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Hybrid LSTM-XGBOOST Model for Sector-Specific Electricity Consumption Prediction in Iran: Incorporating Climate Scenarios and Sophisticated Machine Learning Methods

Fatemeh Karimidehkordi1[1*], Reza Samizadeh[2], Mohammad Ameri[3]

[1]Department of Industrial Engineering, Faculty of Engineering, Alzahra University, Tehran, Iran

[2]Associate Professor, Alzahra University- Faculty of Engineering, Al-Zahra University, Deh Vanak St., Tehran Iran

[3]Department of Mechanical and Energy Engineering, Shahid Beheshti University (SBU), Tehran, Iran.

*Corresponding author:Fatemeh Karimidehkordi,fateme_karimi1369@yahoo.com

Abstract

Abstract: Precise forecasting of electricity use is crucial for efficient energy management, particularly in areas with diverse meteorological and economic circumstances. This study presents an innovative hybrid forecasting model that integrates Long Short-Term Memory (LSTM) networks with Extreme Gradient Boosting (XGBOOST) to anticipate power consumption in five principal sectors in Iran: industrial, agricultural, commercial, public, and residential. The model utilizes sophisticated feature selection and hyperparameter optimization to identify both linear and nonlinear consumption patterns, while integrating climate change scenarios (A1B, A1FI, and A1T) to evaluate future energy demand under diverse environmental conditions. The hybrid LSTM-XGBOOST model consistently outperforms individual models, exhibiting the lowest Mean Absolute Percentage Error (MAPE) values (4.20% to 10.79%) and the highest R^2 values across all sectors. The model's outstanding performance is particularly evident in its capacity to discern complex consumption patterns during peak periods and seasonal fluctuations. The study highlights the significant influence of regional characteristics, as evidenced by the exceptional forecast accuracy in provinces such as Bushehr and Semnan. It offers valuable insights for policymakers and energy system operators in Iran during their transition to renewable energy sources by proposing a robust and adaptable forecasting model that addresses sector-specific and regional issues, thereby advancing energy planning.

Keywords: Electricity consumption forecasting, LSTM, XGBOOST, climate change scenarios, hybrid model, Iran, energy management.

Introduction

Precise forecasting of energy consumption is crucial for effective management and optimal planning in the contemporary electrical sector, which is required for sustainable growth Benkhalfallah et al. (2024). This need is particularly pronounced in countries like Iran, where diverse climates, varied geographical distributions, and structural differences across economic sectors necessitate precise forecasts for optimal resource allocation and responsiveness to demand fluctuations. Recent studies demonstrate that inaccuracies in power sector projections can substantially increase operational expenses and jeopardize network reliability. (Elhadj et al., 2024) illustrate that significant discrepancies in pricing and load projections necessitate suboptimal scheduling choices, leading to increased costs and operational challenges on the demand side.

Climate change is a significant challenge of the century, exerting extensive effects on energy consumption patterns, especially on electricity. The Intergovernmental Panel on Climate Change (Chapter) has proposed several scenarios to forecast future climate change, with the A1 family of scenarios being particularly significant(Nakicenovic et al., 2000). The A1 family scenarios (A1B, A1FI, and A1T) exemplify several pathways of technological progress and climate fluctuations. These scenarios are based on the assumption of rapid economic growth, an increase in the global population until mid-century followed by a decline, and the rapid implementation of advanced and more efficient technologies. A1B: Equilibrium between fossil and non-fossil energy sources. A1FI: Emphasis on fossil fuel use. A1T: Emphasis on non-fossil energy source utilization. These scenarios exert varying influences on electricity usage habits. In the A1FI scenario, a temperature rises of 2-4°C results in a 30% increase in electricity consumption for cooling systems(Chapter, 2018). The A1B scenario most closely aligns with the trends in temperature fluctuations and energy usage in Iran over the past decade. Conversely, the A1T scenario may exert a diminished influence on augmenting electricity demand by enhancing energy efficiency and utilizing renewable resources. In response to the necessity for accuracy, power demand forecasting has evolved significantly from basic statistical methods to advanced artificial intelligence systems. This highlights the increasing complexity of energy systems and the imperative for accurate forecasting to provide energy security, economic planning, and the integration of renewable energy sources into existing infrastructure (Li, 2018). Typically, research in this domain can be classified into four groups.

1. Traditional Time Series and Statistical Methods

1.1 ARIMA and Variations

Classical time series models, especially the autoregressive integrated moving average (ARIMA) and its variants, have been widely utilized to forecast electricity consumption(Chujai et al., 2013; Elsaraiti et al., 2021; Ozturk & Ozturk, 2018; Parreño, 2022). (Samadi et al., 2008)ARIMA models were employed to assess energy consumption in the Iranian industrial sector, achieving moderate accuracy for short-term forecasts, while encountering significant difficulties in estimating complex consumption patterns characterized by nonlinear properties. The constraints become especially evident during periods of substantial volatility or shifts in consumer behavior. (Nepal et al., 2020)aimed to enhance ARIMA performance by integrating clustering techniques for predicting electrical load in buildings. The methodology employed clustering of load profiles before ARIMA modeling, which enhanced accuracy by reducing heterogeneity in consumption patterns. However, their findings demonstrated that traditional time series models still encounter difficulties in accurately representing complex nonlinear relationships and external influencing factors. In addition to conventional ARIMA models, scholars have investigated advanced statistical methods. A multi-stage methodology was developed by(Jornaz & Samaranayake, 2019), utilizing daily lines to represent 24-hour power load profiles. This method addresses particular limitations of traditional time series models by enabling adaptable modeling of intraday variations and seasonal patterns. The spline-based approach demonstrated enhanced accuracy relative to traditional statistical methods, particularly in capturing intricate daily consumption curves.

2. Machine Learning Approaches

Electricity consumption forecasting has progressed, with machine learning methods emerging as viable alternatives to conventional techniques. (Eseye et al., 2019)introduced a machine learning-based integrated feature selection approach for predicting electricity demand in decentralized energy systems. Their research demonstrated that meticulous feature selection improves prediction accuracy by pinpointing the most relevant predictors from a broad spectrum of potential variables. The research revealed accuracy enhancements of up to 18% relative to models lacking optimal feature selection. (Jember et al., 2024)present a machine learning approach for short-term energy forecasting in decentralized systems, employing diverse baseline models and sophisticated feature selection to improve accuracy. Their collaborative methodology, especially the Stacking technique, markedly diminishes forecast inaccuracies and enhances R-squared values, providing a resilient solution for smart grid applications.

2.1 Support Vector Machines and Decision Trees

(Chen & Tan, 2017)Examined hybrid support vector regression for short-term forecasting of building energy consumption to enhance prediction accuracy, particularly for structures with complex usage patterns. Their research demonstrated significant effectiveness in evaluating nonlinear relationships among occupancy, environment, and consumption. (Fu et al., 2015)presented a novel support vector machine (SVM) methodology for hourly electrical load forecasting in diverse building systems, exhibiting enhanced performance compared to conventional forecasting techniques including ARIMAX, decision trees, and artificial neural networks. This study constructs 24 distinct SVM models, each corresponding to an hour, utilizing weather forecasts and historical electrical load data as inputs. The methodology effectively forecasts system-level electrical loads for public buildings, resulting in an overall CV_RMSE of 15.2% and a N_MBE of 7.7%. In this case, (Chen & Tan, 2017; Jindal et al., 2016) forecasted using the SVM algorithm. XGBOOST (Extreme Gradient Boosting), an ensemble learning method based on decision trees, has received significant recognition for its predictive performance. In this regard, studies (Abbasi et al., 2019; Liao et al., 2019) are particularly relevant. Furthermore, (Li et al., 2018)combined ARMA with XGBOOST in a fog computing framework to forecast short-term electricity consumption. Their hybrid approach leveraged ARMA's capacity to capture linear temporal trends while utilizing XGBOOST to model nonlinear interactions, resulting in substantially improved forecasting accuracy across various time frames.

2.2 Ensemble and Stacking Methods

Ensemble learning techniques have shown significant potential for forecasting electricity consumption. (Lee et al., 2019)devised a day-ahead electric load forecasting method for residential buildings utilizing a self-organizing map and stacking ensemble learning approach. Their study specifically tackled the challenge of limited data availability, a prevalent concern in numerous forecasting contexts. By integrating numerous base learners through stacking, they generated durable predictions even with minimal datasets, yielding error reductions of roughly 15% relative to individual models.

3. Deep Learning Techniques

Long Short-Term Memory (LSTM) neural networks have gained prominence in power consumption forecasting due to their capacity to comprehend long-term relationships in time series data. (Tajour, 1403) employed LSTM networks to predict electricity consumption in Iranian provinces, showcasing superior efficacy relative to conventional methods. However, their model did not explicitly integrate climate parameters, which could have improved forecasting precision. Additionally, studies (Alizadegan et al., 2025; Le et al., 2019; Torres et al., 2022; Wang et al., 2020)in the same domain utilized the LSTM methodology for power consumption prediction. Also, (Kiprijanovska et al., 2020)presented HousEEC, an advanced deep learning methodology for forecasting day-ahead household electrical energy consumption. Their model integrated diverse temporal features and household attributes to yield precise predictions. Comparative analysis demonstrated that their deep learning approach surpassed traditional methods by effectively capturing intricate consumption patterns and temporal dependencies, attaining MAPE values below 10% for the majority of household types. (Buitrago & Asfour, 2017)investigated the application of nonlinear autoregressive artificial neural networks with exogenous vector inputs (NARX) for short-term electric load forecasting. Their research clearly illustrated the nonlinear relationships between power use and external factors, such as weather conditions and time-related aspects. The NARX architecture was highly effective in capturing dynamic temporal correlations and integrating external inputs, leading to enhanced forecasting accuracy relative to conventional feed-forward networks. (Liu et al., 2019)presented an innovative two-stage approach for calculating household power consumption by edge deep sparse coding. Their methodology utilized edge computing frameworks to assess data at its origin, minimizing latency and computational demands while preserving excellent predictive accuracy. The sparse coding technique accurately identified the fundamental patterns in consumption data, exhibiting strong performance across diverse dwelling types and consumption contexts.

