Research Article

Electrical Load Prediction Using Statistical, Deep Learning, and Hybrid Time Series Models

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Abstract: The efficient operation, planning and reliability of modern power systems rely on accurate electrical load forecasting. Accurate demand forecasting allows for optimal use of resources by cutting unnecessary expenditures and improving grid stability. Since electricity usage is particularly volatile and nonlinear in time, conventional forecasting methods frequently have trouble identifying the complex temporal patterns. Finally, this study examines the performance of models based on time-series and deep learning for electrical load forecasting over several time horizons. Several statistical models (Autoregressive Integrated Moving Average — ARIMA and Seasonal ARIMA — SARIMA) are compared to a Long Short-Term Memory (LSTM) neural network to evaluate their forecasting performance. In addition, a hybrid ARIMA–LSTM model is presented to jointly reflect linear, seasonal, and nonlinear features of load series. The temporal and climatic-enhanced historical electricity consumption data are preprocessed and subject to stationarity tests and data consistency checks. Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE) are used to assess the performance of model in short-, medium- and long-term forecasting, respectively. From the experimental results, we show that the hybrid ARIMA–LSTM model enables to always outperform individual models, producing the lowest prediction errors over all forecasting horizons. The results show that incorporating classical statistical method with deep learning methods can lead to better accuracy and robustness in this electrical load prediction problem.

***Keywords*:** Electrical Load Forecasting, ARIMA and SARIMA, Long Short-Term Memory (LSTM), Hybrid Forecasting Models, Time-Series Modeling, Power System Planning, Energy Demand Prediction

1. Introduction

Electrical load forecasting is an essential part of the operation, planning and energy management process of the modern power system. Predicting the demand for electricity accurately helps grid operators balance supply and demand in real time, schedule generation optimally, reduce operational costs, and helps maintain the reliability of the system. The expansion of smart grids, large scale integration of renewable energy, and electrification of transportation have caused electricity consumption behavior to increasingly become complex, nonlinear, and time varying, making it difficult for conventional forecasting methods[1][2].

Traditional time-series approaches such as Autoregressive Integrated Moving Average (ARIMA) and Seasonal ARIMA (SARIMA) have been used for electrical load forecasting as they have a relatively simple mathematical structure and are easy to interpret. Modeling these are based on lineage of the models that model the linear trending and seasonality of the past load data. On the other hand, practical electricity demand is a dynamic process driven by diverse factors such as weather, human behavior, economic activity, and political interventions, which bring along complex nonlinear and non-stationary traits that the solely statistical methods cannot be maximally reliable [3].

Deep Learning methods particularly Long Short-Term Memory (LSTM) networks have attracted great attention recently for load forecasting problems. LSTM models can learn long-term temporal dependencies in a time series and the complex nonlinear relationship of the time series data of electricity demand. Many studies have shown that LSTM-based models are more accurate than classical statistical models especially for medium- and long-term forecasting horizons [4] [5]. Deep learning, with its impressive prediction accuracy, lacks interpretability, requires more computing powers, and is sensitive to data quality. Moreover, recent studies [21] on short-term load forecasting also highlighted that combining classical time-series techniques with machine learning models can significantly improve predictive accuracy in modern power systems, particularly under complex and nonlinear demand patterns.

To address the shortcomings of each modeling method on its own, hybrid forecasting frameworks that combine statistical models with deep learning methods have been proposed with promising results. Mixed models (for example ARIMA–LSTM) are applied in an attempt to capture linear and seasonal components with statistical method and model residuals as nonlinear patterns with neural networks. State-of-the-art studies show that these hybrid methods gain higher precision and resilience when compared with individual models across different forecasting horizons and applications [6][7].

On the strength of these observations, this paper offers a wide-ranging examination of traditional time-series models (ARIMA and SARIMA) [8], a deep learning model (LSTM), and a combined ARIMA–LSTM [9] model for electrical load forecasting. We assess the performance and the stability of the models through several error metrics and for short-, medium-, and long-term forecasting horizons. The results obtained from this work are expected to be useful for practitioners on the use of hybrid modeling approaches for enhancing load forecasting performance in contemporary power systems.

1.1 Contributions

The contributions of this paper to the problem of electrical load forecasting are threefold.

