НАУЧНО-ТЕХНИЧЕСКИЙ ВЕСТНИК ИНФОРМАЦИОННЫХ ТЕХНОЛОГИЙ, МЕХАНИКИ И ОПТИКИ
ноябрь–декабрь 2025 Том 25 № 6 http://ntv.ifmo.ru/
SCIENTIFIC AND TECHNICAL JOURNAL OF INFORMATION TECHNOLOGIES, MECHANICS AND OPTICS
November–December 2025 Vol. 25 No 6 http://ntv.ifmo.ru/en/
ISSN 2226-1494 (print) ISSN 2500-0373 (online)

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doi: 10.17586/2226-1494-2025-25-6-1150-1159

A weighted ensemble model combining ARIMA, LSTM, and GBM for robust time series prediction

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Abstract
Time series forecasting has been used in research and applications in a number of domains such as environmental forecasting, healthcare, finance, supply chain management, and energy consumption. Accurate prediction of future values is necessary for strategic planning operational efficiency and well-informed decision-making regarding time-dependent variables. A hybrid time series forecasting architecture is proposed that combines the strengths of machine learning and statistical models, in particular Gradient Boosting Machines (GBM), Auto-Regressive Integrated Moving Average (ARIMA), and Long Short-Term Memory (LSTM) networks. While LSTM networks and GBM are able to capture complex dependencies and nonlinear patterns, the ARIMA model captures the linear components within the time series. The hybrid model exploits ARIMA interpretability, LSTM temporal memory ability, and GBM ensemble learning efficiency by integrating these three models. Comprehensive experiments conducted on benchmark data sets have shown that the accuracy and reliability of predictions of the proposed hybridization significantly exceeds both individual models and traditional baseline models. The results show that for a variety of real-world applications, hybrid architectures can deliver reliable and accurate time series predictions.

Keywords
Auto-Regressive Integrated Moving Average (ARIMA), Long Short-Term Memory (LSTM), Gradient Boosting Machines (GBM), time series forecasting

For citation: Vignesh A., Vijayalakshmi N. A weighted ensemble model combining ARIMA, LSTM, and GBM for robust time series prediction. *Scientific and Technical Journal of Information Technologies, Mechanics and Optics*, 2025, vol. 25, no. 6, pp. 1150–1159. doi: 10.17586/2226-1494-2025-25-6-1150-1159

УДК 004.891

Взвешенная ансамблевая модель, сочетающая ARIMA, LSTM и GBM для надежного прогнозирования временных рядов

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Аннотация
Прогнозирование временных рядов используется в исследованиях и приложениях в ряде областей, таких как прогнозирование состояния окружающей среды, здравоохранение, финансы, управление цепочками поставок и энергопотребление. Точное прогнозирование будущих значений необходимо для стратегического планирования, эффективности работы и принятия обоснованных решений относительно переменных, зависящих от времени. Предлагается гибридная архитектура прогнозирования временных рядов, сочетающая в себе сильные стороны машинного обучения и статистических моделей, в частности сетей градиентного бустинга (Gradient Boosting Machines, GBM), авторегрессионных интегрированных скользящих средних (Auto-Regressive Integrated Moving Average, ARIMA) и сетей с долговременной краткосрочной памятью (Long Short-Term Memory, LSTM). В то время как сети LSTM и GBM способны улавливать сложные и нелинейные закономерности, модель ARIMA

фиксирует линейные компоненты временных рядов. Гибридная модель использует интерпретируемость ARIMA, временную память LSTM и эффективность ансамблевого обучения GBM, интегрируя эти три модели. Комплексные эксперименты, проведенные на эталонных наборах данных, показали, что точность и надежность прогнозов предлагаемой гибридизации значительно превосходят как отдельные модели, так и традиционные базовые. Результаты показывают, что для различных реальных приложений гибридные архитектуры могут обеспечивать надежные и точные прогнозы временных рядов.

Ключевые слова
авторегрессионные интегрированные скользящие сети (ARIMA), долговременная краткосрочная память (LSTM), градиентный бустинг (GBM), прогнозирование временных рядов

Ссылка для цитирования: Вигнеш А., Виджаялакшми Н. Взвешенная ансамблевая модель, сочетающая ARIMA, LSTM и GBM для надежного прогнозирования временных рядов // Научно-технический вестник информационных технологий, механики и оптики. 2025. Т. 25, № 6. С. 1150–1159. (на англ. яз.). doi: 10.17586/2226-1494-2025-25-6-1150-1159