4. Hybrid Methods

Hybrid models that combine traditional statistical methods with advanced machine learning techniques have shown remarkable effectiveness in predicting electricity consumption. A thorough analysis by (Wahba et al., 2022)revealed that hybrid models outperform individual strategies in approximately 78% of cases across various forecasting contexts. Their research highlighted that the amalgamation of complementary methodologies allows models to discern both linear and nonlinear patterns in consumption data. Moreover, sophisticated hybrid models utilizing deep learning methodologies have demonstrated potential in predicting industrial loads. For instance, (Zhao et al., 2021)created a model that combines CNN and Transformer topologies for short-term load forecasting, illustrating the efficacy of hybrid methods in capturing the intricate dynamics of power use.(Gochhait et al., 2024) propose an innovative hybrid deep learning model utilizing a 1D CNN BI-LSTM approach for short-term electricity load forecasting, addressing the limitations of traditional CNN models in capturing multi-scale features and temporal dependencies. The proposed model integrates a feature extraction module, Densely Connected Residual Block (DCRB) layer, Bidirectional Long Short-Term Memory (Bi-LSTM) layer, and an ensemble layer to effectively extract and analyze complex electricity load patterns, achieving a remarkable Root Mean Square Error (RMSE) of 0.952 using half-hourly load data from the Telangana State Northern Power Distribution Company Limited (TSNPDCL). By demonstrating superior accuracy compared to conventional models like ARIMA and Artificial Neural Networks, the research contributes significant insights into power system management, offering potential applications in demand-side management, energy allocation optimization, and predictive modeling across various domains.(Li et al., 2018)Innovatively combined ARMA with XGBOOST in fog computing. ARMA and XGBOOST were utilized to identify linear temporal dependencies and nonlinear interactions within their hybrid model. This combination markedly improved short-term electricity demand forecasts, exceeding the effectiveness of each technique alone. Zhu et al. (2011) present the MA-C-WH hybrid forecasting model for energy demand in Chinese power networks, integrating moving average, combined forecasting, and adaptive particle swarm optimization. Their model surpasses conventional SARIMA models, improving short-term demand forecasting and energy output scheduling. Furthermore, within the same domain, research has also employed a hybrid methodology to forecast power consumption(Dong et al., 2016; Grandón et al., 2024; Pierre et al., 2023; Xiao et al., 2018).

5. Sector-Specific Forecasting Approaches

5.1 Residential Sector

The unpredictable actions of domestic and appliance usage present considerable difficulties in forecasting energy consumption in the residential sector. A novel short-term artificial learning system, utilizing household-specific data and behaviors, developed by (El-Baz & Tzscheutschler, 2015), estimates residential electricity use, enhancing accuracy by up to 20% compared to generic models. (Hsiao, 2014)underscored the importance of contextual knowledge and consumer analysis derived from meter data in evaluating residential energy consumption. This approach effectively uncovered complex energy consumption patterns by incorporating detailed contextual information about household activities and routines, especially in homes with consistent usage patterns, thereby improving forecasting precision. (Amara et al., 2017)introduced a method for adaptive conditional density estimation to assess domestic power usage, providing probabilistic estimates alongside prediction error. This approach demonstrated considerable effectiveness across all home categories and consumption scenarios, facilitating informed energy management decisions with a focus on risk awareness. Additionally, (Gerossier et al., 2018)concentrated on enhancing day-ahead forecasting of household electricity demand by tackling operational challenges such as data irregularities and unforeseen consumption patterns. Through the integration of robust mechanisms, they attained reliable predictions, thereby improving practical energy management applications.(Yousaf et al., 2021) introduces a novel hybrid load forecasting methodology for residential electricity consumption that amalgamates time series autoregression, machine learning feature selection, and an innovative integration strategy, resulting in a 17% enhancement in MAPE. Employing BGA-PCA for feature optimization and ANFIS for data analysis from 10 households in Pakistan, the study underscores the efficacy of advanced machine learning in smart grid applications.

5.2 Commercial and Public Buildings

Commercial buildings exhibit unique consumption patterns shaped by business hours, occupancy rates, and operational activities. (Pîrjan et al., 2017) Formulated precise hourly forecasting models for power use in commercial centers. Their methodology encompassed the distinctive attributes of commercial operations, such as opening hours, customer traffic patterns, and seasonal buying trends, leading to precise projections tailored to this industry. In a comparable scenario,(Nepal et al., 2020) utilized clustering techniques alongside ARIMA models to estimate electricity load in buildings. Their approach enhanced forecasting precision for diverse building types and operational schedules by integrating analogous load profiles before employing time series modeling, thus tackling the variability in building energy consumption patterns. Moreover, (Yu et al., 2020)established a specialized estimating model for electricity consumption in new metro stations, catering to the distinct energy demands of transportation infrastructure. Their model included station-specific attributes, operational timetables, and passenger flow dynamics to produce precise consumption predictions. This sector-specific simulation highlighted the necessity for customized solutions for specialized infrastructure with unique consumption patterns.

5.3 Industrial Sector

The industrial sector presents distinct obstacles for predicting electricity usage due to complex operational processes and manufacturing timelines. (Zhao et al., 2021) developed a Transformer-based model for short-term load forecasting, demonstrating the effectiveness of deep learning techniques in capturing intricate patterns in power usage. Furthermore,(Dou et al.)present a Human-Climate-Spatiality framework to analyze electricity consumption across 12 Chinese urban regions, uncovering alterations in consumption patterns shaped by spatial and economic determinants. The research highlights the significance of monocentric structures and regional industrial transformation, providing insights into prospective trends and the effects of low-carbon policies.

6. Influence of External Factors

6.1 Weather and Climate Considerations

Climatic factors substantially affect energy use, especially for heating, cooling, and lighting. Salkuti (2018) underscored the necessity of incorporating meteorological factors in short-term electrical load forecasting, utilizing radial basis function neural networks that explicitly integrated temperature, humidity, and other climatic data. Their studies revealed that the inclusion of meteorological information reduced forecast errors by up to 25%, particularly during intense weather events.(Zhao et al., 2021)emphasized the necessity of integrating regional and seasonal factors into energy demand predictions in Australia. Research indicates that variables including temperature, day type, and seasonal characteristics significantly influence electricity consumption patterns and the accuracy of forecasts.

6.2. Temporal and Regional Factors

Alongside weather, various temporal and contextual factors influence energy usage patterns. (Hsiao, 2014)underscored the importance of analyzing user daily routines and contextual information obtained from meter data to improve the precision of residential electricity consumption predictions. Their methodology incorporated data on daily routines, occupancy trends, and appliance usage behaviors, effectively reflecting the temporal dynamics of home consumption and improving prediction accuracy. (Dou et al.) utilize a Human-Climate-Spatiality paradigm to analyze power usage in 12 Chinese urban agglomerations. Their findings suggest a shift in consumption patterns from the northeast to the southwest, with monocentric metropolitan structures obstructing growth. The research highlights the significance of low-carbon policy and technical advancements for sustainable urban development. In a similar perspective, consider temporal and regional factors for predicting (Dahl et al., 2018; Kong et al., 2019).

7. Innovation and research limitations

1-This thorough cross-sector research examines the residential, commercial, and industrial sectors individually. The modeling and comparison of consumption patterns across several sectors rely on extensive frameworks that facilitate the identification of sector-specific characteristics and linkages.

2-Research particularly incorporating long-term climate change scenarios, such as those from the IPCC's A1 family, into models for projecting electricity consumption is insufficient.

3- Although regional differences in consumption patterns are well known, rigorous study on the adaptation or transfer of forecasting models across regions with different meteorological, economic, and cultural settings is lacking.

This work presents a hybrid forecasting model combining Extreme Gradient Boosting (XGBOOST) with Long Short-Term Memory (LSTM) networks to handle the complexity of power consumption forecasting in different economic sectors of Iran. The proposed model identifies both linear and nonlinear patterns in energy use through deep learning and ensemble methodologies. This work's primary innovation lies in the application of hyperparameter optimization and enhanced feature selection techniques, thereby augmenting the model's ability to identify relevant predictors and adapt to varying consumption patterns.
The hybrid LSTM-XGBOOST model is formulated to tackle the distinct issues presented by Iran's climatic variability, geographical dispersion, and sector-specific energy requirements, encompassing industrial, agricultural, commercial, public, and residential sectors. The model integrates weather data, temporal variables, and external factors like holidays and weekdays, delivering a comprehensive and adaptive forecasting system that surpasses independent models in accuracy and reliability.

Method

This research utilizes ARIMA, XGBOOST, LSTM, LSTM-Random Search, and a hybrid model (LSTM-XGBOOST) to predict electricity consumption across five essential sectors of the Iranian economy. A brief overview of the methodologies applied is included below.