- Conducts a complete comparative study between ARIMA, SARIMA, LSTM and hybrid ARIMA–LSTM models in terms of different forecast horizons (short-term, mid-term, and long- term).
- Proposes a hybrid ARIMA–LSTM model to combine linear, seasonal, and nonlinear components based on residual learning.
- Model performance is tested based on MAE, RMSE and MAPE to show that the model is robust and can be reliably used for various forecasting purposes.
- Spotlights research gaps and developing trends such as ensemble learning, transfer learning, XAI, and federated/edge-based forecasting for smart grid applications.

The rest of the paper is organized as follows: Section 2 presents a brief literature review and provides background on related work on electric load forecasting, which are mainly classified into statistical methods, deep learning based models and hybrid models. In Section 3, we describe the methodology used and it includes data acquisition, preprocessing and the implementation of statistical techniques, deep learning approaches and hybrid models. - Section 4 provides the results and discussion of forecast performance at different horizons with comparisons on accuracy and robustness between models. Lastly, Section 5 completes the study by presenting the main conclusions and shedding a light on potential future research avenues in advanced load forecasting strategies.

2. Literature Review

Recent research on electrical load forecasting can be broadly categorized into four main directions: (i) classical statistical time-series models, (ii) deep learning-based approaches, (iii) hybrid forecasting frameworks, and (iv) emerging trends such as explainable AI and edge-based forecasting.

2.1 Statistical Time series model

For decades, statistical algorithms like ARIMA, SARIMA and exponential smoothing methods have been exploited in the electricity load forecasting area. These approaches use historical data to describe trends, seasonality and autoregression features. The research (conducted 2020~2023) also validates the efficacy of ARIMA-based models for short-term forecasting considering stable demand condition [9]. However, they suffer in dynamic and nonlinear patterns as well as in the presence of external disturbances (e.g., extreme weather or policy changes) [10].

2.2 Deep Learning Based Forecasting

The state-of-the-arts of electrical load forecasting have made great progress due to deep learning techniques, which can model nonlinear and long-term temporal correlations. For smart meter and wide-area grid datasets, the LSTM, GRU and CNN-LSTM models have been highly studied for load prediction use cases. After 2020, the models based on LSTM method are consistently better than traditional statistical methods in all indicators like MAE, RMSE, and MAPE especially for medium and long term forecasts [12][13][14]. However, deep learning models depend on big datasets and extensive hyperparameter space exploration as well as high computing power which may prevent real-time application.

2.3 Hybrid Forecasting Models

Hybrid forecasting methods have become popular for their capacity to capitalize on both the statistical and machine learning models. In such frameworks, linear and seasonal components are often captured by statistical models whereas the nonlinear residual patterns are modelled using machine learning or deep learning models. Recent studies between 2020 and 2025 show that hybrid ARIMA–LSTM, SARIMAX–LSTM models outperforms single models in terms of forecast accuracy, especially under complex demand adoptions and renewable integration [15][7]. Hybrid models perform better than isolated deep learning methods, but they can lead to complex system design and are more sensitive to overfitting.

2.4 Emerging trend and Research Gaps

Recent advancements on ensemble learning, transfer learning, explainable AI (XAI), federated/edge-based forecasting emphasize robustness and flexibility to smart grid environments, and have been reviewed in the literature for electrical load forecasting. Meta- and ensemble-learning frameworks that combine heterogeneous base models (e.g., tree-based methods and LSTM) have achieved improved prediction accuracy and interpretability, frequently leveraging explainability tools such as SHAP to understand model behaviour [16]. Transfer learning and state-of-the-art deep architectures (i.e. Transformer-based models) have shown better generalization and performance in low data conditions [17]. Federated learning methods allow for joint model training over a large number of distributed devices while still being able to maintain the privacy of the data, but they introduce further computational and communication complexity overhead [18]. The author presents a AIOT enabled traffic congestion using Deep Neural Networks [19]. The authors present a survey on Operating systems applications for applications of the Internet of things [20]. Although there have been advances in either short-term or long-term horizons, comparable evaluation of statistical, deep learning and hybrid models on a common experimental framework is still lacking, which demonstrates the need for systematic benchmarking in multiple forecasting horizons.

3. Methodology

This part provides an overview of the designed forecasting platform that collects and assesses statistical, deep learning and hybrid models for estimating electrical load. The proposed approach aims at systematically capturing the linear, seasonal and nonlinear properties of electricity consumption via a several-stages modeling procedure.