Introduction

Time series forecasting has long been used in research and applications in a number of domains, such as environmental forecasting, healthcare, finance, supply chain management, and energy consumption. Accurate prediction of future values is necessary for strategic planning operational efficiency and well-informed decision-making regarding time-dependent variables. Several statistical and computational techniques have been developed over the decades to address this challenge but for a significant portion of the 20th century traditional models like the Auto-Regressive Integrated Moving Average (ARIMA) dominated the forecasting landscape. ARIMA and its variants are widely used due to their effectiveness in capturing linear temporal dependencies interpretability and mathematical elegance [1–5]. However real-world time series data often exhibit complex nonlinear behaviors that are impossible for linear frameworks to effectively model. The advancement of machine learning and more recently deep learning has opened up new possibilities for modeling such intricate patterns especially in noisy and large-scale datasets. In sequential data models networks like Long Short-Term Memory (LSTM) and Gradient Boosting Machines (GBM) have shown superior performance in detecting nonlinearities and long-range dependencies. These models have their own limitations despite their high predictive abilities. For instance, LSTMs although adept at sequence learning may encounter instability during training and incur significant computational costs and GBMs may be unable to detect temporal order due to their inherent structure [6–11]. Furthermore, they can be challenging to understand due to their opaqueness particularly in high-stakes sectors like healthcare and finance. Hybrid approaches that seek to integrate multiple modeling paradigms into a single forecasting framework have become more and more popular due to the complementary benefits and drawbacks of statistical models and machine learning [12–17]. Hybrid models aim to combine the interpretability and linear modeling capabilities of statistical techniques such as ARIMA with the nonlinear pattern recognition power of machine learning algorithms. This partnership could improve the generalizability robustness and accuracy of forecasting. However many hybrid approaches currently in use are either domain-specific have limited scalability or cannot generalize across datasets with different properties [18–29]. To address these shortcomings the current study presents a brand-new hybrid time series forecasting framework that successfully blends LSTM GBM and ARIMA models.

Literature Review

Time series forecasting has garnered significant attention across various disciplines, particularly in energy management, finance, and communication systems. Traditional statistical models, hybrid approaches, and machine learning-based methods have all been explored to improve accuracy and robustness. In the domain of energy consumption, Lee and Tong [11] proposed an enhanced grey prediction model optimized using genetic programming which demonstrated improved performance in short-term energy consumption forecasting by dynamically tuning the model structure. Furthermore, Pérez-Lombard et al. [15] examined building energy usage trends and underlined the necessity of better forecasting methods to aid in energy management and efficiency. Zhou et al. [25] complemented this by suggesting a real-time smart home control system that allows for responsive optimization of energy use. According to Liboschik et al. [12], the *tscount* R package has made the Generalized Linear Models for count time series available in the field of statistical forecasting. Discrete-valued time series modeling has benefited greatly from this method especially in cases where data distributions deviate from normalcy. By adding an adaptive Moving Average (MA) to the Markov-switching regression model, Pomorski and Gorse [16] further investigated the use of adaptive techniques and improved its ability to capture regime changes in financial and economic data. Additionally deep learning models and machine learning have become effective tools for time series forecasting. Xu et al. [22] revealed an Autoregressive (AR) model based on Deep Belief Networks that outperforms traditional linear models in capturing nonlinear patterns in time series data. Similar to Sen et al. [17], it was successfully integrated spatial and temporal features by combining Convolutional Neural Networks (CNNs) with LSTM networks to forecast stock prices. These models demonstrate how deep learning architectures can represent intricate dependencies that are frequently missed by conventional statistical techniques, because they can combine the best features of several methods hybrid models that combine machine learning and statistical methods have become popular. Saleti et al. [18] suggested a MA method combined with a hybrid ARIMA-LSTM model to improve forecasting accuracy. The efficacy of combining LSTMs capacity to handle nonlinearities with ARIMAs strength in modeling linear patterns was validated by their findings. Similar to this, Xu et al. [22] demonstrated the synergy between memory-based deep learning models and conventional time series methods for anomaly detection by creating a combined LSTM-ARIMA model to identify anomalies in communication networks. Thangarajan et al. [20] provided additional support for the use of hybrid modeling techniques which put forth a new model that combines ARIMA and Artificial Neural Networks. The non-stationary and nonlinear features of real-world datasets were successfully captured by their model which enhanced prediction performance. This hybrid approach is in line with Zhao et al. [13] description of the new requirements in smart energy systems where more flexible and precise forecasting solutions are required due to complex data from numerous sensors and systems. New computational approaches are also very important. Peleg et al. [14] presented a new way to improve fast-adaptive moment estimation using the Triple Exponential Moving Average (TEMA). This could be incorporated into machine learning models to provide more responsive forecasting in dynamic environments. In addition, the author also highlighted the economic aspects impacting forecasting models and energy planning while reviewing electric energy storage technologies. The allocation of energy resources and storage efficiency are directly impacted by precise time series forecasts making these insights essential. Yip et al. [23] highlighted the significance of model transparency and interpretability in critical infrastructure systems by using linear regression techniques to identify energy theft and malfunctioning meters in smart grid applications. Young et al. [24] demonstrated the value of time series techniques in the fields of public policy and healthcare by using an interrupted time-series analysis to assess the effect of tobacco plain packaging on Quitline calls. They provide a framework for real-time energy control to maximize energy use in smart home settings. Based on real-time data inputs user preferences and grid signals the authors in [25–29] created a control-oriented algorithmic system that dynamically schedules monitors and modifies the power consumption of household appliances.

