Short-Term Energy Consumption Forecasting: A Comparative Study of ARIMA and LSTM Models

Research Report

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Abstract

Time series constitute a type of data that is widely encountered across many domains, including finance, healthcare, and energy. Their availability represents a significant opportunity for organizations seeking to produce reliable forecasts in order to support decision-making. Numerous approaches have been developed for analyzing and predicting such data, ranging from classical statistical models such as ARIMA to more recent methods derived from deep learning, particularly recurrent neural networks such as Long Short-Term Memory (LSTM). In response to the growing need for robust and accurate solutions for time series processing, this study proposes a comparative analysis of the performance of ARIMA and LSTM models for short-term energy consumption forecasting. Experiments conducted on a public dataset demonstrate that the LSTM model outperforms the ARIMA model in terms of Mean Squared Error (MSE). This work represents a first step in the model selection process for time series forecasting within organizations.

1 Introduction

Time series data constitute a type of data widely encountered across many domains such as finance, healthcare, and energy. This ubiquity has led to the development of various methods aimed at exploiting these data to produce reliable forecasts. In this context, the choice of a prediction approach becomes a crucial issue. Among the most commonly used methods are classical statistical models, such as ARIMA, as well as more recent approaches based on deep learning, particularly LSTM neural networks.

For instance, Bakar and Rosbi (2017) used the ARIMA model to predict the movements of *Bitcoin*, a financial asset known for its high volatility [1]. Subsequently, Vennerod et al. (2021) highlighted the relevance of recurrent neural networks of the LSTM (Long Short-Term Memory) type for time series modeling and forecasting [2]. Given the diversity of these approaches, it becomes imperative to identify methods that are both reliable and well aligned with the application context.

In this study, we propose a comparative analysis of ARIMA and LSTM models for short-term energy consumption forecasting. The remainder of this paper is organized as follows: Section 2 presents the ARIMA and LSTM models along with their experimental implementation; Section 3 reports the obtained results; Section 4 is devoted to the discussion and analysis of the results; finally, Section 5 concludes the paper.

2 Methods

2.1 ARIMA: Autoregressive Integrated Moving Average

The Autoregressive Integrated Moving Average (ARIMA) model is a fundamental statistical approach used for forecasting values within time series data [1]. This model relies on a key principle: the concept of data stationarity. In practice, for such a model to be effective, the statistical properties of the series, such as the mean and variance, must not vary significantly over time.

To address potential non-stationarity in a raw time series, the model employs a differencing process, denoted by d. Instead of working directly with the raw data at time t (denoted as a_t), the model processes the difference between two successive observations, for example $\Delta a_t = a_t - a_{t-1}$. This transformation step corresponds to the Integrated component of the model and helps stabilize the series.

The predictive capability of the model then relies on two other key components. On the one hand, the parameter p represents the order of the Autoregressive (AR) part and defines the number of past values, or lags, taken into account to predict the current value. On the other hand, the parameter q denotes the Moving Average (MA) component, which incorporates past forecast errors or random shocks in order to adjust future estimates.

Thus, an ARIMA model is conventionally summarized by the notation (p, d, q), which fully characterizes the prediction process. However, with the evolution of artificial intelligence, new methods based on deep learning, such as recurrent neural networks, have emerged to handle even more complex time series dynamics.

2.2 LSTM: Long Short Term Memory

The LSTM (Long Short-Term Memory) model, notably used by Vennerod et al. (2021) in the context of time series forecasting, is a Deep Learning model belonging to the family of recurrent neural networks (RNNs) [2]. It was designed to overcome the limitations of classical RNNs, particularly the issues of vanishing and exploding gradients when learning long-term dependencies.

An LSTM network is composed of memory cells that incorporate three control mechanisms known as gates: the forget gate, the input gate, and the output gate (Fig. 1). These gates respectively regulate the information to be forgotten, integrated, and transmitted, by controlling the evolution of the cell's internal state c_t as well as the hidden state h_t.

Thanks to this architecture, the LSTM is able to retain and exploit information from previous states over long temporal sequences. This ability to model complex temporal dependencies makes the LSTM a particularly effective alternative to traditional statistical models for the analysis and prediction of non-linear time series.