3.1 Data Acqusition and Preprocessing

Using real historical hourly electricity load data, the proposed approach is examined experimentally. The dataset consists of time-indexed load values in conjunction with additional meteorological and calendar-based features. In order to guarantee data integrity and model reliability, a number of preprocessing operations are performed.

To maintain the continuity of the load sequence, missing observations are filled with time-based interpolation. This detects extreme values using the interquartile range (IQR) method, and replaces these extreme values with statistically consistent estimates to ensure minimal distortions during model training. We applied min–max normalization to all input features to ensure stable convergence of the neural network during training, defined as:

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (1)$$

The Augmented Dickey–Fuller (ADF) test is applied on the load series to check the stationarity of the series. If non-stationarity is detected, then differencing is performed. Also, we extracted temporal features such as, hour of the day, day of the week, and month of the year, to better learn periodic demand profiles.

3.2 ARIMA Model

The ARIMA model is employed to capture linear dependencies in the electricity load series. An ARIMA (p, d, q) process is mathematically expressed as:

The Autoregressive Integrated Moving Average (ARIMA) approach is used to detect linear dependencies in the electricity load series. Mathematically, an ARIMA (p, d, q) process can be expressed as:

$$Y_t = \sum_{i=1}^{p} \emptyset_i Y_{t-i} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j} + \epsilon_t \quad (2)$$

where Y_t denotes the load at time t, p is the autoregressive order, d is the differencing order, q is the moving average order, $\emptyset_i$ and θ_j are mode coefficients, and ϵ_t is a white noise error term. Using autocorrelation and partial autocorrelation diagnostics, the suitable parametric values are chosen.

3.3 Seasonal ARIMA Model

Since electricity demand tends to have seasonal variations that repeat over time, the model of the Seasonal ARIMA (SARIMA) is used to model the response. The SARIMA (p, d, q) $(P, D, Q)_m$formulation includes a non-seasonal and a seasonal component and is written as:

$$\Phi_P(B^m)\phi_p(B)\nabla_m^D \nabla^d Y_t = \Theta_Q(B^m) Q_q(B)\epsilon_t \quad (3)$$

Here, m is the seasonal period, $P, D,$ and Q are the seasonal autoregressive, differencing, and moving average terms, respectively, and B is the backshift operator. With this formulation, it can effectively model periodic load fluctuations such as daily and weekly patterns.

3.4 LSTM

A LSTM neural network is employed in order to represent nonlinear and long-range temporal dependencies in the demand of electricity. The LSTM architecture has gating mechanisms that ensure the flow of information using memory cells is controlled.

The working of an LSTM cell are characterized as below:

Forget gate:

$$f_i = \sigma(W_f[h_{t-1}, x_t] + b_f) \quad (4)$$

Input gate:

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \quad (5)$$

Cell state update:

$$C_t = f_t \odot C_{t-1} + i_t \odot tanhW_c[h_{t-1}, x_t] + b_c) \quad (6)$$

Output gate:

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \quad (7)$$

Hidden state:

$$h_t = o_t \odot \tanh{(C_t)} \quad (8)$$

where x_t represents the input vector, h_t is the hidden state, and C_t denotes the internal memory cell.

3.5 Hybrid ARIMA-LSTM Forecasting Framework

A hybrid ARIMA-LSTM model is created to combine the advantageous features of the statistical and deep learning models. The ARIMA model is first trained to reproduce the linear and seasonal structure, and as a result, a baseline forecast $\hat{Y}_t^{AEIMA}$obtained. The remaining series is then calculated as follows:

$$e_t = Y_t - \hat{Y}_t^{AEIMA} \qquad (9)$$

These residuals, which primarily contain nonlinear information, are modeled using an LSTM network to generate $\hat{e}_t^{LSTM}$. The final hybrid forecast is obtained by combining both components:

The LSTM network is used to predict these residues that mainly include nonlinear information, $\hat{e}_t^{LSTM}$ The hybrid forecast is calculated as a sum of the two parts:

$$\hat{Y}_t^{Hybrid} = \hat{Y}_t^{AEIMA} + \hat{e}_t^{LSTM} \qquad (10)$$

The approach is an improved forecasting technique that considers the linear, seasonal and nonlinear demand attributes as a combined model that improves forecasting.