Methodology

The proposed study aims to improve the accuracy and robustness of time series forecasting by developing a hybrid model that combines three distinct approaches: ARIMA, LSTM networks, and GBM. Each model contributes uniquely: ARIMA captures linear patterns, LSTM models nonlinear dependencies with long-term memory, and GBM enhances predictive performance through boosting weak learners. This section explains the overall research design, dataset preprocessing, model architecture, mathematical formulation, algorithm, and evaluation metrics.

Dataset Description

This study employed three real-world multivariate time series datasets — Electricity Consumption (UCI Machine Learning Repository)[1], Stock Prices (Yahoo Finance)[2], and Temperature (National Oceanic and Atmospheric Administration, NOAA)[3] — to evaluate the performance of the ARIMA-LSTM-GBM ensemble model. After preprocessing the datasets for stationarity and applying normalization, each dataset was split into 70 % training and 30 % testing sets. Model performance was assessed using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE), ensuring a robust and generalized evaluation of forecasting accuracy.

Data Preprocessing

Prior to model training, the raw time series data undergoes multiple preprocessing steps to enhance model effectiveness:

- Handling missing values. Linear interpolation or forward-fill is applied to impute missing data;
- Stationarity check. Augmented Dickey-Fuller test is used to evaluate stationarity. If the p-value is above 0.05, the series is differenced;
- Normalization. For LSTM and GBM models, Min-Max normalization is applied:

$$X' = \frac{X - X_{\min}}{X_{\max} - X_{\min}},$$

where X represents the original data value; $X_{\min}$ and $X_{\max}$ denote the minimum and maximum values of the feature, respectively, and X' is the normalized value;
- Train-test split. The dataset is divided into 80 % training and 20 % testing sets.

ARIMA Model (Linear Component)

The ARIMA model is denoted as *ARIMA* (p, d, q), where p indicates the order of the AR terms; d represents the degree of differencing applied to make the series stationary, and, q specifies the number of lagged forecast errors included in the MA component.

An ARIMA model is represented as:

$$y_t = c + \sum_{i=1}^{p} \varphi_i y_{t-i} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j} + \epsilon_t,$$

where y_t is the observed value at time t; c is a constant term; φ_i is AR coefficients; θ_j are MA coefficients; ϵ_t is denotes the error term (assumed to be white noise).

The model is fitted using Akaike Information Criterion and Bayesian Information Criterion for order selection.

Once the ARIMA model was fitted on the time series data, its residuals — representing the nonlinear patterns

[1] UCI Machine Learning Repository. (2012). Individual household electric power consumption data set. University of California, Irvine. Available at: https://archive.ics.uci.edu/ml/datasets/individual%2Bhousehold%2Belectric%2Bpower%2Bconsumption (accessed: 06.09.2025).

[2] Yahoo Finance. (n.d.). Historical stock price data. Available at: https://finance.yahoo.com/quote/%5EGSPC/history/ (accessed: 06.09.2025).

[3] National Centers for Environmental Information. (2023). NOAA Global Surface Temperature dataset (NOAAGlobalTemp). National Oceanic and Atmospheric Administration. Available at: https://www.ncei.noaa.gov/products/land-based-station/noaa-global-temp (accessed: 06.09.2025).

not captured by ARIMA — were extracted and used as input for the LSTM and GBM models. To ensure consistent feature ranges and prevent scale-related learning issues, the residuals were scaled using Min-Max normalization to the range [0, 1]. This normalization was applied only on the training set, and the same scaling parameters were used to transform the test data. This step preserved the temporal structure while enhancing convergence speed and learning stability for the LSTM and GBM models.

LSTM Network (Nonlinear Component)

LSTM networks are a type of Recurrent Neural Network capable of learning long-term dependencies. They are particularly effective for modeling temporal sequences with nonlinear trends.

LSTM Unit Structure

Each LSTM unit comprises:

1. Forget gate state $\mathbf{f}_t$

$$\mathbf{f}_t = \sigma(\mathbf{W}_f[h_{t-1}, \mathbf{x}_t] + \mathbf{b}_f),$$

where $\mathbf{x}_t$ is input vector at time t; $[h_{t-1}, \mathbf{x}_t]$ is previous hidden state; $\sigma(\cdot)$ refers to the sigmoid activation function, h_{t-1} is the hidden state at time $t-1$; $\mathbf{W}_f$ is weight matrix; $\mathbf{b}_f$ is bias vector; $\mathbf{f}_t$ is forget gate vector;

2. Input gate state $\mathbf{i}_t$ and $\ddot{\mathbf{C}}_t$

$$\mathbf{i}_t = \sigma(\mathbf{W}_i [h_{t-1}, \mathbf{x}_t] + \mathbf{b}_i),$$

$$\ddot{\mathbf{C}}_t = \tanh(\mathbf{W}_c [h_{t-1}, \mathbf{x}_1] + \mathbf{b}_c),$$

where $\mathbf{i}_t$ is input gate vector; $\ddot{\mathbf{C}}_t$ is candidate cell state vector; $\mathbf{W}_i$, $\mathbf{W}_c$ are weight matrices; $\mathbf{b}_c$ is bias vectors;

