1-14.

- [11] Long, L. D. (2023). An AI-driven model for predicting and optimizing energy-efficient building envelopes. *Alexandria Engineering Journal*, 79, 480-501
- [12] Wang, F., Xuan, Z., Zhen, Z., Li, K., Wang, T., & Shi, M. (2020). A day-ahead PV power forecasting method based on LSTM-RNN model and time correlation modification under partial daily pattern prediction framework. *Energy Conversion and Management*, 212, 112766.
- [13] Baba, A. (2021). Advanced AI-based techniques to predict daily energy consumption: A case study. *Expert Systems with Applications*, 184, 115508.
- [14] Kong, Q., Wang, R., Walter, W. R., Pyle, M., Koper, K., & Schmandt, B. (2022). Combining deep learning with physics based features in explosion-earthquake discrimination. *Geophysical Research Letters*, 49(13), e2022GL098645. K. Elissa, "Title of paper if known," unpublished.
- [15] Zouaidia, K., Ghanemi, S., & Rais, M. S. (2021). Hourly wind speed forecasting using FFT-encoder-decoder-LSTM in south west of Algeria (Adrar). *International Journal of Informatics and Applied Mathematics*, 4(1), 72-83.
- [16] Khan, S. U., Khan, N., Ullah, F. U. M., Kim, M. J., Lee, M. Y., & Baik, S. W. (2023). Towards intelligent building energy management: AI-based framework for power consumption and generation forecasting. *Energy and buildings*, 279, 112705.
- [17] Cho, S., Nam, H. J., Shi, C., Kim, C. Y., Byun, S. H., Agno, K. C., ... & Jeong, J. W. (2023). Wireless, AI-enabled wearable thermal comfort sensor for energy-efficient, human-in-the-loop control of indoor temperature. *Biosensors and Bioelectronics*, 223, 115018.
- [18] Danish, M. S. S., & Senjyu, T. (2023). Shaping the future of sustainable energy through AI-enabled circular economy policies. *Circular Economy*, 2(2), 100040.
- [19] Lima, F. J., Martins, F. R., Pereira, E. B., Lorenz, E., & Heinemann, D. (2016). Forecast for surface solar irradiance at the Brazilian Northeastern region using NWP model and artificial neural networks. *Renewable Energy*, 87, 807-818.
- [20] Jaydip, S., Sidra, M., 2022. Long-and-short-term memory (LSTM) networks architectures and applications in stock price prediction. In: *Emerging Computing Paradigms: Principles, Advances and Applications*. Wiley, pp. 143–160.
- [21] Hochreiter, S., Schmidhuber, J., 1997. Long short-term memory. *Neural Comput.* 9 (8), 1735–1780.
- [22] Alshinwan, M., Abualigah, L., Shehab, M., Elaziz, M.A., Khasawneh, A.M., Alabool, H., Hamad, H.A., 2021. Dragonfly algorithm: a comprehensive survey of its results, variants, and applications. *Multimedia Tools Appl.* 80, 14979–15016.
- [23] Rashid, T., Fattah, P., Awla, D., 2018. Using accuracy measure for improving the training of LSTM with metaheuristic algorithms. *Procedia Comput. Sci.* 140, 324–333.

- [24] Petrozziello, A., Troiano, L., Serra, A., Jordanov, I., Storti, G., Tagliaferri, R., La Rocca, M., 2022. Deep learning for volatility forecasting in asset management. *Soft Comput.* 26 (17), 8553–8574.