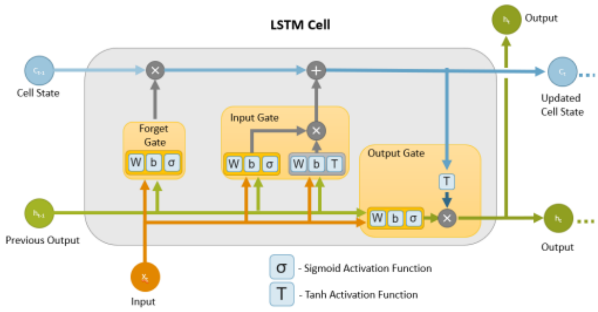
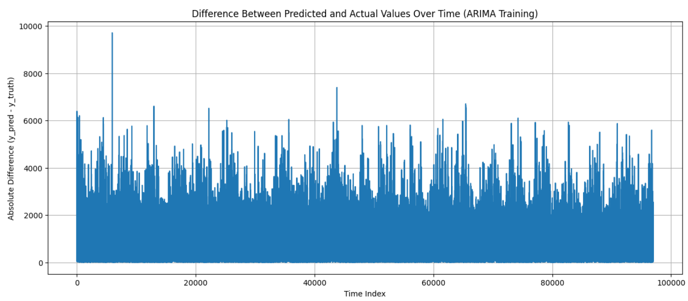


Figure 1: The Architecture of a LSTM Cell [2]

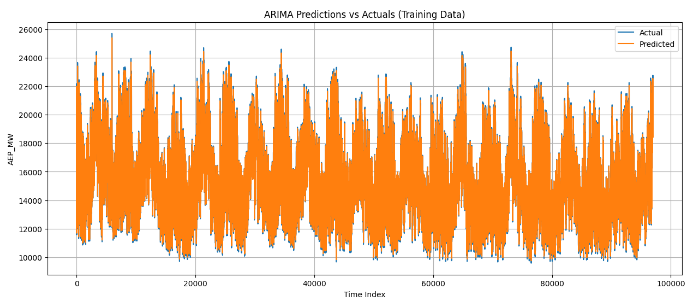
2.3 Implementation

The implementation of both models was carried out in the Python programming language, using the `statsmodels` library for the ARIMA model and `PyTorch` for the LSTM model. The experiments were conducted on the public dataset *Hourly Energy Consumption* available on Kaggle, which contains hourly electricity consumption data.

3 Results

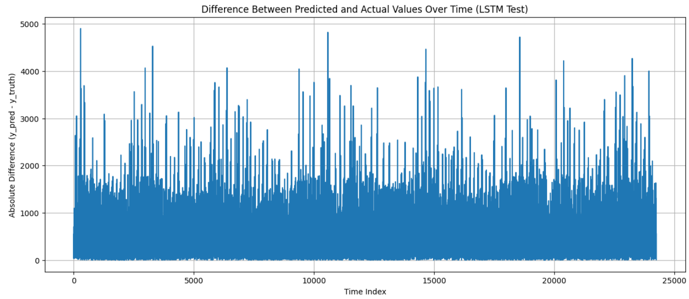


(a) Difference between y_{pred} and y_{truth}

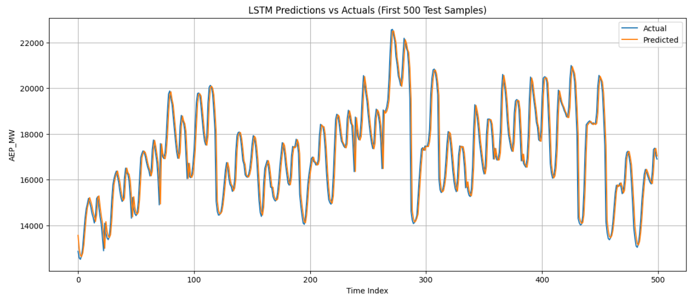


(b) ARIMA predictions vs Actuals

Figure 2: ARIMA results



(a) Difference between y_{pred} and y_{truth}



(b) LSTM predictions vs Actuals

Figure 3: LSTM results

Table 1: Comparison of prediction performance using Mean Squared Error (MSE)