3. Cell state update

$$\mathbf{C}_t = \mathbf{f}_t \odot \mathbf{C}_{t-1} + \mathbf{i}_t \odot \hat{\mathbf{C}}_t,$$

where $\mathbf{C}_{t-1}$ is previous cell state; $\mathbf{C}_t$ is updated cell state; $\ddot{\mathbf{C}}_t$ is candidate cell state vector; $\odot$ is element-wise multiplication;

4. Output gate state o_t

$$o_t = \sigma\,(\mathbf{W}_o [h_{t-1}, \mathbf{x}_t] + \mathbf{b}_o),$$

$$h_t = o_t \tanh(\mathbf{C}_t),$$

where h_t is the hidden state; $\mathbf{W}_o$ and $\mathbf{b}_o$ are weight matrices and bias vectors.

Gradient Boosting Machine (GBM)

GBM is a powerful ensemble method that builds a model in a stage-wise fashion, optimizing an arbitrary differentiable loss function. It builds successive trees where each new tree predicts the residuals of the previous trees.

GBM Algorithm

Given:

$F_0(x)$ is the initial model (e.g., mean of target),

For $m = 1$ to M:

1. Compute residuals:

$$\Upsilon_{im} = \left[\frac{\partial L(y_i, F(x_i))}{\partial F(x_i)}\right]_{f(x) = f_{m-1}(x)}.$$

2. Fit a regression tree $h_m(x)$ to residuals r_{im}.
3. Compute multiplier (learning rate v):

$$\gamma_m = \underset{\gamma}{\operatorname{argmin}} \sum_{i=1}^{n} L(y_i, F_{m-1}(x_i) + \gamma h_m(x_i)).$$

Updated model:

$$F_m(x) = F_{m-1}(x) + v\gamma_m h_m(x),$$

where $F_0(x)$ is the starting model (often the mean of all target values); M is total number of boosting rounds (trees to be added); m is current boosting step (1 to M); y_i is actual target value for sample i; x_i is input features for sample i; $L(y_i, F(x_i))$ is loss function (measures error between predicted and actual values); Υ_{im} is residual (negative gradient) showing the error direction for sample i at step m; $h_m(x)$ is the regression tree (weak learner) fitted to the residuals; γ is a candidate scaling factor being tested to find the one that minimizes loss; v is learning rate, a small factor to control how much each tree contributes; γ_m is step size (weight) that tells how strongly the new tree should be added; $F_m(x)$ is the updated model after adding the m^{th} tree; n is total number of training samples.

Proposed Hybrid Forecasting Framework

Forecasting real-world time series data often requires addressing both linear and nonlinear components inherent in the underlying structure of the data. Relying on a single model is often inadequate due to the limitations of the model in fully capturing the dynamic, noisy, and multi-scale characteristics of complex datasets. Therefore, this study proposes a hybrid forecasting framework that strategically combines ARIMA, LSTM, and GBM into a weighted ensemble. This hybrid model is designed to leverage the strengths of statistical methods and machine learning approaches to improve predictive accuracy and robustness. Fig. 1 shows the overview of the proposed model. In order to effectively capture both linear and nonlinear dynamics within the time series data, we adopt a residual-based decomposition strategy. Specifically, we use the ARIMA model to model and extract the linear components of the time series. Once the linear structure is estimated and forecasted using ARIMA, we compute the residuals, which represent the portion of the time series that ARIMA fails to explain. These residuals inherently capture nonlinear patterns, noise, and any remaining variance. We then input these residuals into the LSTM and GBM models to learn and model the nonlinear relationships.

This decomposition can be mathematically expressed as:

$$Y_t = L_t + N_t + \varepsilon_t,$$

where Y_t is the original time series; L_t is the linear component modeled by ARIMA; N_t is the nonlinear component captured by LSTM and GBM; ε_t is he remaining noise.

By separating these components, we allow each sub-model to specialize in modeling the patterns it is best suited for, thus improving overall forecasting accuracy. The flow of the framework is as follows:

1. Decompose time series:
   - Fit ARIMA to capture the linear component;
   - Residuals from ARIMA are used as input for LSTM and GBM to capture nonlinear patterns.