3.6 Evalution Metrices:

Forecasting performance is assessed using three widely adopted error measures:

$$MAE = \frac{1}{N}\sum_{t=1}^{N} |Y_t - \hat{Y}_t| \qquad (11)$$

$$RMSE = \sqrt{(\frac{1}{N}\sum_{t=1}^{N}(Y_t - \hat{Y}_t)^2} \qquad (12)$$

where N denotes the number of observations.

$$MAPE = \frac{100}{N}\sum_{t=1}^{N} | \frac{Y_t - \hat{Y}_t}{Y_t} | \qquad (13)$$

Table.1 and Figure.1 signifies the whole process of the suggested hybrid ARIMA-LSTM forecasting framework.

Table 1:Stepwise Algorithm of the Proposed Hybrid ARIMA–LSTM Forecasting Framework

Step No.	Description	Reference Equation(s)
Step 1	Collect historical electricity load data and remove duplicate or missing records.	—
Step 2	Normalize the input data to ensure numerical stability during training.	Eq. (1)
Step 3	Perform stationarity testing and apply differencing if non-stationarity is detected.	Embedded in Eq. (2)
Step 4	Identify optimal ARIMA parameters ((p, d, q)) using autocorrelation analysis.	—
Step 5	Train the ARIMA model and generate baseline load forecasts.	Eq. (2)
Step 6	Compute the residual series between actual and ARIMA-predicted values.	Eq. (9)
Step 7	Convert residual values into supervised learning sequences using time-lag windows.	—
Step 8	Train the LSTM network to learn nonlinear residual patterns through gated memory operations.	Eqs. (4)–(8)
Step 9	Predict residual values using the trained LSTM model.	—
Step 10	Combine ARIMA forecasts and LSTM residual predictions to obtain the final hybrid forecast.	Eq. (10)
Step 11	Evaluate forecasting performance using MAE, RMSE, and MAPE metrics.	Eqs. (11)–(13)

Step 12	Output the final hybrid forecast along with performance evaluation results.	—

