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Electricity Consumption Forecasting Using the LSTM Method in Iran's Industrial Sector

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ABSTRACT

Objective: The growing energy crisis, particularly in the electricity sector, caused by rising demand and depletion of fossil fuel resources, necessitates accurate electricity consumption forecasting. This study aims to develop a reliable prediction model using Long Short-Term Memory (LSTM) networks to capture long-term temporal dependencies and nonlinear patterns in electricity usage.

Methods: Key factors influencing electricity consumption were identified, and historical data were normalized and split into training and testing sets. A two-layer LSTM network with ReLU activation was employed to model electricity consumption patterns. The model's predictive performance was evaluated using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Coefficient of Determination (R^2), and Mean Absolute Percentage Error (MAPE).

Results: The LSTM model effectively captured complex temporal patterns in electricity consumption, producing predictions that closely matched actual values. The evaluation metrics demonstrated the model's high accuracy and robustness compared to classical forecasting approaches.

Conclusion: The proposed LSTM-based approach provides a practical tool for accurate electricity consumption forecasting. These results can support energy planning, optimize electricity management, and reduce the economic and social costs associated with overconsumption, contributing to more sustainable energy provision.

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1. Introduction

Electricity, as one of the most versatile and widely utilized forms of energy, holds paramount importance in modern society due to its ease of conversion, relative safety, environmental advantages, and efficient transmission capabilities. In 2017, electricity accounted for 11% of total final energy consumption (Tavanir Specialized Holding Company, 2023). Beyond fulfilling the energy requirements of various economic sectors, electricity plays a pivotal role in enhancing quality of life, advancing social welfare, driving industrial development, and increasing national income. Consequently, it is regarded as a fundamental infrastructure service and a critical driver of economic growth.

Electric power infrastructure and equipment represent essential public assets, with their development having a direct and measurable impact on economic progress. This relationship is particularly pronounced in developing countries, where the success of industrial initiatives and improvements in public welfare are heavily dependent on the expansion and reliability of the electricity sector (Shirsath & Singh, 2010). Moreover, ensuring a stable and sustainable electricity supply requires meticulous planning and accurate consumption forecasting. The increasing number of electricity consumers, as illustrated in Figure 1, underscores the growing demand for electricity and the necessity of effective management strategies (Tavanir Specialized Holding Company, 2023).

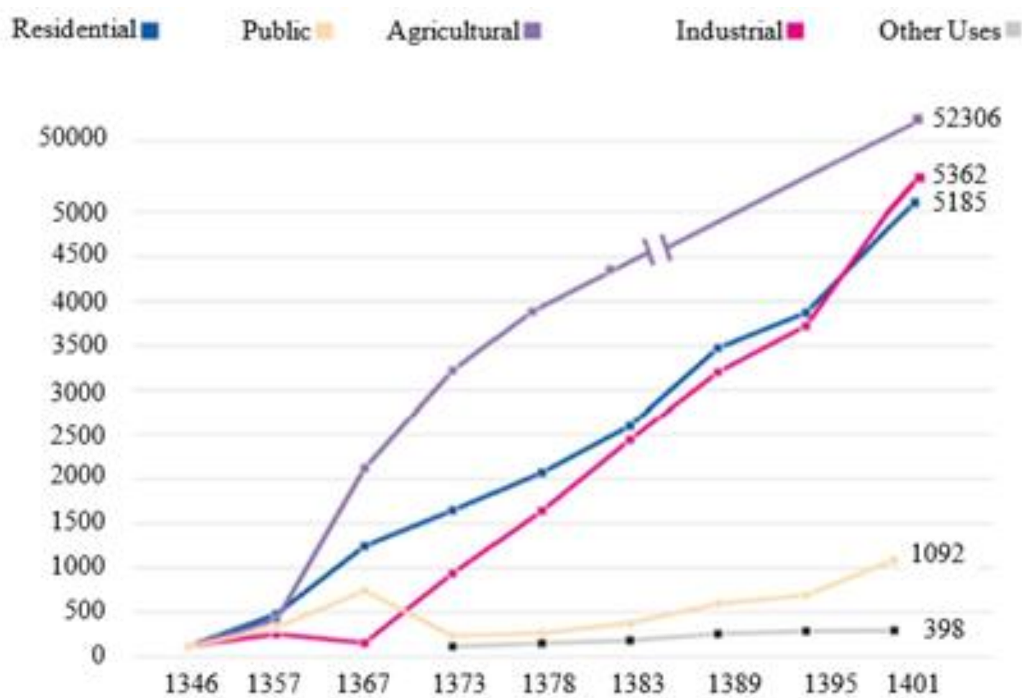

Figure 1. Electricity Consumer Growth Index.