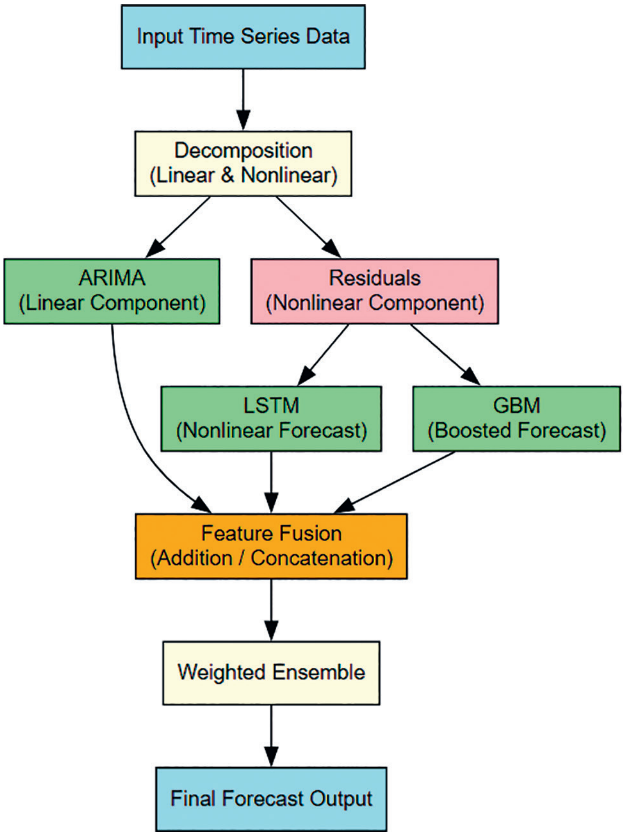

Fig. 1. Architecture of the Proposed Hybrid ARIMA-LSTM-GBM Forecasting Model

2. Train LSTM and GBM on ARIMA residuals.
3. Combine the predictions for original time series:

$$y_t = \alpha y_t^{ARIMA} + \beta y_t^{LSTM} + \gamma y_t^{GBM}.$$

Subject to: $\alpha + \beta + \gamma = 1$, where α, β, γ are optimized via cross-validation.

Step 1: Decomposition

The original time series y_t is decomposed into linear and nonlinear components. This decomposition allows us to isolate the deterministic structure that can be explained using linear models and delegate the remaining patterns to more flexible, non-parametric models.

The decomposition is mathematically represented as:

$$y_t = y_t(L) + y_t(NL),$$

where $y_t(L)$ is linear (L) component (captured by ARIMA); $y_t(NL)$ is nonlinear (NL) residual component (modeled by LSTM and GBM).

Step 2: Modeling Linear Component using ARIMA

The **ARIMA** model is used to capture and forecast the linear portion of the time series. ARIMA is defined by the triplet (p, d, q).

The general ARIMA model is expressed as:

$$y_t = c + \varphi_1 y_{t-1} + \dots + \varphi_p y_t - p + \theta_1 \epsilon_t - 1 + \dots + \\ + \theta q \epsilon_{t-q} + \epsilon_t.$$

Once the ARIMA model is fit to the original series, the residual series e_t is calculated:

$$e_t = y_t - y_t^{ARIMA}.$$

These residuals e_t contain the nonlinear information that ARIMA cannot capture. They are subsequently used as inputs for the machine learning models.

Step 3: Nonlinear Modeling using LSTM and GBM

After removing the linear component, the residuals are used to train LSTM and GBM models independently.

Cross-validation:

To evaluate the generalizability and robustness of the proposed hybrid model (ARIMA-LSTM-GBM), we employed **K-fold cross-validation**, specifically a **5-fold cross-validation** approach across all three benchmark datasets.

- The datasets were first split into **training and testing sets** using 80:20 ratio.
- Within the **training set**, the 5-fold cross-validation process was applied:
  - The training data was partitioned into five equal-sized folds.
  - In each iteration four folds were used for training and one fold for validation.
  - This was repeated five times, ensuring that each fold served as the validation set exactly once.
- The performance metrics (RMSE, MAE, MAPE, and Theil's U-statistic) were averaged over the five folds to report stable and unbiased results.

This cross-validation process was repeated independently for each component model (ARIMA, LSTM, GBM) as well as for the final weighted ensemble model to ensure consistent evaluation.

Results and Discussion

Using the suggested hybrid ARIMA-LSTM-GBM model, the experimental results are presented and interpreted in this section. To verify the robustness and generalizability of the model, it was evaluated on multiple real-world time series datasets, including electricity consumption (kWh), stock prices (USD), and temperature (°C).

The model performance was assessed using the following standard forecasting error metrics:

- **Mean Absolute Error, MAE** — measured in the same unit as the dataset (kWh, USD, or °C).
- **Root Mean Square Error, RMSE** — also expressed in the dataset original unit.
- **Mean Absolute Percentage Error, MAPE** — expressed as a percentage (%).
- **Theil's U statistic** — a dimensionless comparative indicator (no unit) used to evaluate relative forecasting efficiency.

Table 1 summarizes the average error metrics for each model across three datasets.