1.Short-Term Memory Networks (LSTM)

Long Short-Term Memory Networks (LSTM) are a category of recurrent neural networks designed for simulating sequential data. LSTMs, developed by (Hochreiter & Schmidhuber, 1997), mitigate the vanishing gradient problem common in traditional RNNs with the integration of memory cells and gating mechanisms. The architecture of LSTMs enhances the retention of long-term information, thereby improving efficacy in time series forecasting, natural language processing, and other sequential data applications. An LSTM network's fundamental structure comprises a memory block containing memory cells and three types of gates: input, forget, and output. These gates regulate the flow of information to and from memory cells, enabling the network to discern what to retain or discard over time. The operations executed within an LSTM cell can be expressed by the following equations:

1. Forget Gate:

$$ft = \sigma(Wf \cdot [ht - 1, xt] + bf)$$

where *ft* represents the fraction of the prior cell state *Ct*−1 that should be ignored.

2. Input Gate:

$$it = \sigma(Wi \cdot [ht - 1, xt] + bi)$$

$$\widetilde{C_t} = tanh(WC \cdot [ht - 1, xt] + bC)$$

3. Cell State Update:

The input gate *it* determines the new information to be retained in the cell state, while $\widetilde{C_t}$ signifies the prospective values for the new cell state.

$$Ct = ft \cdot Ct - 1 + it \cdot \widetilde{C_t}$$

The cell state *Ct* is modified by integrating information from the forget gate and the input gate.

4. Output Gate:

$$ot = \sigma(Wo \cdot [ht - 1, xt] + bo)$$

$$ht = ot \cdot tanh(Ct)$$

The output gate *ot* regulates the output of the cell state, while *ht* represents the hidden state at time *t*.

In this context, σ signifies the sigmoid function, tanh represents the hyperbolic tangent function, *W* and *b* designate the weight matrices and bias vectors, respectively, and *xt* refers to the input at time *t (Torres et al., 2022)*.

2.Hyperparameter Optimization with Random Search

The efficacy of LSTM networks is significantly influenced by the selection of hyperparameters, including the number of layers, units per layer, learning rate, and dropout rate. Random search is a commonly employed method for hyperparameter optimization, which entails the selection of arbitrary hyperparameter combinations from a specified search space, succeeded by the training and evaluation of the model for each combination. In the realm of LSTMs, random search can be conducted with frameworks like Keras-Tuner, which facilitate the automated exploration of hyperparameter configurations.

3.ARIMA

ARIMA, which stands for AutoRegressive Integrated Moving Average, is a statistical model commonly used for forecasting time series data. It is recognized for its ability to identify linear patterns by incorporating the relationships among data through autoregressive and moving average components. Thus, it has demonstrated efficacy as a good instrument for studying patterns and seasonality in electricity consumption data (Box et al., 2015). ARIMA is characterized by its simplicity, interpretability, and efficiency in handling linear pattern data(Hyndman & Athanasopoulos, 2018). This approach is incapable of modeling non-linear patterns. The model posits that the time series data is stationary, indicating that its statistical properties remain invariant over time. To fulfill this assumption, preliminary steps such as data discretization are often required to standardize the data format. ARIMA is commonly utilized for time series forecasting, particularly when the data display distinct linear trends, despite its limitations (Brockwell & Davis, 2002).

4.Extreme Gradient Boosting (XGBOOST)

XGBOOST is a scalable machine learning algorithm based on gradient boosting decision trees. XGBOOST, developed by (Chen & Guestrin, 2016), addresses regression and classification problems, especially in high-dimensional and constrained data scenarios. XGBOOST constructs a series of decision trees to minimize a defined loss function. Each tree forecasts the residuals of the prior tree, with the final prediction being the sum of the initial prediction and the residuals from all subsequent trees. This iterative method allows the model to recognize intricate data patterns. The objective function in XGBOOST is modified to control model complexity and reduce overfitting. The regularized objective function (x) is expressed as:

$$\mathcal{L}(f) = \sum_{i=1}^{n} \ell(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(\varphi_k)$$

Here, $\ell(y_i, \hat{y}_i)$ represents the loss function that measures the discrepancy between the actual value y_i and the predicted value $\hat{y}_i$. The term $\Omega(\varphi_k)$ acts as the regularization component for the *k*-th tree, imposing a penalty on model complexity. It is represented as:

$$\Omega(\phi) = \gamma T + \frac{\lambda c^2}{2}$$

In this context, γ and λ denote penalty coefficients, T indicates the number of leaves in the tree, and c signifies the weight assigned to each leaf. The XGBOOST training procedure comprises initial prediction, residual computation, tree construction, model refinement, and regularization. The procedure is done a designated number of times or until the residuals are minimized (Siqueira-Filho et al., 2023)

5.LSTM-XGBOOST Hybrid Method

The LSTM-XGBOOST hybrid method enhances the accuracy of time series forecasting in scenarios characterized by complex temporal relationships and nonlinear dynamics by combining LSTM networks with XGBOOST. LSTM networks effectively capture long-term dependencies in sequential data, whereas XGBOOST demonstrates superior performance with structured data and in generating accurate ensemble predictions.

The LSTM-XGBOOST hybrid methodology includes the following steps:

1. Feature Extraction: The LSTM network is utilized to extract temporal features from the time series data. The LSTM model is engineered to recognize long-term dependencies and sequential patterns in the data.
2. Residual Prediction: The residuals produced by the LSTM model serve as inputs for the XGBOOST model. XGBOOST is employed to forecast these residuals, effectively recognizing nonlinear correlations and patterns that the LSTM model could overlook.

The most precise predictions are obtained by amalgamating forecasts from both the LSTM and XGBOOST models. This combination leverages the advantages of each model, resulting in a more accurate and robust forecast.

Data

This study examines the interplay of meteorological, socioeconomic, and regional variables affecting electricity consumption in Iran, employing data from nine provinces. Twenty meteorological variables were identified as critical predictors of energy use, in conjunction with social factors including demographics, geographical location, and temporal aspects such as time of day, week, holidays, and weekdays. This method seeks to clarify the impact of weather patterns and human behaviors on energy consumption across residential, commercial, industrial, agricultural, and public sectors. This study assesses the potential effects of climate change on future energy consumption by analyzing various A1 family scenarios predicting mid-century temperature rises. The scenarios analyzed include A1T, A1B, and A1FI, forecasting temperature rises of 1.75°C, 1.59°C, and 1.86°C, respectively. The study's data was systematically collected over four years, from March 21, 2018, to March 20, 2022, including daily weather records from the Iran weather Organization and electrical usage data from regional companies (Appendix 1). This comprehensive analysis seeks to elucidate how local and regional factors, in conjunction with climate change, may influence power consumption patterns in Iran. The research employed the K-Nearest Neighbor (KNN) technique for data preprocessing, eliminating missing features and addressing outliers. Multiple transformations were examined to mitigate skewness, and a normalization technique was employed to standardize data scale and units. Data preprocessing and analysis were conducted utilizing Python software on a Core i7 machine. Table 1 outlines the temporal characteristics and percentage allocation of the training and testing subgroups of the data. The training set constitutes 80% of the data, while the testing set encompasses the remainder.

Table1.Data Partitioning for Training and Testing Subsets

Subset	From	To	Percent
Training	3/21/2018	6/1/2021	80%
Test	6/2/2021	3/20/2022	20%

Figure 1 depicts the seasonal fluctuations in temperature, encompassing both minimum and maximum temperatures, during a four-year period. The charts reveal a consistent trend, with temperatures peaking in summer and reaching their nadir in winter, indicating a cyclical pattern in these fluctuations. Furthermore, the disparity between the highest and lowest minimum temperatures is less pronounced than the overall temperature variations. Conversely, the annual fluctuations in maximum temperatures are more prominent than those observed in minimum temperatures.

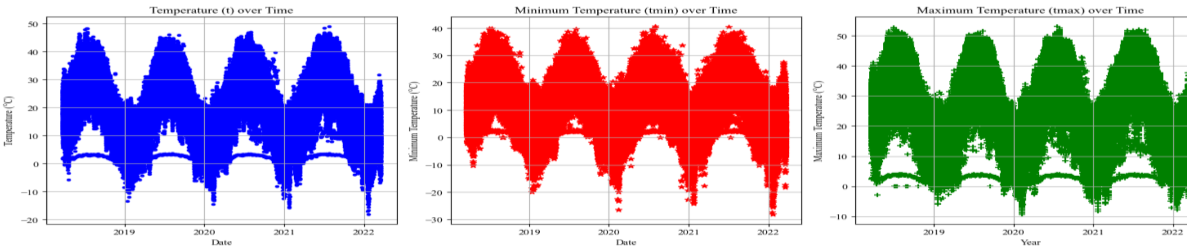

Figure 1. seasonal fluctuations in temperature

Figure 2 depicts a circular diagram that illustrates the distribution of energy consumption across various sectors (industrial, agricultural, public, commercial, and residential) from 2018 to 2022. The public and commercial sectors are the predominant energy consumers, whereas the industrial and agricultural sectors exhibit the least energy consumption.