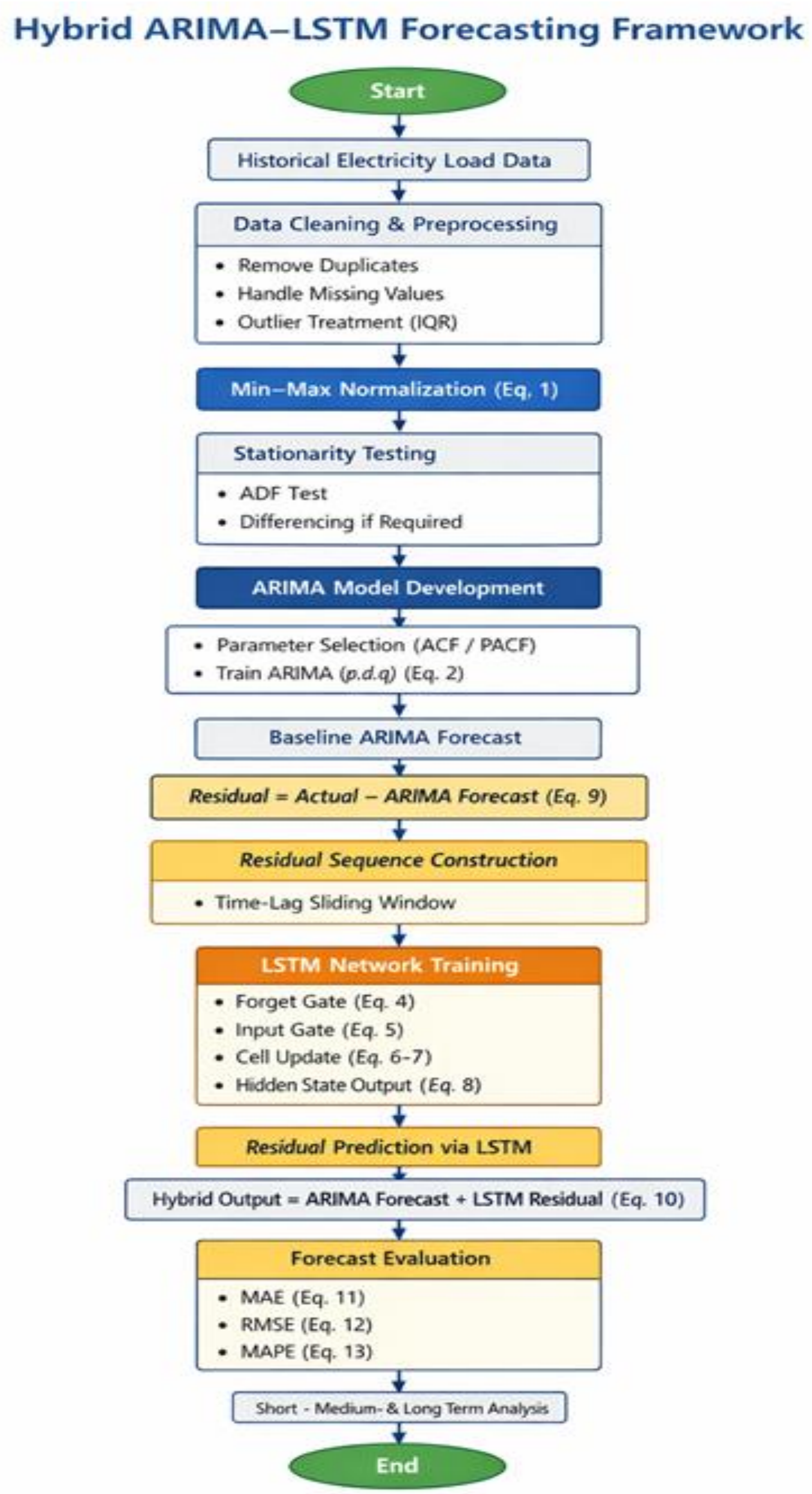

Figure 1: Proposed Hybrid ARIMA-LSTM forecasting framework

4. Results and Discussions:

This section presents a comprehensive evaluation of the forecasting performance of the ARIMA, SARIMA, LSTM, and hybrid ARIMA–LSTM models across multiple prediction horizons. Both quantitative metrics and visual analyses are employed to assess accuracy, robustness, and horizon-wise behavior.

4.1 Overall forecasting accuracy:

Table 2 provides the overall forecasting performance in the measured models of the models concerning MAE, RMSE, and MAPE. The hybrid ARIMA and LSTM model has the lowest values of errors of all measures, which means that it is the best predictor.

The LSTM minimizes the forecasting errors much compared to classical statistical models because it is sensitive to the complicated nonlinear time-dependencies. The hybrid framework also enhances performance by acquiring residual nonlinear relationships that cannot be well modeled by the linear ARIMA constituent. To offer a summary of the multi-metric visualization in a compact format, Figure. 2 aids inverted normalized radar plot (the higher the better) with the hybrid model having the greatest area under all the criteria, which proves its balanced and consistent accuracy.