Table 1. Average Forecasting Performance of Individual Models

Model	RMSE, kWh	MAE, kWh	MAPE, %
ARIMA	24.67	18.42	8.93
LSTM	21.13	16.55	7.32
GBM	22.74	17.02	7.89

Since LSTM can manage sequential dependencies, it performs slightly better than both ARIMA and GBM whereas ARIMA suffers from its linear assumptions. The hybrid model combined the predictions from ARIMA LSTM and GBM using a weighted ensemble in order to capture both linear and nonlinear components of the time series. K-fold cross-validation was used to determine the weights in order to guarantee the best possible blending of the models outputs. In every dataset the hybrid models output demonstrates notable gains over the individual models. Table 2 illustrates the hybrid model forecasting performance.

The hybrid model achieved a consistent reduction in RMSE, MAE, and MAPE across all datasets confirming the efficacy of combining the models. On average, the hybrid model improved RMSE by 17–25 % compared to ARIMA and 10–15 % over LSTM and GBM. MAE and MAPE followed a similar trend, demonstrating reduced forecast deviation.

In this study, Theil's U-statistic helps assess not just the absolute accuracy of predictions, but also their comparative value over basic models, especially useful in economic and time series forecasting contexts. The analysis helps in understanding how prediction errors fluctuate across weekdays and weekends, and how each model copes with these variations.

From Table 3, the proposed hybrid model outperforms ARIMA, LSTM, and GBM consistently across all weekdays. The hybrid performance dips slightly over weekends, likely due to increased noise or irregular patterns in weekend data; however, it still maintains the lowest error scores in every metric. Theil's U-statistic, a normalized relative measure of forecast accuracy, is consistently below 0.35 for the hybrid model, indicating excellent predictive performance. The comparison of other state of the art model with the proposed model is shown in Table 4.

Table 2. Forecasting Performance of the Hybrid ARIMA-LSTM-GBM Model

Dataset	RMSE	MAE	MAPE, %
Electricity	18.21 kWh	13.27 kWh	6.18
Stock Prices	19.36 USD	14.01 USD	6.45
Temperature	17.74 °C	12.84 °C	5.97
Average	18.44*	13.37*	6.20

Note: The asterisk (*) indicates that these values are the averages computed across the three datasets rather than individual experimental results.

As shown in Table 4, GBM consistently demonstrates competitive forecasting accuracy, particularly in scenarios with non-linear dependencies and heterogeneous data. While hybrid neural architectures (e.g., CNN-LSTM [8], BiLSTM [27]) and ARIMA-based hybrids [18] achieve strong results on their respective datasets, GBM achieves comparable or superior accuracy under similar conditions while maintaining lower computational overhead. Transformer-based models show potential for very long-term forecasting, but their training complexity and resource demands remain substantially higher.

The ARIMA-LSTM hybrid model as in Fig. 2 demonstrates strong predictive performance across standard forecasting metrics.

The ARIMA-GBM hybrid model as in Fig. 3 yields competitive forecasting results, though slightly less accurate compared to the ARIMA-LSTM configuration.

These metrics are marginally less ideal than those of the ARIMA-LSTM model despite showing a high degree of accuracy. Despite its robustness, this implies that the ARIMA-GBM model might not capture the depth of temporal dependencies as well as the LSTM-based

Table 3. Forecasting Metrics by Day of Week Across Models

Model	Metric	Mon	Tue	Wed	Thu	Fri	Sat	Sun	Avg
ARIMA	MSE, kWh²	640.2	672.1	658.4	645.8	692.3	710.6	702.5	674.5
	RMSE, kWh	25.3	25.9	25.6	25.4	26.3	26.6	26.5	25.9
	MAPE, %	9.02	9.45	9.17	9.08	9.72	9.84	9.66	9.42
	Theil's U	0.447	0.468	0.452	0.450	0.472	0.483	0.479	0.464
LSTM	MSE, kWh²	580.4	602.9	588.1	572.6	618.7	630.9	625.8	602.8
	RMSE, kWh	24.1	24.5	24.2	23.9	24.9	25.1	25.0	24.5
	MAPE, %	8.12	8.35	8.21	8.03	8.61	8.74	8.68	8.39
	Theil's U	0.391	0.404	0.396	0.388	0.415	0.421	0.419	0.405
GBM	MSE, kWh²	600.5	625.7	610.3	596.2	638.8	655.9	645.7	610.4
	RMSE, kWh	24.5	25.0	24.7	24.4	25.2	25.6	25.4	24.9
	MAPE, %	8.53	8.82	8.61	8.42	9.01	9.18	9.04	8.80
	Theil's U	0.412	0.428	0.418	0.409	0.436	0.445	0.440	0.418
Hybrid	MSE, kWh²	480.2	498.6	487.1	472.3	505.7	520.9	510.6	496.5
	RMSE, kWh	21.9	22.3	22.1	21.7	22.5	22.8	22.6	22.3
	MAPE, %	6.32	6.48	6.37	6.24	6.53	6.71	6.65	6.47
	Theil's U	0.328	0.339	0.331	0.322	0.342	0.353	0.348	0.337