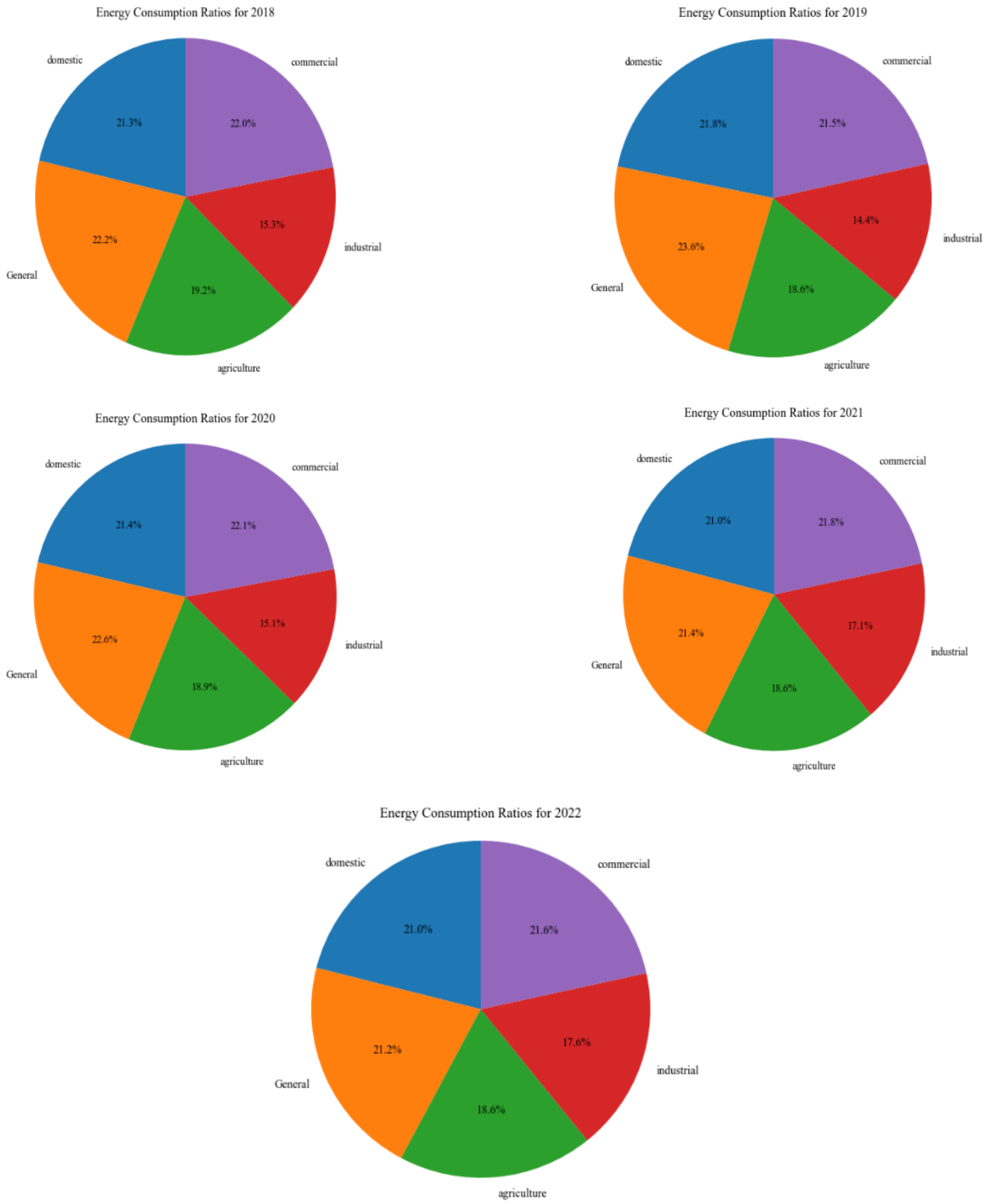

Figure 2. Comparative Analysis of Energy Consumption Ratios by Sector for 2018-2022

Figure 3 depicts the comprehensive electricity consumption throughout several provinces of Iran from 2018 to 2022. Each bar signifies a province, with the colored segments within each bar denoting consumption for a specific year. Khuzestan consistently exhibits the greatest consumption levels for the entire period, while Sanandaj displays the lowest consumption levels.

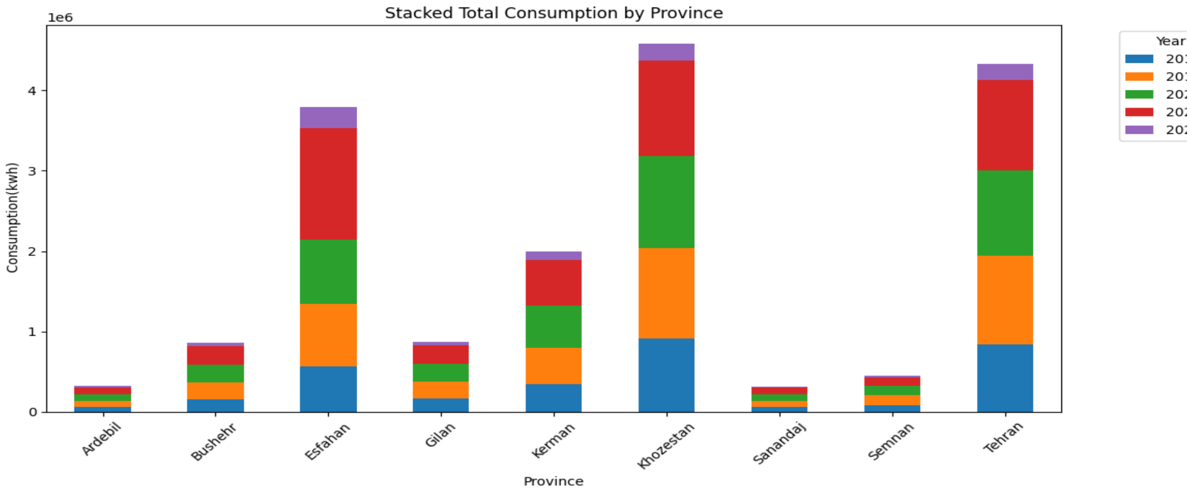

Figure 3. Total electricity consumption for various provinces of Iran

Table 2 displays the outcomes of the Dickey-Fuller test for stationarity across different sectors, both before and after transformation, revealing markedly enhanced test statistics and p-values post-transformation, showing stationarity. The model fit statistics include the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values for each sector, facilitating the evaluation of model appropriateness.

Table 2. Results of the Dickey-Fuller Test for Stationarity and Model Fit Statistics Before and After Transformation

Before Transformation					
	Domestic	**General**	**Agriculture**	**Industrial**	**Commerical**
Test Statistic	-2.5727	-1.7483	-1.7483	-2.5384	-2.5382
p-value	0.0988	0.4064	0.4064	0.1064	0.1065
1% Critical Value	-3.4349	-3.4349	-3.4349	-3.4349	-3.4349
5% Critical Value	-2.8636	-2.8636	-2.8636	-2.8636	-2.8636
10% Critical Value	-2.5678	-2.5678	-2.5678	-2.5678	-2.5678
After Transformation - Dickey-Fuller Test					
	Domestic	**General**	**Agriculture**	**Industrial**	**Commerical**
Test Statistic	-6.3916	-5.5851	-5.5851	-6.355	-6.4441
p-value	0	0	0	0	0
1% Critical Value	-3.4349	-3.4349	-3.4349	-3.4349	-3.4349
5% Critical Value	-2.8636	-2.8636	-2.8636	-2.8636	-2.8636
10% Critical Value	-2.5678	-2.5678	-2.5678	-2.5678	
Model Fit Statistics - MA Transformation					
	Domestic	**General**	**Agriculture**	**Industrial**	**Commerical**
AIC	12846.6731	10779.4281	10779.4281	12317.7305	8999.2686

BIC	12857.2455	10790.0005	10790.0005	12328.3029	9009.841

Table 3 specifies the minimum and maximum values of hyperparameters for both LSTM and LSTM-Random Search methods, including hidden layers, units per layer, dropout rate, and learning rate. The LSTM-Random Search approach exhibits a constant range for hidden layers and a broader range for units per layer compared to the traditional LSTM method.

Table 3. Hyperparameter Ranges for LSTM and LSTM-Random Search Models

Parameter	LSTM-Randomsearch		LSTM	
Min.	Max.	Min.	Max.	
Hidden layers	2	2	3	3
Units per layer	32	128	64	256
Dropout rate	0.1	0.3	0.3	0.3
Learning rate	0.001	0.01	0.001	0.001