Numerous studies have been conducted in recent years to identify the key parameters influencing electricity consumption growth. These studies indicate that factors such as population dynamics, Gross Domestic Product (GDP), electricity tariffs, and consumption control policies (including the number of consumers) are among the most significant determinants of electricity consumption patterns (Edomah, 2021).

However, electricity consumption has exhibited a persistent upward trajectory in recent years, driven by factors including population growth, urbanization, improved living standards, tariff adjustments, climate variations, and the expansion of industrial and commercial activities. Notably, this trend has continued even during periods of low or negative economic growth, and the implementation of targeted subsidy reform policies has had minimal impact on curbing consumption growth.

Without fundamental reforms in electricity consumption management, the country faces substantial economic and social consequences. The rapid escalation of energy consumption in Iran has raised serious concerns regarding the nation's capacity to maintain its energy export potential in the coming decades (Khiabani, 2016).

The electricity industry serves as a critical infrastructure sector underpinning both industrial advancement and social welfare provision. Given the sharp increase in electricity consumption and the growing challenges in securing necessary resources, the implementation of optimized consumption management solutions has become increasingly urgent. Achieving this optimization requires a thorough analysis of the entire electricity supply chain, from generation to final consumption. Forecasting electricity consumption in a power network, as depicted in Figure 2, necessitates a comprehensive understanding of the energy transmission pathway from generation to end-use. Electrical energy, after generation at power plants, is transmitted through step-up transformers and high-voltage transmission lines (765, 500, 345, 230, and 138 kV) to reach various consumer categories. Accurate consumption prediction at each stage of this transmission chain contributes significantly to optimizing electricity generation and distribution ("Electric power distribution," n.d.).

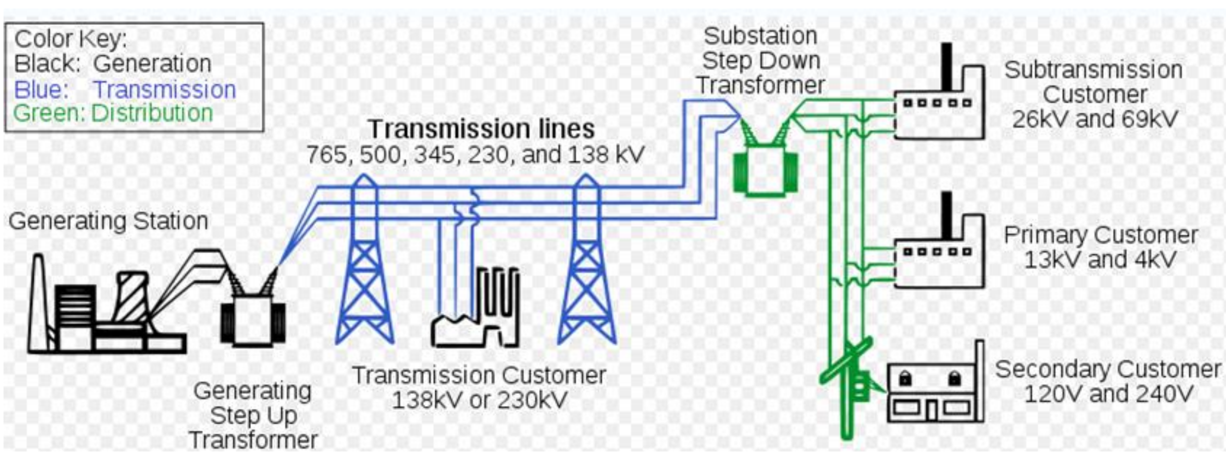

Figure 2. Electricity Supply Chain.