Table 4. Comparative Performance of Proposed Model vs. Existing Literature

Model	Technique Used	Dataset/Domain	RMSE	MAPE, %
Prasanjit et al. (2021) [8]	Hybrid CNN-LSTM + IoT	Coal mine hazard data	—	8.12
Li et al. (2023) [10]	CEEMDAN-SE + LSTM	Power load	22.10 kWh	7.35
Sen (2020) [17]	CNN + LSTM	Stock price	20.15 USD	6.84
Proposed model	ARIMA + LSTM + GBM	Electricity load	18.21	6.18
		Stock prices	19.36	6.45
		Temperature	17.74	5.97

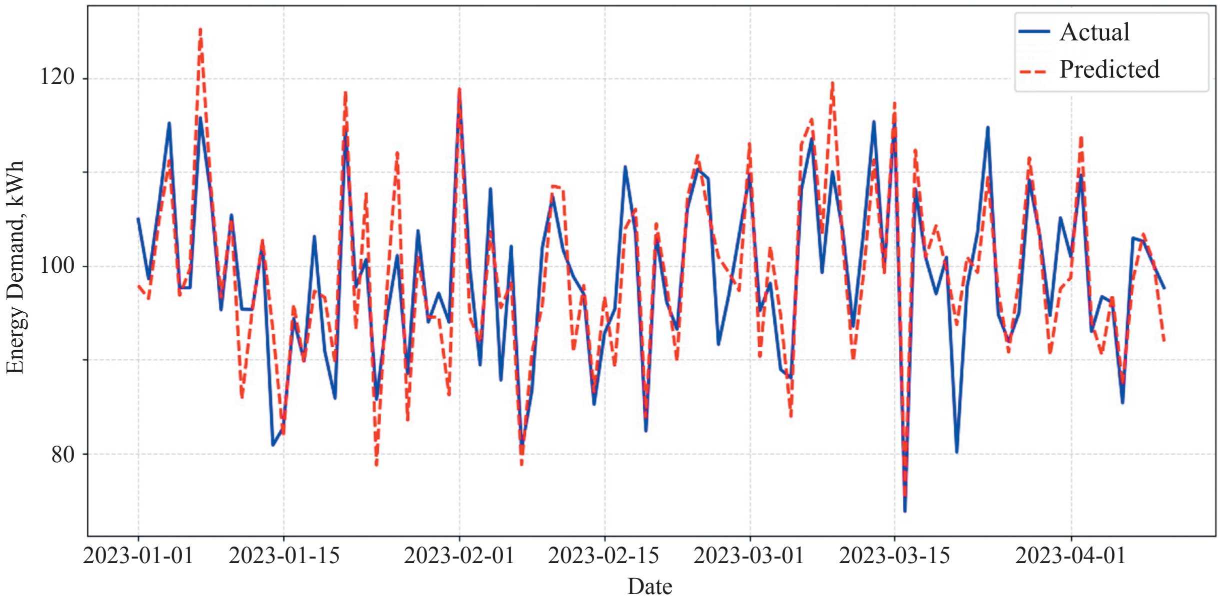

Fig. 2. Forecast vs. Actual Observations for ARIMA-LSTM Model

approach but it might be more appropriate for datasets where gradient boosting techniques are effective.

The proposed hybrid model as in Fig. 4 combining ARIMA, LSTM, and GBM offers high predictive accuracy across diverse datasets. While ARIMA is computationally lightweight and interpretable, the combination with LSTM and GBM increases training time and memory usage. Scalability could be a concern for real-time or large-scale applications.