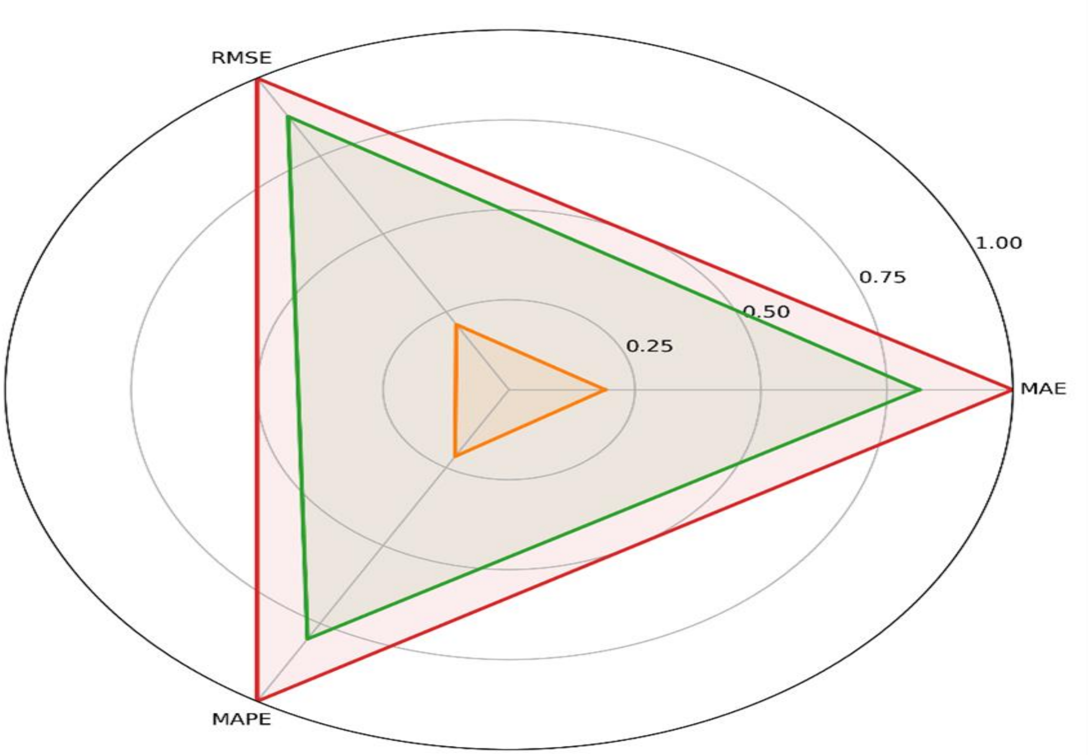

Figure 2 Normalized radar comparison of ARIMA, SARIMA, LSTM, and hybrid ARIMA–LSTM using inverted min–max scores for MAE, RMSE, and MAPE (higher is better).

Table 2: OVERALL FORECASTING ACCURACY (LOWER IS BETTER)

Model	MAE	RMSE	MAPE (%)
ARIMA	5.23	7.65	2.45
SARIMA	4.89	7.12	2.30
LSTM	3.78	5.43	1.89
Hybrid ARIMA–LSTM	**3.45**	**5.12**	**1.75**

4.2 Short-Term Forecasting Analysis:

Short-term forecasting performance is evaluated using MAE, as shown in Figure. 3. The hybrid ARIMA–LSTM model achieves the lowest short-term error, followed closely by the LSTM model. In contrast, ARIMA and SARIMA exhibit comparatively higher MAE values, reflecting their limited capability to adapt to short-term nonlinear variations.

These results indicate that incorporating nonlinear residual learning significantly enhances short-term prediction accuracy, particularly during rapid demand fluctuations.

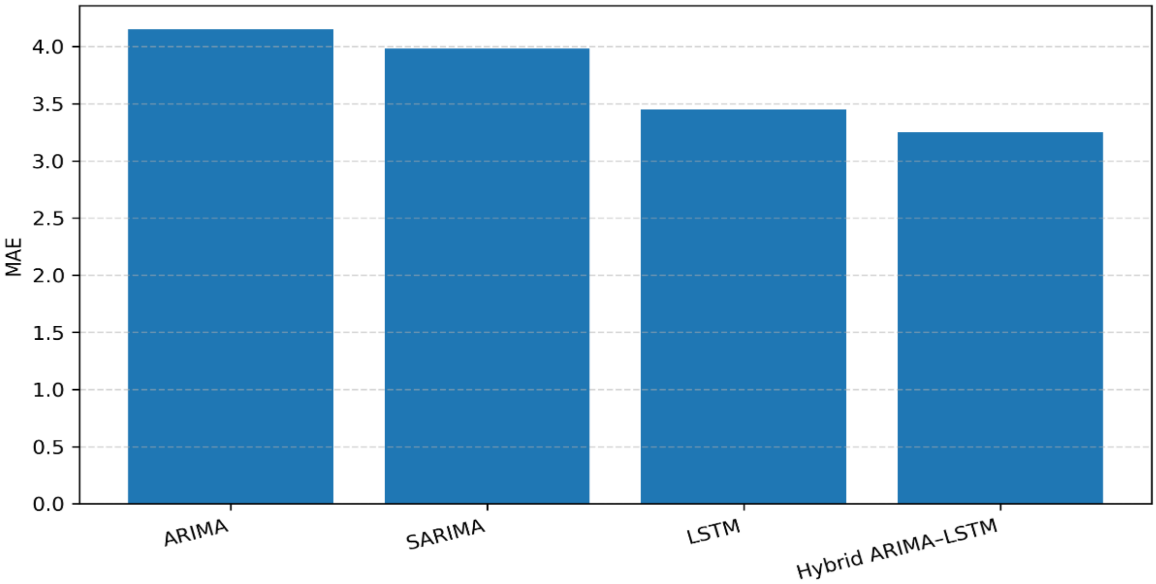

Figure 3: Short-term forecasting MAE comparison of ARIMA, SARIMA, LSTM, and hybrid ARIMA–LSTM (lower is better).