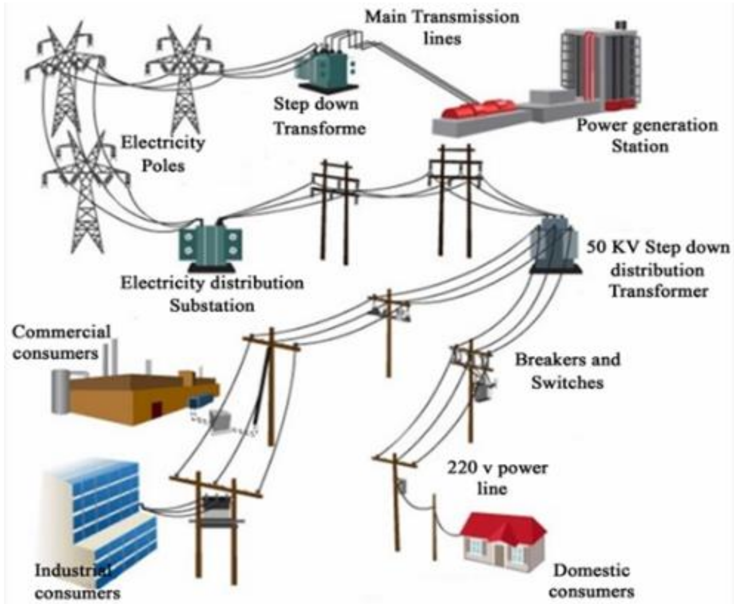

Figure 3. The Interconnection of Networks in the Electricity Supply Chain.

Figure 3 provides detailed insight into the distribution network structure, illustrating the connection pathways for commercial, industrial, and residential consumers (Selvaraj et al., 2014). Among these consumer categories, industrial users play a particularly crucial role in load management due to their substantial share of total consumption and their operational flexibility. Precise consumption forecasting for industrial consumers, especially during peak demand periods, can substantially improve grid management efficiency. Industrial facilities possess the capability to minimize load during peak hours and shift high-consumption activities to off-peak periods. Consumption pattern prediction in this sector, based on the network structure shown in Figure 3, enables more effective planning for electricity generation and distribution.

On the other hand, industrial consumers are notably more sensitive to power interruptions than other user categories. Therefore, strategic placement of industrial facilities in areas with minimal electrical disruptions becomes essential for ensuring operational continuity and economic efficiency. This underscores the critical importance of accurate consumption forecasting and proactive planning for reliable electricity supply in industrial zones.

The implementation of consumption management policies and precise electricity demand forecasting in the industrial sector is therefore essential, particularly given the complex structure of the distribution network illustrated in the figures. Accurate consumption forecasting within this framework can contribute significantly to cost reduction, enhanced grid stability, and optimized electricity generation and distribution.

This study employs the Long Short-Term Memory (LSTM) method for forecasting electricity consumption in the power industry. Subsequently, the model's validity is evaluated using standard error measurement metrics to assess the accuracy and reliability of the electricity consumption predictions.

2. Literature Review

In the Iranian economy, petroleum products, natural gas, and electricity are fundamental to economic stability and energy security. However, economic policies centered on low energy pricing have impeded consumption optimization and hindered productivity growth. Subsidized energy prices have resulted in increased consumption and inefficiency, particularly within the industrial sector. Furthermore, due to the monopolistic nature of energy transmission and limited storage infrastructure, electricity prices in Iran remain substantially lower than in developed nations. Empirical evidence, discussed in subsequent sections, demonstrates that energy demand in Iran exhibits price and income inelasticity.

Early studies on electricity demand elasticity established important baseline findings. Ang (1988) analyzed electricity demand across East Asian countries, revealing that nations with higher per capita income exhibit lower income elasticity of electricity demand. Similarly, Eltony and Mohammad (1993) found that government subsidies in Gulf Cooperation Council (GCC) countries resulted in inelastic electricity demand. Al-Aziz and Hawdan (1999) further demonstrated that price and income elasticity of energy demand varies significantly across different countries and economic contexts.

Within the Iranian context, several foundational studies have examined electricity demand characteristics. Fakhraei (1992) and Kazemi (1996) estimated electricity demand functions for the industrial sector, both concluding that electricity demand in this sector demonstrates inelasticity with respect to price and income fluctuations. Subsequent research by Asgari (2001) and Samadi et al. (2009) reinforced these findings, showing that Iranian electricity consumers exhibit minimal responsiveness to price and income changes. Changi Ashtiani and Jallouli (2012) and Latifalipur et al. (2015) employed various econometric models to estimate electricity demand functions across residential and industrial sectors, consistently finding evidence of inelastic demand. Additionally, Sadegi and Ebrahimi (2013) identified a positive and significant relationship between financial development and electricity consumption in Iran.