Results

In this section, we present the analysis of electricity consumption forecasting in nine provinces of Iran, utilizing various machine learning models to assess their performance under varying conditions. The results, illustrated through figures and tables, reveal the influence of feature selection, time intervals, and external factors like weather, working days, and holidays on the accuracy of the forecasts. Figure 4 demonstrates the efficacy of different forecasting models in projecting power consumption across five sectors: industrial, commercial, public, residential, and agricultural. This study encompasses daily and weekly consumption predictions, evaluating the efficacy of Hybrid, XGBOOST, LSTM, LSTM-RandomSearch, and ARIMA models. Figure 4-a (Industrial Sector (Daily)) illustrates that actual consumption displays a consistent trend, with the hybrid model accurately mirroring these patterns, particularly during peak consumption intervals. The XGBOOST model demonstrates adequate accuracy but shows heightened volatility during fluctuations. In contrast, the ARIMA model consistently diverges, particularly during abrupt changes, underscoring its limitations in managing complex time series data. In Figure 4-b (Agricultural Sector (Daily)), the hybrid model closely aligns with real consumption, especially during notable variations. The LSTM model exhibits exceptional performance however encounters heightened volatility during peak periods. The LSTM-RandomSearch model exhibits difficulty in precisely predicting peaks, whereas XGBOOST demonstrates inconsistency during abrupt fluctuations in consumption. The ARIMA model significantly deviates from real values during peak periods, underscoring its forecasting limitations. Figure 4-c (Commercial Sector (Daily)) illustrates that real consumption exhibits an oscillatory pattern that aligns more closely with the hybrid predictions. The XGBOOST model effectively tracks actual consumption; however, discrepancies arise during peak periods. The LSTM-RandomSearch model demonstrates inferior forecasting accuracy, while the LSTM model reveals inconsistent performance and difficulties in peak predictions. The ARIMA model markedly diverges from actual values during pivotal periods, highlighting its constraints. Our findings corroborate previous research(Singh et al., 2024), highlighting the limitations of traditional models such as ARIMA and accentuating the necessity for advanced forecasting techniques in energy consumption analyses. Figures 4-d and 4-e (General and domestic Sectors (Daily)) demonstrate the effectiveness of several forecasting models in predicting daily power consumption in both the general and household sectors. In the general sector, the hybrid projections roughly correspond with actual consumption statistics. Alternative models like XGBOOST and LSTM-RandomSearch exhibit variability during certain demand intervals, while ARIMA inadequately captures fluctuations, particularly during high usage times. In the domestic sector, actual consumption shows notably consistent figures. The various models, particularly the hybrid, align closely with the real data over time despite minor discrepancies. The ARIMA model, represented by the gray line, exhibits considerable deviation from the real data at specific time periods. Figures 4-f, 4-h, and 4-j depict the efficacy of various models in predicting weekly energy use in the domestic, agricultural, and commercial sectors. In Figure 4-f, the hybrid model precisely reflects actual consumption patterns and effectively captures fluctuations, while ARIMA significantly diverges during peak periods. Figure 4-h corroborates the efficacy of the Hybrid, which accurately monitors actual consumption levels, whereas ARIMA continues to demonstrate significant inaccuracies. In Figure 4-j, the XGBOOST model has a strong correlation with actual consumption trends and outperforms all other models, including ARIMA, which fails to fully capture critical trends. The capacity to document oscillations is crucial for energy management systems. Figures 4-w and 4-x illustrate the efficacy of several forecasting models in estimating weekly power consumption in both the general and industrial sectors. In Figure 4-w, the hybrid model accurately reflects actual consumption patterns, particularly during fluctuations. XGBOOST performs satisfactorily; however, other models display increased unpredictability, especially ARIMA, which reveals substantial discrepancies. Figure 4-x demonstrates that the hybrid model's forecasts closely correspond with actual consumption for the designated period. The XGBOOST and LSTM-RandomSearch models provide commendable performance, albeit with increased variability during peak usage intervals. The ARIMA model ultimately distorts consumption, markedly diverging from the data. The statistics suggest that the hybrid model forecasts power consumption with greater accuracy than all other models, as evidenced in studies (Azevedo et al., 2024; Sajid et al., 2024), except in the commercial sector, where the XGBOOST model outperforms. Consistent with prior research, our findings indicate that deep learning models exceed conventional methods employed in studies (Abbasimehr & Paki, 2022) and(Singh et al., 2024).LSTM-based approaches demonstrate superior capability in modeling nonlinear energy consumption patterns compared to ARIMA, which typically yields inferior results in analogous scenarios.

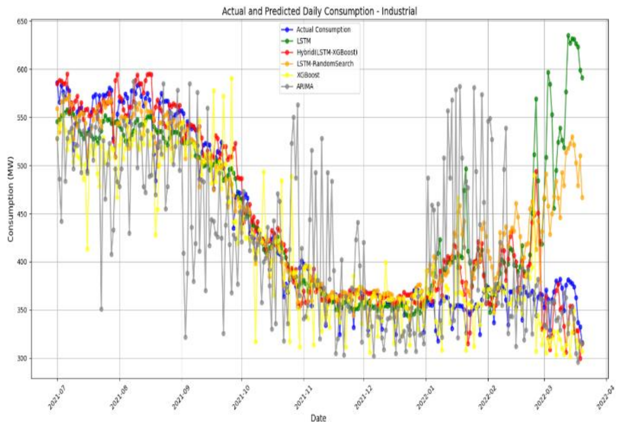

Figure 4-a. Industrial Sector (Daily))

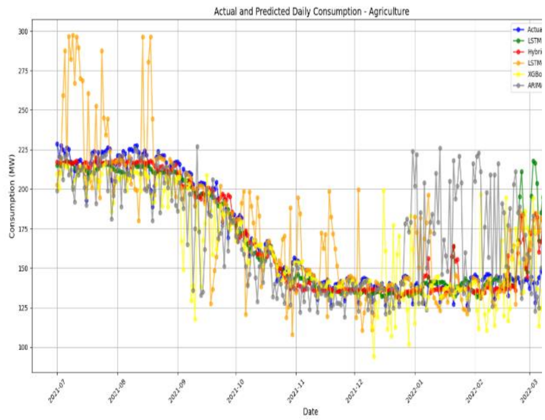

Figure 4-b. Agricultural Sector (Daily)

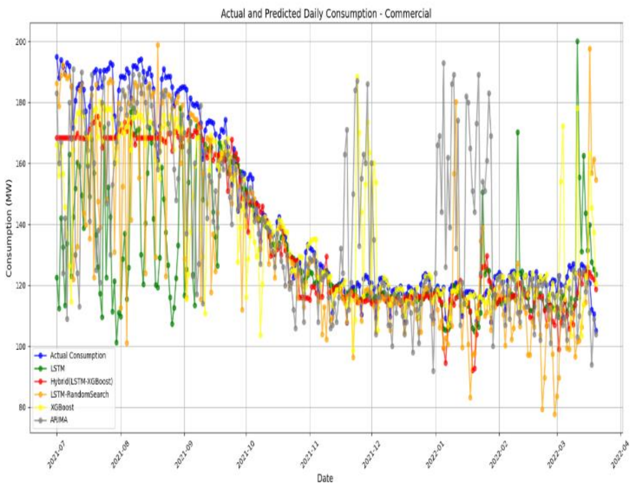

Figure 4-c. Commercial Sector (Daily)

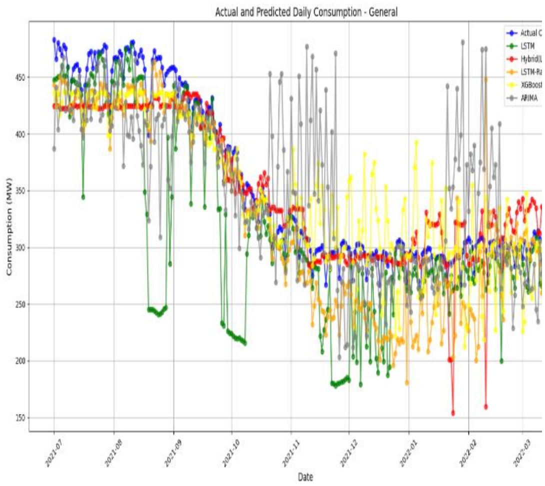

Figure 4-d. General Sectors (Daily)

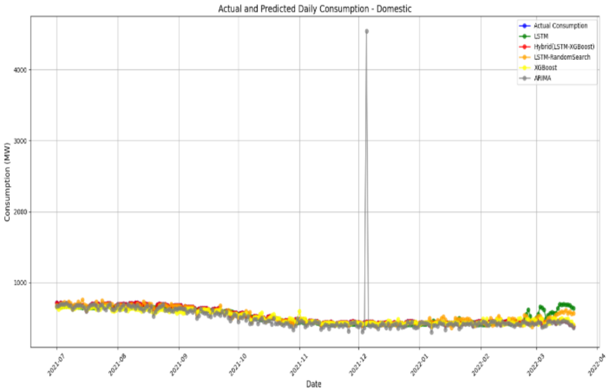

Figure 4-e. Domestic Sectors (Daily))

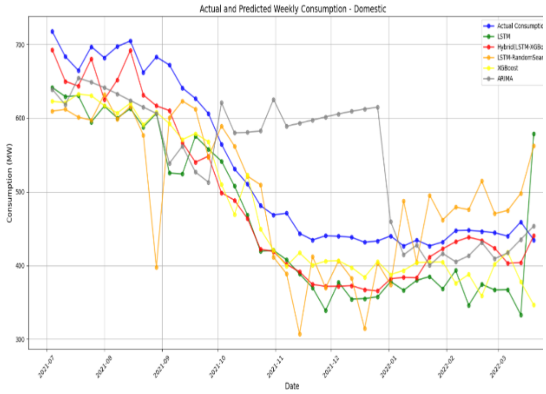

Figure 4-f. Domestic Sector (Weekly)

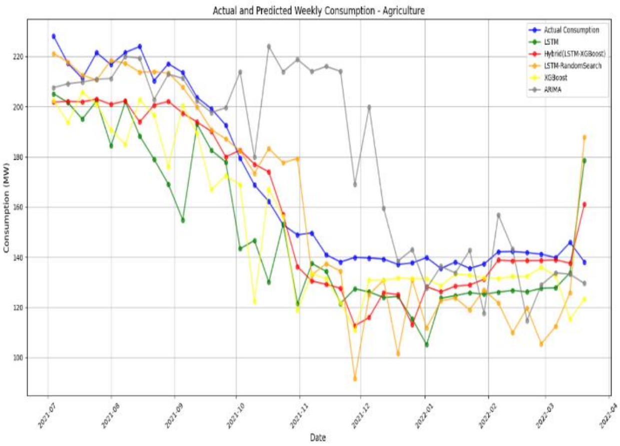

Figure 4-h. Agricultural Sector (Weekly)

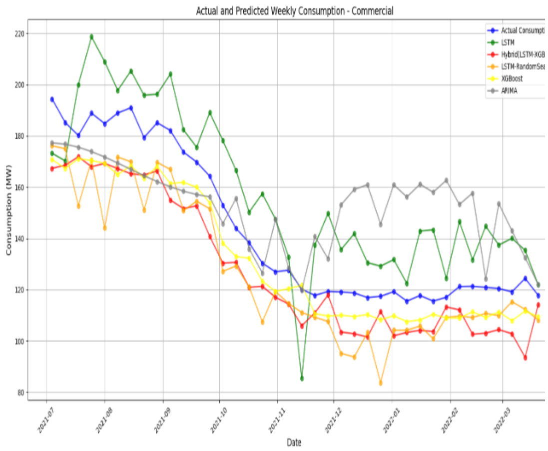

Figure4-j. Commercial Sector (Weekly)