4.3 Medium-Term Forecasting Analysis:

Medium-term forecasting results are illustrated in Figure. 4. As the prediction horizon increases, error accumulation becomes more pronounced for classical statistical models. Both the LSTM and hybrid ARIMA–LSTM models maintain stable performance, demonstrating stronger generalization capabilities.

Notably, the hybrid model consistently achieves the lowest MAE, indicating its ability to mitigate error propagation by jointly modeling linear trends and nonlinear residual structures.

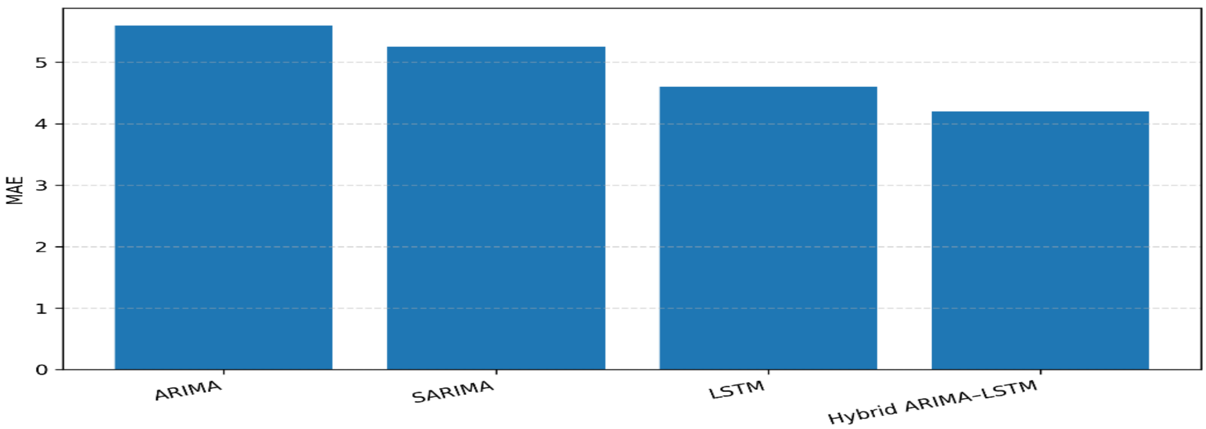

Figure 4: Medium-term forecasting MAE comparison of ARIMA, SARIMA, LSTM, and hybrid ARIMA–LSTM (lower is better).

4.4 Long-Term Forecasting Analysis:

Long-term forecasting accuracy is presented in Figure. 5. Over extended horizons, ARIMA and SARIMA experience substantial performance degradation, highlighting their sensitivity to long-term uncertainty and accumulated errors. While the LSTM model performs better, it still exhibits increasing error variance.

In contrast, the hybrid ARIMA–LSTM model demonstrates improved robustness and reduced error growth, confirming its suitability for long-range demand forecasting scenarios where stability and reliability are critical.