Model	**MSE**
ARIMA $(1, 0, 0)$	1250099.61
LSTM	434007.12

4 Discussion

The experimental results highlight the superiority of the LSTM model over the ARIMA model for the time series prediction under study. Analysis of Figures 2a and 2b demonstrates that, although the ARIMA model $(p = 1, d = 0)$ manages to follow the overall trend, the gap between the predicted value y_{pred} and the ground truth y_{truth} fluctuates significantly without ever reaching stability. This residual variability suggests that the ARIMA model struggles to capture the underlying complexity of the data, primarily due to the lack of differencing $(d = 0)$, which limits its ability to handle non-stationary components.

Conversely, the evaluation of the LSTM model's performance presents a much more favorable diagnostic. While Figure 3a indicates that the error also varies over time, a phenomenon often attributable to the stochastic nature of the data or measurement noise, Figure 3b reveals an extremely precise alignment between the predicted values and the actual observations. This effectiveness is further confirmed by Table 1, where the Mean Square Error (MSE) of the LSTM model is substantially lower than of ARIMA. This finding underscores the capability of Deep Learning methods to model complex sequential dependencies that traditional statistical models fail to capture.

However, scientific rigor requires noting that these performances are highly dependent on hyperparameter tuning, particularly the number of epochs used during the LSTM training phase. While this choice may introduce some sensitivity into the study, the overall results confirm that this work represents a significant first step toward adopting more robust and reliable prediction methods.

Code Availability

The implementation source code for this study can be found on GitHub: `https://github.com/yann-fk-21/Short-Term-Energy-Consumption-Forecasting--A-Comparative-Study-of-ARIMA-and-LSTM-Models`. Additionally, the dataset utilized in the experiments is hosted on Kaggle: `https://www.kaggle.com/datasets/robikscube/hourly-energy-consumption/data`.

5 Conclusion

This study provided a comparative analysis of the ARIMA and LSTM models for short-term energy consumption forecasting. Our experimental results demonstrate that the LSTM model significantly outperforms the classical ARIMA approach, achieving a much lower Mean Squared Error (MSE). While the ARIMA model ($p = 1, d = 0, q = 0$) was able to capture the general trend of the data, it failed to accurately model the complex non-linearities and seasonal fluctuations inherent in energy consumption patterns. In contrast, the LSTM network showed a remarkable ability to align its predictions with the ground truth, even on unseen test data.

Despite the superior performance of the Deep Learning approach, it is important to acknowledge that the success of the LSTM model depends on careful hyperparameter selection and sufficient computational resources. Future work could extend this research by exploring hybrid models that combine the statistical rigor of ARIMA with the learning capacity of RNNs, or by incorporating exogenous variables such as weather data to further improve forecasting accuracy. Ultimately, this work confirms that LSTM networks represent a robust and reliable tool for organizations seeking to optimize their energy management through precise short-term forecasting.

References

[1] Nashirah Abu Bakar and Sofian Rosbi. "Autoregressive Integrated Moving Average (ARIMA) Model for Forecasting Cryptocurrency Exchange Rate in High Volatility Environment: A New Insight of Bitcoin Transaction". In: *IJAERS* 4.11 (2017), pp. 130–137. ISSN: 23496495, 24561908. DOI: `10.22161/ijaers.4.11.20`. URL: `http://ijaers.com/detail/autoregressive-integrated-moving-average-arima-model-for-forecasting-cryptocurrency-exchange-rate-in-high-volatility-environment-a-new-insight-of-bitcoin-transaction/` (visited on 01/15/2026).

[2] Christian Bakke Vennerød, Adrian Kjærran, and Erling Stray Bugge. *Long Short-term Memory RNN*. May 14, 2021. DOI: `10.48550/arXiv.2105.06756`. arXiv: `2105.06756[cs]`. URL: `http://arxiv.org/abs/2105.06756` (visited on 01/15/2026).