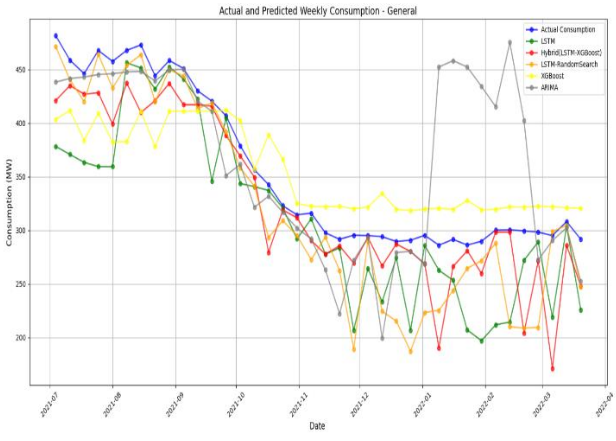

Figure 4-w. General Sector (Weekly)

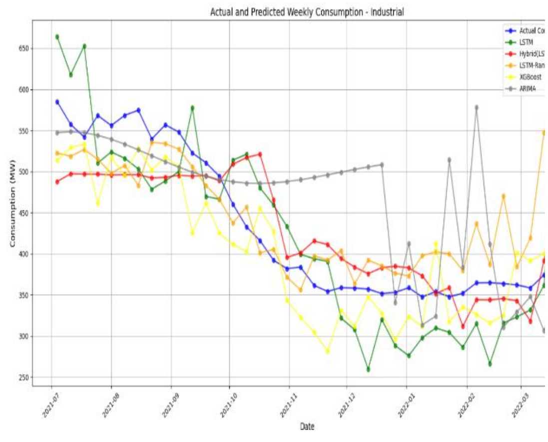

Figure 4-x. Industrial Sector (Weekly)

Figure 4. Performance of Forecasting Models

Figures 5-1 and 5-2 are radar graphs illustrating the mean absolute percentage error (MAPE) for different models predicting energy consumption across five sectors in Iran on a daily and weekly basis: public, commercial, agricultural, residential, and industrial. The analysis reveals that the hybrid model with the lowest mean absolute percentage error (MAPE) outperforms all other models in forecasting power consumption on both daily and weekly scales. The XGBOOST methodology is ranked second, especially when compared to traditional methods such as ARIMA. The hybrid model's ability to identify fluctuations and manage energy consumption patterns makes it crucial for energy management and control.

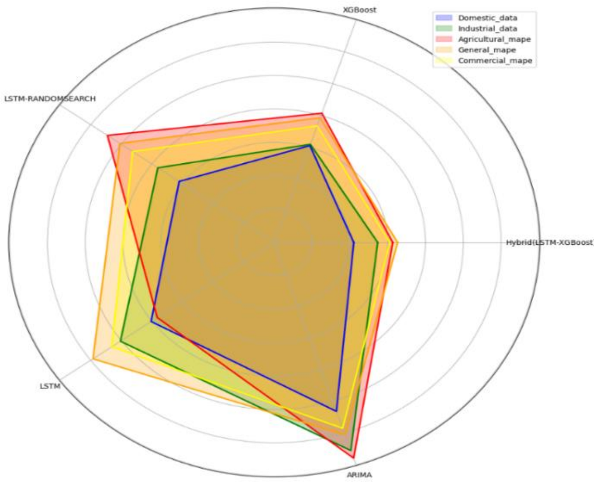

Figure (5-1). Comparison of MAPE Values in different sectors-Daily.

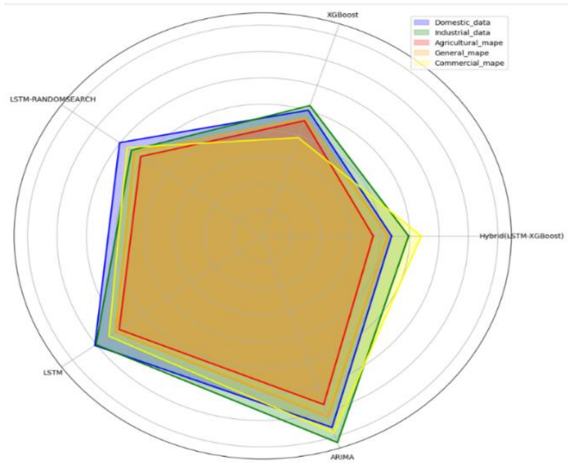

Figure (5-2). Comparison of MAPE Values in different sectors-Weekly.

Figure 5. Comparison of MAPE values for different models

Figure 6 shows the average weekly electricity consumption using several modeling methodologies for different scenarios A1B, A1FI and A1T. Figure 6-a illustrates the forecast of power consumption in Iran considering several climate scenarios using the XGBOOST model. The A1B scenario has minor discrepancies relative to real usage. The model aims to illustrate a slight increase in demand; however, it does not accurately represent the actual surges, especially in late September when consumption surpasses 2000 MW. The A1FI scenario exhibits greater variability, indicating sensitivity to higher temperatures and subsequent changes in electricity demand. The A1T scenario exhibits variations, although demonstrates greater consistency than A1FI. Nonetheless, it fails to attain the projected consumption levels, suggesting that despite the assumptions of rising temperatures, consumption may not escalate as anticipated due to enhancements in efficiency or technological advancements.

Figures 6-b and 6-c illustrate the anticipated electricity usage in Iran under various weather conditions, utilizing the LSTM-RandomSearch and hybrid models. Figure 6-b reveals a significant anomaly in the A1FI scenario for July 2021, marked by a considerable increase in usage to around 4500 MW, surpassing actual consumption by more than a factor of two. This significant variance suggests the model's potential instability in managing specific input conditions. The model accurately monitors real consumption throughout the August-September 2021 period, with the majority of possibilities aligning with the blue line indicative of actual consumption. Since October 2021, all scenarios have progressively aligned with actual consumption, signifying enhanced prediction dependability during periods of stable consumption trends. The comprehensive prognosis indicates considerable fluctuation, especially in August and December 2021. Figure 6-c depicts an anomalous surge, akin to the LSTM-RandomSearch model, particularly in the A1B scenario during September 2021, attaining around 4,800 MW. In contrast to the LSTM-RandomSearch model, the hybrid model consistently undervalues consumption from June to September 2021, with all scenario projections frequently falling below actual consumption levels. The model's accuracy markedly enhances from November 2021 onwards, with forecasts closely aligning with actual consumption patterns.

Figures 6-d and 6-e demonstrate the expected energy consumption in Iran under varied weather situations applying ARIMA and LSTM models. Figure 6-d illustrates that from June to early August 2021, all scenarios nearly coincide with actual usage, with low variance from the recorded data. Starting in mid-August, the A1B scenario demonstrates a significant deviation, considerably underestimating consumption until it rapidly converges with more accurate forecasts in late September. In November 2021, a notable anomaly is detected, as the A1T scenario demonstrates a considerable increase nearing 2,900 MW, indicating an overestimation over 120% of the actual consumption. Beginning in December 2021, all scenarios exhibit considerable variability. The A1T and A1FI scenarios intermittently fluctuate between over- and under-estimations, while the A1B scenario consistently enhances its tracking accuracy in the final months. Figure 6-e illustrates a substantial surge in the A1T scenario in late June 2021, attaining approximately 4,500 MW—exceeding actual consumption by more than twofold. Subsequent to this first aberration, all scenarios demonstrate markedly improved tracking of actual consumption relative to the ARIMA model, particularly from July to October 2021. Between November 2021 and April 2022, all scenarios demonstrate a declining trend in consumption; however, the A1B scenario continuously overestimates consumption by approximately 100 to 200 MW in early 2022. In contrast to ARIMA, the LSTM model demonstrates more stable performance during the winter months (December 2021 to March 2022). The examination of electricity demand forecasting models across various climate scenarios (A1B, A1FI, and A1T) provides significant insights into their efficacy. The incorporation of climatic scenarios represents a methodological advancement, akin to (Hong, 2014). The analysis reveals significant discrepancies among scenarios, indicating heightened climate sensitivity within the Iranian context or possible avenues for model enhancement. Hybrid and LSTM models typically surpass ARIMA in performance and exhibit enhanced stability.