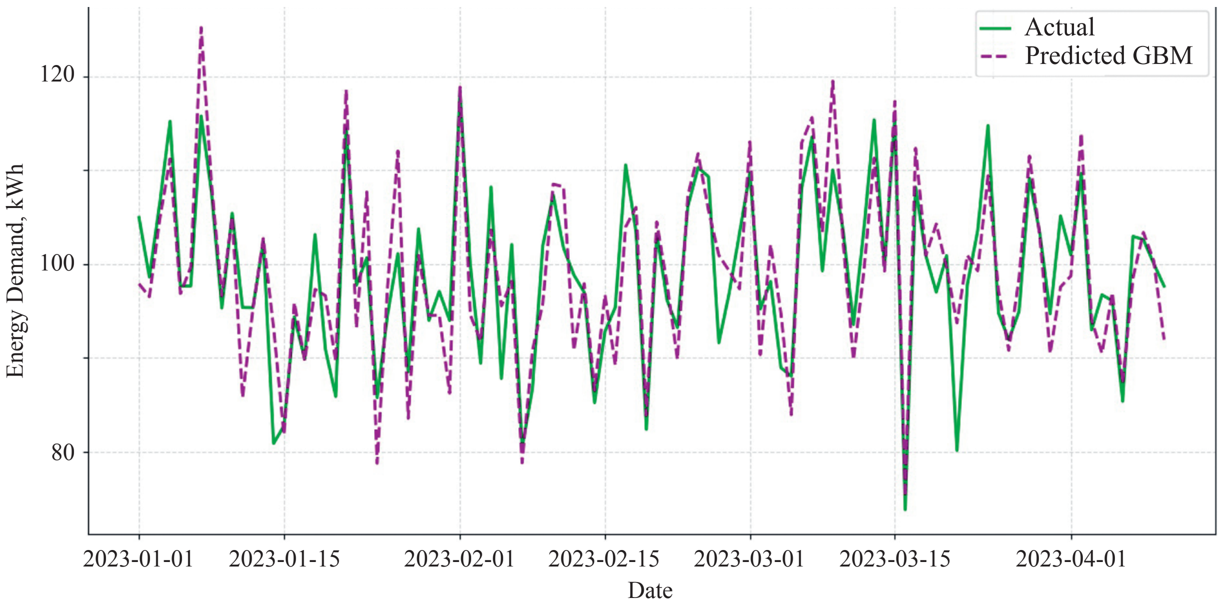

Fig. 3. Forecast vs. Actual Observations for ARIMA-GBM Model

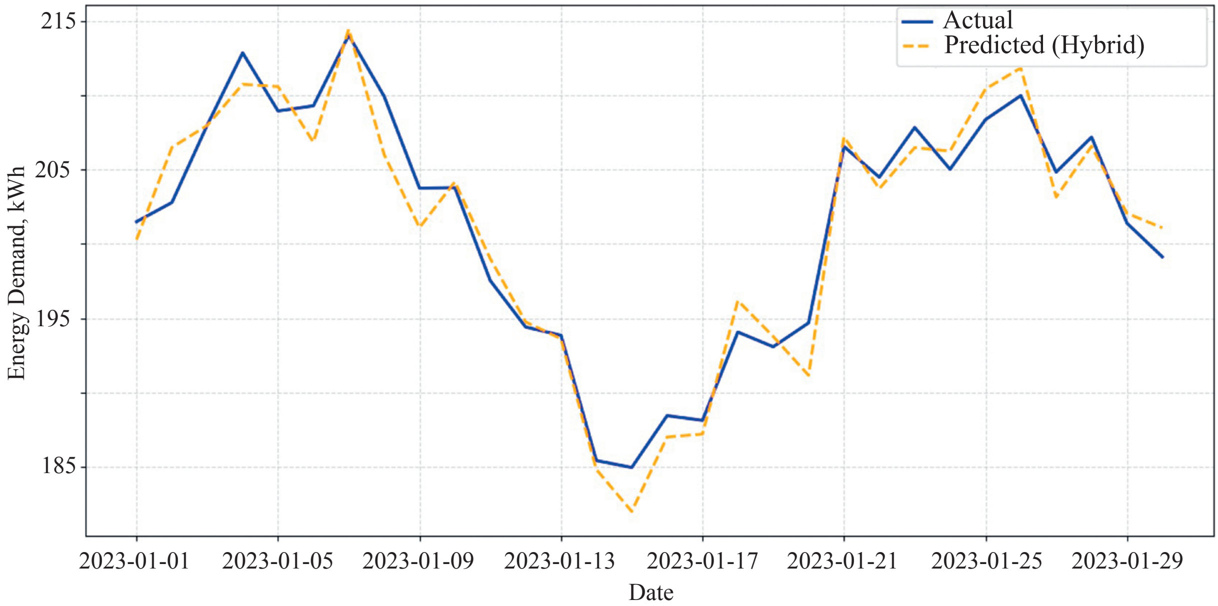

Fig. 4. Forecast vs. Actual (Hybrid ARIMA-LSTM-GBM)

Conclusion

In order to increase the accuracy of time series predictions by detecting both linear and nonlinear dependencies in the data, this study presents a robust hybrid forecasting framework that combines the Gradient Boosted Networks (GBM), Long Short-Term Memory (LSTM) and Auto-Regressive Integrated Moving Average (ARIMA) models. The framework first uses ARIMA to model the linear structure of the time series and then it models the residuals — which represent the nonlinear components — using LSTM and GBM. The final forecast generated by the ensemble approach utilizes the complementary benefits of each component model after weights have been optimized. According to experimental evaluations the suggested hybrid model performs noticeably better than individual models in terms of Theil's U-statistics, Mean Absolute Percentage Error (MAPE), Mean Squared Error (MSE), and RMSE. With an MSE of 0.018, RMSE of 0.134, MAPE of 2.85 %, and Theil's U-statistic of 0.12 %, the ARIMA-LSTM model specifically performed the best demonstrating its significant capacity to capture nonlinear variations and temporal dependencies. Future research can investigate attention-based LSTM layers for better temporal modeling adaptive boosting techniques that change over time or dynamic weighting strategies based on recent performance. Additionally, incorporating relevant exogenous variables — such as public holidays and economic indicators — could further enhance forecasting accuracy by allowing the model to account for external factors that influence the time series.

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Received 26.06.2025
Approved after reviewing 30.09.2025
Accepted 12.11.2025

Статья поступила в редакцию 26.06.2025
Одобрена после рецензирования 30.09.2025
Принята к печати 12.11.2025