Recent advances in artificial intelligence and machine learning have revolutionized electricity consumption forecasting methodologies. Raeisi-Gahruei and Beheshti (2022) implemented a multilayer perceptron neural network (MLP) optimized with the Zagan algorithm for electricity consumption prediction, demonstrating superior performance compared to alternative heuristic algorithms. Saranj and Zolfaghari (2022) combined the Ant Colony Optimization (ACO) algorithm with ARIMAX-GARCH models, utilizing wavelet decomposition to forecast electricity consumption across different time horizons. In the domain of grid resilience, Lee et al. (2024) developed predictive models for power outages caused by winter storms using ensemble machine learning methods including Random Forest, XGBoost, and Support Vector Machines (SVM). Rizvi (2024) explored the application of SVM and neural networks in smart grid systems, focusing on real-time energy optimization and renewable energy integration.

Statistical and hybrid modeling approaches have also demonstrated significant potential. Rabbi et al. (2020) employed the ARIMAX model incorporating external variables such as population growth and GDP to forecast electricity demand in Bangladesh, showing that multivariate models outperform univariate alternatives. Collino and Ronzio (2021) applied ARIMAX methodology to short-term and very short-term photovoltaic generation forecasting, integrating meteorological and satellite data as exogenous inputs. Arjmand et al. (2019) emphasized the critical role of data preprocessing and transformation techniques in enhancing forecast accuracy, demonstrating that Box-Cox transformations yield superior results compared to conventional methods. Armano and Pegoraro (2022) proposed novel techniques for feature importance assessment in electricity demand forecasting, facilitating interpretation of neural network hidden layer dynamics.

In electricity price forecasting, Jalebi et al. (2023) utilized time series models including Ordinary Least Squares (OLS), GARCH, and copula methods to predict electricity prices in spot and forward markets, finding that trigonometric functions effectively capture seasonal price behavior. Ding et al. (2018) applied a modified gray prediction model to forecast electricity consumption in China, demonstrating improved accuracy relative to benchmark models.

Table 1 provides a comprehensive summary of recent studies in electricity consumption forecasting, categorized by methodology, geographic context, and key findings. The table highlights the evolution from traditional econometric approaches to advanced machine learning techniques, demonstrating the increasing sophistication of forecasting methodologies in recent years.

Table 1. Literature Review.

Reference	TSA	ARIMA/ARIMAX	ARDL	ANN	LSTM	GARCH	ML	HM	EG	ET	ED	EC	FN	SG	RE	PE	IE	CF	PF
Fakhraie (1992)	✓											✓					✓	✓	✓
Eltony & Mohammad ,(1993)	✓											✓					✓	✓	
Kazemi (1996)												✓					✓	✓	✓
Aang (1998)	✓																		
Al-Aziz & Hawilan (1999)	✓								✓			✓					✓	✓	✓
Asgari (2002)	✓			✓								✓					✓	✓	✓
LotfaliPour et al. (2004)	✓											✓					✓	✓	✓
Shi & Palsk (2005)	✓									✓							✓		✓
Metcalf (2008)	✓									✓							✓	✓	✓
Liu & Han (2008)	✓							✓		✓									✓
Wing (2008)	✓									✓							✓	✓	✓
Samadi (2008)		✓										✓					✓	✓	✓
Zhenxiang & Stephens (2010)				✓				✓	✓		✓	✓							✓
Ashtiani & Jalili (2012)	✓											✓					✓	✓	✓
Sadeghi & Ebrahimi (2013)	✓		✓									✓						✓	✓
LotfaliPour et al. (2015)	✓							✓				✓					✓	✓	✓
Ding et al. (2018)	✓							✓	✓	✓		✓							✓
Arjmand et al.(2019)																			
Rabbi et al. (2020)				✓				✓											✓
Collino & Ronzio(2021)	✓	✓							✓							✓			
Raeisi-Gahruei1& Beheshti(2022)																			
Saranj & Zolfaghari (2022)		✓			✓	✓		✓	✓					✓					✓
Armano & Attilio Pegoraro (2022)				✓															✓
Jalebi et al. (2023)	✓					✓													
Rizvi (2024)				✓				✓							✓	✓			✓
Leea et al. (2024)								✓				✓							
This research					✓							✓							✓

TSA: Time Series Analysis, **ARDL**: Autoregressive Distributed Lag Model, **ANN**: Neural Networks, **LSTM**: Long Short-Term Memory; **ML**: Machine Learning; **GARCH**: Generalized Autoregressive Conditional Heteroskedasticity; **HM**: Hybrid Models; **EG**: Electricity Generation; **ET**: Electricity Transmission; **ED**: Electricity Distribution; **EC**: Electricity Consumption; **FN**: Fuzzy Networks; SG: Smart Grid; RE: Renewable Energy; **PE**: Price Elasticity; **IE**: Income Elasticity; **CF**: Consumption Forecasting; **PF**: Price Forecasting.