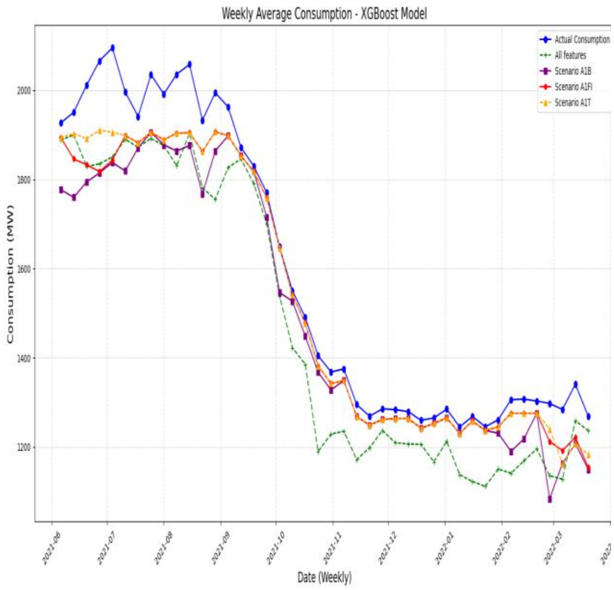

Figure 6-a. XGBOOST Model Performance

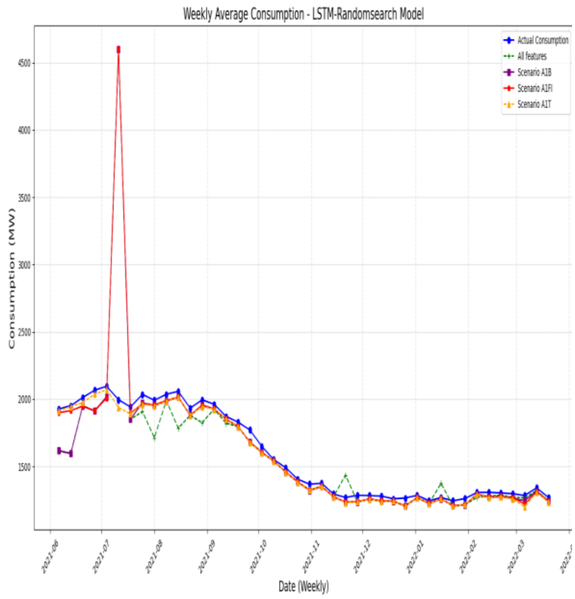

Figure 6-b. LSTM-RandomSearch Model Performance

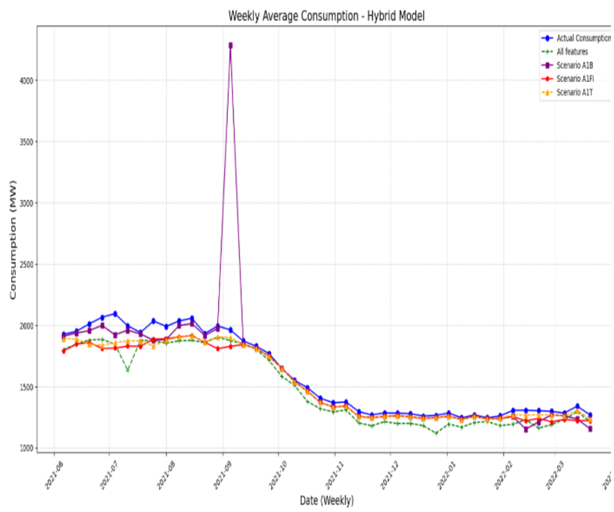

Figure 6-c. hybrid Model Performance

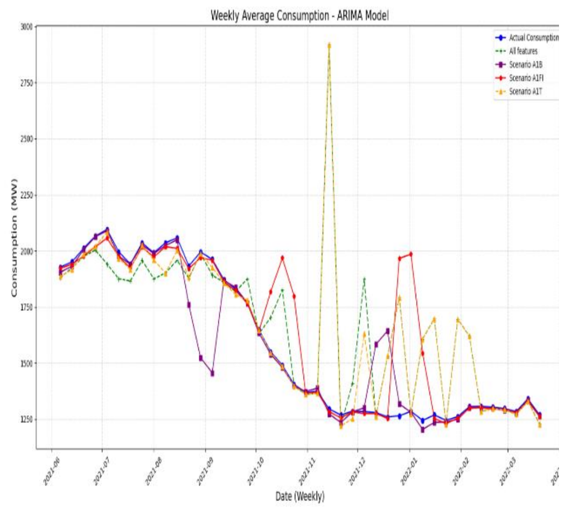

Figure 6-d. ARIMA Model Performance

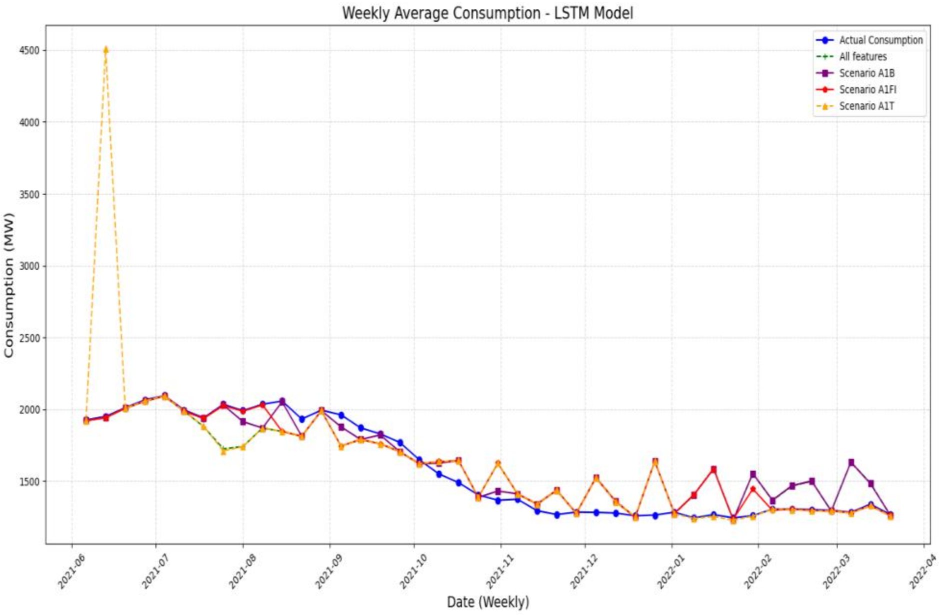

Figure 6-e. LSTM Model Performance

Figure 6. Comparative analysis of different models for electricity consumption forecasting - under different climate scenarios

Figure 7 shows the average predicted electricity consumption in five key sectors—agriculture, commercial, residential, public, and industrial—during holidays compared to weekdays. The forecasts generated by both the hybrid method and XGBOOST show that household consumption significantly outperforms consumption by other sectors in both scenarios, as shown in Figures 7-a and 7-b. This finding supports earlier studies, emphasizing the substantial influence of day type and customer behavior on domestic energy usage (Bouktif et al., 2018)The industrial sector exhibits greater consumption levels than the public sector, with XGBOOST indicating a more pronounced disparity in industrial loads between holidays and weekdays; however, the hybrid model marginally mitigates this imbalance. Conversely, agricultural demand remains remarkably stable, demonstrating little fluctuations across holidays and weekdays, signifying those agricultural operations persist at a consistent rate irrespective of the day type. The consumption hierarchy indicates that household usage is predominant, succeeded by industrial use, while agricultural and commercial sectors occupy the bottom tiers. This trend aligns with prior research that similarly highlighted the residential and industrial sectors.

Figures 7-c, 7-d, and 7-e depict the projected average electricity consumption as predicted by the LSTM-RandomSearch, LSTM, and ARIMA techniques for both holidays and weekdays. In all three models, household consumption consistently ranks as the highest, often exceeding 450 to 560 MW. Despite variations in numerical outputs across the models, the dominant trend indicates a significant influence of day type: weekdays typically exhibit marginally greater domestic demand than holidays, with the exception of the LSTM model. This study illustrates that residential energy usage is considerably influenced by weekday activities. The industrial sector occupies the second position in total demand, often exceeding 450 MW. The ARIMA model indicates a slight distinction between holidays and weekdays, whereas both LSTM variants exhibit a more significant disparity. The results indicate that industrial consumption varies with overall economic activity, however is tempered by operational schedules. The agricultural sector demonstrates negligible fluctuations in consumption between holidays and weekdays, consistently maintaining 200 MW in the majority of forecasts. This pattern may signify established operational requirements (e.g., irrigation cycles) that largely operate independently of the distinction between weekdays and weekends. The commercial sector generally remains around approximately 200 MW in these forecasts, with a distinct day-type effect in the ARIMA model, slightly elevated on weekdays, while displaying a reduced variance in the LSTM-based approaches. Consistent with (Bouktif et al., 2018), these findings confirm that residential load mostly affects total electricity usage, emphasizing differences between weekdays and weekends or holidays.

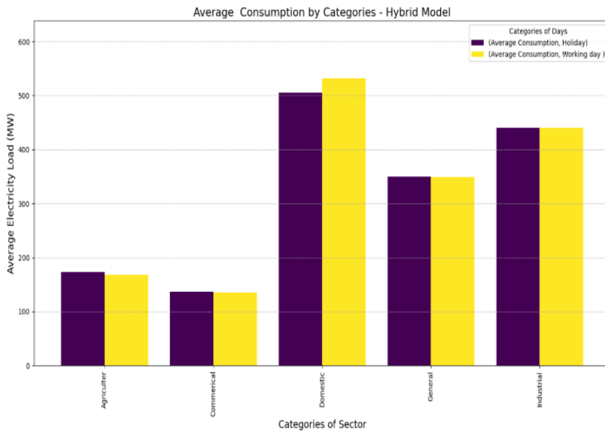

Figure 7-a. Average consumption by holidays and working days- hybrid method

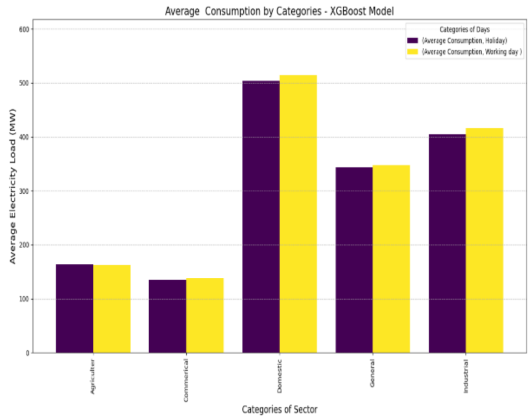

Figure 7-b. Average consumption by holidays and working days- XGBOOST method

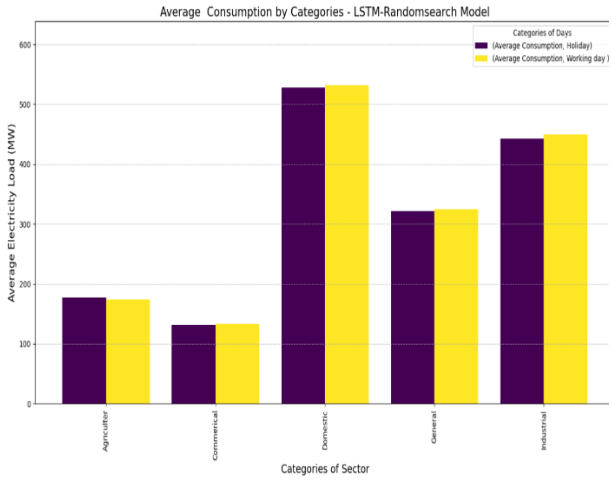

Figure 7-c. Average consumption by holidays and working days- LSTM-Randomsearch method