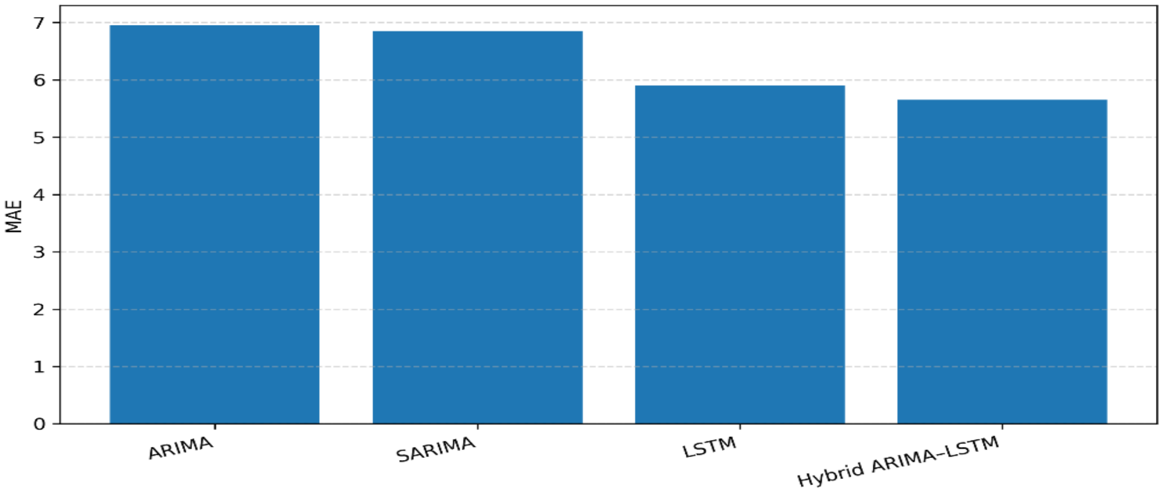

Figure 5: Long-term forecasting MAE comparison of ARIMA, SARIMA, LSTM, and hybrid ARIMA–LSTM (lower is better).

4.5 Horizon-Wise Comparative Evaluation:

Table 3 provides a horizon-wise comparison of MAE values across short-term, medium-term, and long-term forecasting tasks. The hybrid ARIMA–LSTM model consistently achieves the lowest MAE across all horizons.

Performance gains are particularly evident in medium- and long-term predictions, highlighting the effectiveness of residual-based hybrid learning in reducing error accumulation and enhancing forecasting robustness over extended horizons.

Table 3: MAE COMPARISON ACROSS FORECASTING HORIZONS

Model	Short-Term	Medium-Term	Long-Term
ARIMA	4.15	5.60	6.95
SARIMA	3.98	5.25	6.85
LSTM	3.45	4.60	5.90
Hybrid ARIMA–LSTM	**3.25**	**4.20**	**5.65**

5. Conclusions and Future Work:

5.1 Conclusions:

In this work along a complete comparative and hybrid modeling framework of electricity load forecasting is presented, combining classical time-series methods with modern deep learning architectures. Statistical models — including ARIMA and SARIMA — were originally used to model linear relationships and seasonality present in past load data.

Simultaneously, a LSTM was used to catch nonlinear temporal relationships and long-range dependencies which are generally hard to model through traditional methods alone.

A hybrid strategy of ARIMA–LSTM based on residual learning was developed to improve forecasting accuracy. The hybrid model then successfully combined statistical and neural paradigms by decomposing the load series into linear and nonlinear parts. Results of the experiment confirmed that the hybrid framework always outperformed models developed as individual models in all metrics and all forecasting horizons. Thus, it was particularly for the medium- and long-term predictions — where nonlinearities become ever more pronounced — that the largest gains in performance were obtained.

The results validate that classical time-series models are helpful in capturing the baseline trend and seasonality component but are unable to address the complex and dynamic nature of load patterns when used alone. With higher flexibility to adapt, the capabilities of the two models complement each other, thus providing a solid and scalable solution for electricity demand forecasting in real-world systems when integrated through a hybrid approach. In conclusion, the proposed approach shows some promising results in terms of the overall accuracy, stability and ability to generalization that makes it suitable for actual operational energy management and planning systems.

5.2 Future Work:

Inspired of the achievable results from this study, there are multiple research directions which are offered to extend the effectiveness of the proposed framework of forecasting. Firstly, the incorporation of additional exogenous input variables such as near real-time meteorological data, economic indicators, and demand-side management signals may enrich the contextual information and thus enhance forecast accuracy.

Second, deep learning models such as attention-based LSTM variants and Transformer-based temporal models can be explored to better model complex temporal dependencies. In particular, ensemble learning strategies which combine several neural models may also provide higher robustness with respect to highly unstable demand situations.

Third, future work can be undertaken to develop adaptive and online learning mechanisms where the forecasting model automatically updates as new data comes in. This kind of extension would find a great use in smart grid environments typical for fast changing consumption behaviour.

The inexact nature of hybrid modelling may also support a transformation into probabilistic forecasting, allowing not only for prediction intervals to be generated, but uncertainty estimates as well. This would furnish more informative guidance to decision making with respect to power system operation, risk-analysis and the energy market planning.

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