3. Methodology of the Study

3.1 LSTM (Long Short-Term Memory)

LSTM (Long Short-Term Memory) networks are a type of RNN that incorporate additional memory features to address challenges such as the vanishing and exploding gradient problems (Ghulam et al., 2019) .These networks are composed of interconnected blocks known as memory cells, specifically designed to tackle these issues. The memory cells contain gates that determine whether information should be removed from or added to the cell state, as illustrated in **Error! Reference source not found.**. By utilizing these gates, LSTMs are able to model long-term dependencies in input data, which is particularly beneficial for text classification tasks. Overall, LSTMs represent an advanced approach compared to traditional RNNs, enabling more effective handling of complex and sequential data.

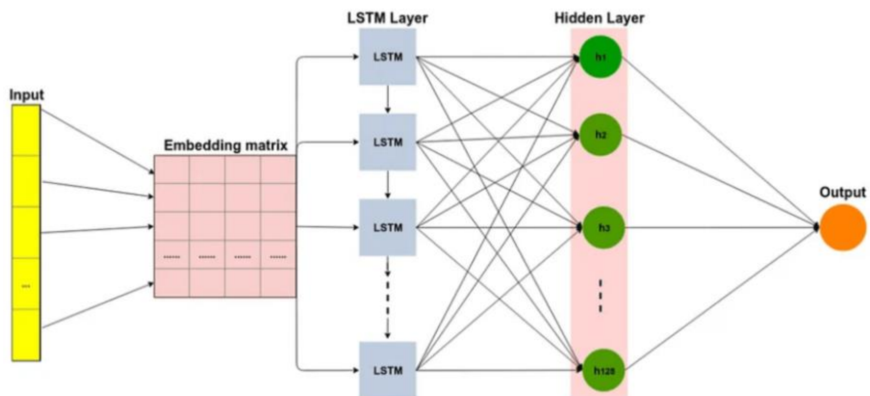

Figure 4. Architecture of Long Short-Term Memory (LSTM).

The architecture of LSTM consists of several gates and memory cells, which enable the network to store and retain information over time and across different time scales (Tran et al., 2016). An LSTM has an input x_t, which may either be the output of a Convolutional Neural Network (CNN) or a direct input sequence. Additionally, the inputs h_{t-1} and c_{t-1} are taken from the previous time step, and the output of the LSTM at this time step is o_t. The LSTM also generates c_t and h_{t-1} for use in the subsequent time step.

Forget Gate: The forget gate determines which information from the previous cell state should be discarded (Kim et al., 2016). This gate takes as input both the previous cell state C_{t-1} and the current input x_t, and produces a value between 0 and 1 for each component of the cell state. The corresponding formula for the forget gate is shown in formula (1):

$$f_t = \sigma\left(W_f.[h_{t-1}, x_t] + b_f\right) \tag{1}$$

Input Gate: The input gate regulates the amount of new information that should be added to the cell state. This gate calculates two values: the candidate values $\widetilde{C_t}$ (the candidate new cell state) and the input gate i_t, which determines the extent to which the candidate values should be incorporated into the cell state. The corresponding formulas for the input gate are given by formulas (2) and (3):

$$i_t = \sigma(W_i.[h_{t-1}, x_t] + b_i) \tag{2}$$

$$\widetilde{C_t} = \tanh(W_C.[h_{t-1}, x_t] + b_C) \tag{3}$$

The input gate, denoted as i_t , determines the extent to which the candidate cell state should be added to the current cell state. The candidate new cell state is represented by $\widetilde{C_t}$. The weight matrices for the input gate and the candidate cell state are denoted as W_i & W_c , respectively, while their corresponding bias terms are represented by b_i & b_C. The activation functions used in the process include the sigmoid function σ and the hyperbolic tangent function (tanh), which play crucial roles in regulating the flow of information within the LSTM cell.

In LSTM, $(\widetilde{C_t})$ is the candidate cell state, generated using the tanh function and modulated by the input gate i_t before updating the final cell state C_t. The tilde (~) notation signifies its intermediate role in the memory update process.

Update Cell State: The new cell state C_t is computed by combining the forget gate, the input gate, and the previous cell state. This is done by retaining part of the previous cell state using the forget gate and adding new information from the input gate and the candidate cell state. The formula for updating the cell state is given by formula (4):

$$C_t = f_t . C_{t-1} + i_t . \widetilde{C_t} \tag{4}$$

The forget gate output, f_t determines how much of the previous cell state C_{t-1} is retained, while the input gate output, i_t regulates the contribution of the candidate cell state $(\widetilde{C_t})$ to the new cell state. These mechanisms collectively control the flow of information and memory retention in the LSTM unit.

Output Gate: The output gate determines the next hidden state h_t and the output of the LSTM cell. It combines the current input x_t and the previous hidden state h_{t-1} to calculate the output gate o_t and the final output. The corresponding formula for the output gate is given by formulas (5) and (6):

$$C_t = f_t . C_{t-1} + i_t . \widetilde{C_t} \tag{5}$$

$$h_t = o_t . \tanh(C_t) \tag{6}$$

Here, o_t represents the output gate, which controls how much of the updated cell state contributes to the final output. The output gate is computed using the sigmoid activation function σ, applied to a weighted sum of the previous hidden state $h_{t-1}$and the current input x_t, along with a bias term b_o. The weight matrix associated with the output gate is denoted as W_o. Together, these components enable the LSTM to regulate memory updates and maintain long-term dependencies in sequential data.

4. Results

In this study, the input dataset comprises four key factors that significantly influence industrial electricity consumption: population, gross domestic product (GDP), industrial electricity prices, and the number of electricity subscribers. Electricity consumption in the industrial sector is designated as the dependent variable, meaning the model aims to predict its fluctuations based on variations in these independent variables.

To enhance prediction accuracy and overall model performance, the dataset underwent a normalization process. This step ensured that all input variables were scaled within the same range, preventing any single variable from disproportionately affecting the model due to differences in unit magnitude. Normalization also facilitated faster convergence during training and improved the model's generalization ability.

Following data pre-processing, the dataset was split into two subsets: a training set (comprising 80% of the data) and a testing set (comprising 20%). The LSTM model was trained using the training dataset, enabling it to learn the intricate relationships between the independent variables and electricity consumption patterns.

The LSTM model architecture consists of two stacked LSTM layers, each containing 50 neurons. A Rectified Linear Unit (ReLU) activation function was employed to introduce non-linearity and enhance the model's capacity to capture complex patterns in the data. The first LSTM layer processes input sequences and extracts relevant features, which are then passed to the second LSTM layer for further refinement, ultimately generating the model's final output. To optimize the training process, the Adam optimization algorithm was utilized. Adam is a widely adopted optimization technique that integrates the benefits of both the AdaGrad and RMSProp algorithms, making it particularly effective for deep learning models. Additionally, the Mean Squared Error (MSE) loss function was used as the performance criterion during training, ensuring that the model minimizes the average squared difference between predicted and actual values.

Upon completing the training phase, the trained LSTM model was used to generate predictions for both the training and testing datasets. These predictions were then compared against actual observed values to evaluate the model’s accuracy and reliability. Several evaluation metrics were employed to quantify the model’s performance, including Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Coefficient of Determination (R^2), and Mean Absolute Percentage Error (MAPE). These metrics provided a comprehensive assessment of the model’s predictive capabilities by measuring error magnitude, variance, and overall model fit.

Figure 2, Figure 3, Figure 1, Figure 4 presents the results obtained from this method, demonstrating the effectiveness of the LSTM model in capturing electricity consumption trends and providing accurate forecasts.

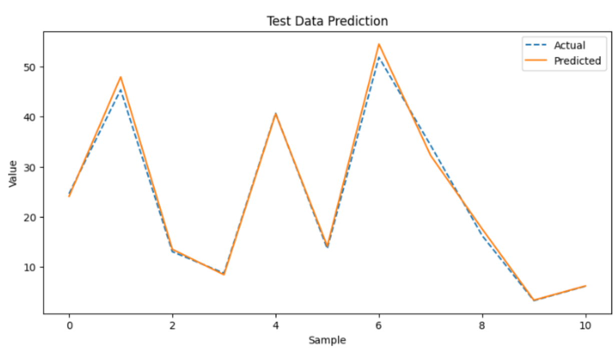

Figure 2. Prediction Results Using the LSTM Method for Test Data

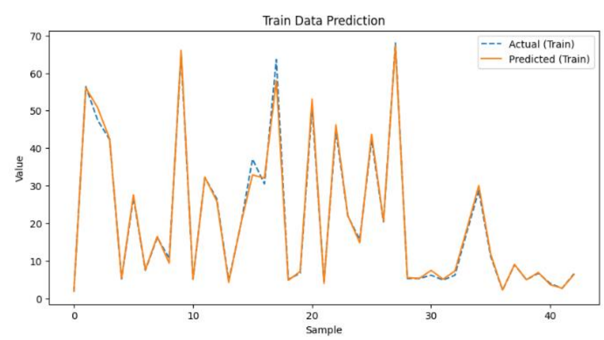

Figure 1. Prediction Results Using the LSTM Method for Training Data

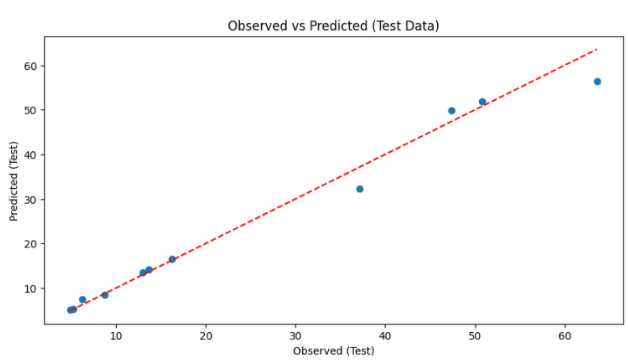

Figure 4. Comparison of LSTM-Predicted Test Data with Actual Values

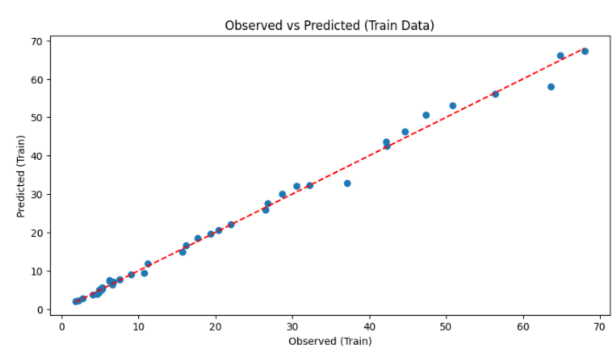

Figure 3. Comparison of LSTM-Predicted Training Data with Actual Values

5. Model Evaluation Metrics

In the previous chapters, the forecasting methods for electricity consumption and the modeling techniques used were reviewed. Now, to evaluate the models, four error metrics, namely the Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Coefficient of Determination (R^2), and Root Mean Squared Error (RMSE), have been used for comparison. Each of these metrics is computed using the following formulas:

$$MAE = \frac{\sum |y_i - \hat{y}_i|}{n} \tag{7}$$

$$MAPE = \sum \left(\frac{(|y_i - \hat{y}_i|)}{y_i} \right) \times 100 \tag{8}$$

$$R^2 = 1 - \frac{\sum_i (y_i - \hat{y}_i)^2}{\sum_i (y_i - \bar{y}_i)} \tag{9}$$

$$RMSE = \sqrt{\frac{\sum_i (y_i - \hat{y}_i)^2}{n}} \tag{10}$$

In error metrics such as MAE, RMSE, and $R2$ y_i represents the actual data points, $\hat{y}_i$ denotes the predicted values, and n indicates the total number of data points. **Error! Reference source not found.** shows the error metrics (MAE, MAPE, R^2, and RMSE) for the LSTM model on both training and testing data.

Table 2. Error Metrics for the LSTM Model for Training and Test Data.

Error	Test	Train
MAE	0.9715	0.836
MAPE	3.827%	4.856%
R^2	0.992	0.994
RMSE	1.364	1.412

The analysis and results demonstrate that the electricity consumption forecasting using this method yields highly accurate and dependable predictions, making it a robust approach for forecasting energy demand.

6. Conclusion

This study utilized data spanning from 2019 to 2022 (1398–1401 Solar Hijri calendar) to forecast electricity consumption in the industrial sector using Long Short-Term Memory (LSTM) neural networks. The results demonstrate that the LSTM-based approach delivers highly accurate and reliable predictions by effectively capturing complex nonlinear relationships among key influencing variables, including population, gross domestic product (GDP), electricity price, and the number of subscribers.

Performance evaluation using multiple statistical metrics—Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Coefficient of Determination (R^2), and Root Mean Squared Error (RMSE)—confirmed the model's exceptional predictive capability. Specifically, the model achieved R^2 values exceeding 0.99 for both training and testing datasets, indicating strong alignment between predicted and observed values. The low MAPE values (3.827% for testing and 4.856% for training) further demonstrate the model's precision in forecasting industrial electricity consumption patterns. These results highlight the LSTM model's robust generalization ability and its effectiveness in capturing temporal dependencies inherent in energy consumption data.

While this study focuses on LSTM model development and validation, it is important to contextualize these results within the broader landscape of electricity consumption forecasting methodologies. Traditional statistical approaches, such as Autoregressive Integrated Moving Average (ARIMA) models, have long been the standard for time-series forecasting due to their mathematical rigor and interpretability. ARIMA models excel in capturing linear temporal dependencies and are particularly effective when consumption patterns follow stationary or near-stationary trends. However, these methods often struggle with nonlinear relationships and complex interactions among multiple variables—limitations that become pronounced in industrial electricity forecasting where consumption is influenced by diverse, interconnected factors.

Machine learning approaches, including Multilayer Perceptron (MLP) networks, offer improved capability in modelling nonlinear relationships but may lack the temporal memory necessary for sequential data analysis. MLPs process data points independently without inherently accounting for temporal order, which can limit their effectiveness in capturing long-term dependencies characteristic of energy consumption patterns.

The LSTM architecture addresses these limitations through its specialized gating mechanisms, which enable the model to selectively retain or discard information across extended time sequences. This capability is particularly valuable for industrial electricity forecasting, where consumption patterns may exhibit complex temporal dependencies spanning multiple time steps. The high R^2 values (> 0.99) and low error metrics achieved in this study suggest that the LSTM model effectively captures these intricate patterns.

However, the absence of direct comparative benchmarking with ARIMA, MLP, and hybrid models in the current study represents a limitation that future research must address. Such comparative analysis would provide quantitative evidence of the LSTM model's relative advantages and identify specific scenarios where different approaches may be preferable. Understanding these trade-offs is essential for developing comprehensive forecasting frameworks that can adapt to various data characteristics and operational requirements.

Accurate forecasting of industrial energy consumption represents a critical advancement toward optimizing large-scale energy planning, managing grid loads, and developing efficient policies for electricity generation and distribution. The implementation of deep learning methodologies, particularly LSTM networks, provides energy planners and policymakers with powerful tools for demand forecasting, consumption optimization, and the formulation of sustainable energy strategies. Such predictive capabilities enable proactive decision-making in resource allocation, infrastructure development, and energy security planning.

7. Study Limitations and Future Research Directions

While the proposed model exhibits strong forecasting performance, several limitations should be acknowledged. First, the analysis is constrained to a four-year dataset, which may limit the model’s ability to capture long-term cyclical dynamics or structural changes in industrial electricity consumption. Second, the model does not incorporate external variables such as weather conditions, seasonal fluctuations, technological advancements, or policy regulations, all of which may significantly influence consumption behavior. Third, the study is based solely on historical consumption patterns and does not account for potential disruptions arising from emerging technologies or shifts within industrial sectors.

Building on the findings of this research, several opportunities for future work can be identified. Future studies should consider integrating additional explanatory variables, including meteorological data, renewable energy trends, and policy interventions, to improve predictive capability. Comparative evaluation against alternative forecasting models—such as ARIMA, MLP networks, hybrid ARIMA-LSTM frameworks, and ensemble-based methods—would also be valuable for assessing relative performance across dimensions such as predictive accuracy, computational efficiency, data dependency, robustness, interpretability, and forecasting horizon suitability. Establishing standardized benchmark datasets for industrial electricity forecasting would further enhance reproducibility and facilitate methodological comparison across studies.

Additionally, hybrid modelling approaches that combine LSTM architectures with other deep learning techniques (e.g., Convolutional Neural Networks or Attention-based mechanisms) or with traditional statistical methods may yield improved performance by leveraging complementary strengths. Extending the analysis to sector-specific forecasting, including sub-industries such as manufacturing, mining, or construction, may provide more tailored insights for policy and planning. Evaluating the model over longer forecasting horizons and exploring real-time deployment frameworks would also contribute to enhancing its practical applicability in energy management and strategic decision-making.

Overall, the study highlights the considerable potential of LSTM neural networks for industrial electricity consumption forecasting and underscores the value of continued research to refine, extend, and operationalize such predictive approaches within dynamic energy systems.

Ethical considerations

The authors avoided data fabrication, falsification, and plagiarism, and any form of misconduct.

The study was approved by the Ethics Committee of the University of ABCD (Ethical code: IR.UT.REC.2024.500).

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Conflict of interest

The authors declare no conflict of interest.

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