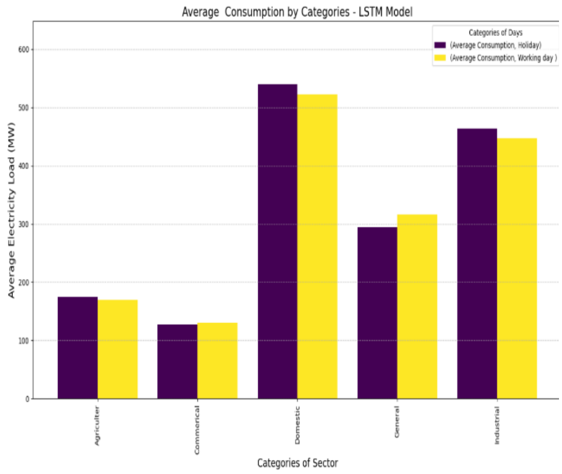

Figure 7-d. Average consumption by holidays and working days- LSTM method

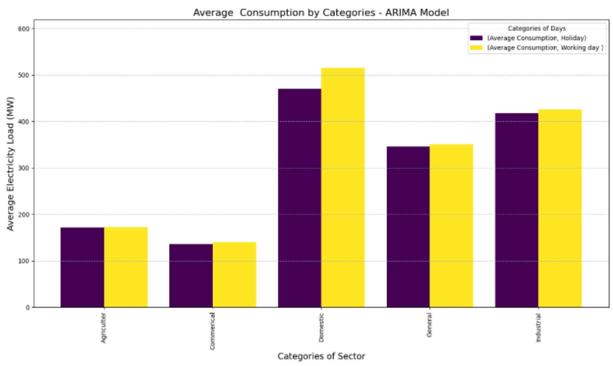

Figure 7-f. Average consumption by holidays and working days- ARIMA method

Figure 7. Comparative Analysis of Average Electricity Consumption by Sector and Day Type

Tables 4 and 5 provide a detailed examination of five forecasting models (Hybrid LSTM-XGBOOST, XGBOOST, LSTM-Randomsearch, LSTM, and ARIMA) across five economic sectors at both weekly and daily time intervals, utilizing four error metrics (RMSE, MAPE, R^2, and MAE). Tables 4 and 5 indicate that the hybrid model (LSTM-XGBOOST) consistently exhibits superior performance across all sectors, evidenced by the lowest

MAPE values (4.20% to 10.79%) and the highest R^2 values, reinforcing the emerging consensus on the integration of deep learning with gradient boosting techniques(Semmelmann et al., 2022).The XGBOOST model exhibits strong predictive efficacy, especially in commercial and public sectors on a weekly basis, indicating that model selection should consider sector-specific characteristics. The findings (Paudel, 2021) reveal that LSTM-Randomsearch generally outperforms the original LSTM, thereby supporting previous conclusions regarding the importance of hyperparameter optimization. The inadequate performance of ARIMA across all domains highlights the model's limited ability to detect complex patterns(Hong & Fan, 2016).

Table 4. Performance Comparison of Different Forecasting Models Across Economic Sectors: Weekly Analysis of Error Metrics

	Model	RMSE	MAPE	R2	MAE
Domestic	Hybrid (LSTM-XGBOOST)	49.9321	8.77	0.7871	44.7507
	XGBOOST	57.7817	10.03	0.7149	53.1793
	LSTM-Randomsearch	80.3148	12.04	0.4492	63.8235
	LSTM	77.7507	14.12	0.4838	72.2805
	ARIMA	94.6247	15.27	0.2354	76.7278
General	Hybrid (LSTM-XGBOOST)	40.6966	8.52	0.686	29.3119
	XGBOOST	39.9664	9.42	0.6972	34.3156
	LSTM-Randomsearch	46.0015	10.78	0.5988	33.8655
	LSTM	55.8715	12.38	0.4082	42.6095
	ARIMA	68.8841	14.42	0.1005	44.7199
Industrial	Hybrid (LSTM-XGBOOST)	51.7664	9.93	0.6557	43.3812
	XGBOOST	49.028	10.4	0.6911	44.4704
	LSTM-Randomsearch	62.0141	11.05	0.5058	44.7623
	LSTM	66.7731	14.02	0.4271	58.3632
	ARIMA	83.5851	16.47	63.2562	0.1023
Agriculture	Hybrid (LSTM-XGBOOST)	14.5769	7.52	0.8203	12.5669
	XGBOOST	19.4825	9.19	0.679	15.9253
	LSTM-Randomsearch	19.9281	10.26	0.6642	15.1951
	LSTM	23.6958	12.07	0.5252	20.4861
	ARIMA	31.1915	13.44	0.1773	20.3354
Commercial	Hybrid (LSTM-XGBOOST)	16.9493	10.79	0.6659	15.5497
	XGBOOST	12.6674	7.84	0.8134	11.5494
	LSTM-Randomsearch	18.0455	11.41	0.6213	16.334
	LSTM	19.4667	12.93	0.5593	17.814
	ARIMA	24.8926	15.7	0.2793	20.5751

Table 5. Performance Comparison of Different Forecasting Models Across Economic Sectors: Daily Analysis of Error Metrics

	Model	RMSE	MAPE	R2	MAE
Domestic	Hybrid (LSTM-XGBOOST)	9.466672265	4.20476747	0.879536357	19.5657
	XGBOOST	58.80867151	6.10094633	0.732528378	35.1916
	LSTM-Randomsearch	43.39552488	6.21790552	0.839474835	30.4102

	LSTM	61.88615194	8.05187581	0.67353232	39.6484
	ARIMA	64.8023275	10.6338911	0.2354	52.5459
General	Hybrid (LSTM-XGBOOST)	29.96857659	6.52068966	0.830049201	22.9807
	XGBOOST	33.82229783	7.85140744	0.783530258	26.6375
	LSTM-Randomsearch	41.00862909	10.0901654	0.681769734	32.9533
	LSTM	66.33477601	11.8519998	0.167328857	41.8006
	ARIMA	57.84312286	12.1132489	0.366867739	40.3785
Industrial	Hybrid (LSTM-XGBOOST)	30.2443	5.47	0.8827	21.7287
	XGBOOST	37.3976	6.18	0.8206	27.3416
	LSTM-Randomsearch	46.0562	7.61	0.7279	29.0382
	LSTM	68.3773	10.06	0.4003	38.8565
	ARIMA	76.5188	13.1	0.249	54.561
Agriculture	Hybrid (LSTM-XGBOOST)	14.5434	6.27	0.8215	9.638
	XGBOOST	20.1243	8.14	0.6581	13.2617
	LSTM-Randomsearch	27.1662	10.91	0.377	17.9128
	LSTM	21.0843	7.65	0.6247	11.6581
	ARIMA	31.0742	13.58	0.1849	20.6653
Commercial	Hybrid (LSTM-XGBOOST)	11.501	6.11	0.8464	15.5497
	XGBOOST	18.0342	7.34	0.6224	10.9779
	LSTM-Randomsearch	21.3214	9.26	0.4722	13.4022
	LSTM	27.7898	10.62	0.1034	17.2768
	ARIMA	25.4372	11.7	0.2488	16.3604

Table 6 presents a comprehensive comparison of forecast accuracy, quantified by the mean absolute percentage error (MAPE %), for five distinct hybrid forecasting models (LSTM-XGBOOST, XGBOOST, LSTM-Randomsearch, LSTM, and ARIMA) across five principal economic sectors (domestic, agricultural, general, industrial, and commercial) in Iran. The evaluation of the comparative results of forecasting models across five economic sectors (residential, agricultural, general, industrial, and commercial) indicates that the hybrid model consistently produced the most favorable outcomes. This strategy demonstrates significant performance in the domestic sector across the Kurdistan and Semnan provinces. The forecasting conditions in Khuzestan were challenging, leading to increased inaccuracies across all models, consistent with regions exhibiting complicated consumption patterns and severe weather conditions. The LSTM-Randomsearch model demonstrated adequate performance in Kurdistan; however, the hybrid model produced superior results. Nevertheless, Isfahan demonstrates a notable inaccuracy, especially in the LSTM model (about 58.57%). In the industrial sector, Bushehr has shown exceptional performance with a remarkable accuracy of the hybrid model (0.78%). Conversely, Kerman exhibits subpar performance, highlighting a substantial disparity consistently indicating the influence of industrial variety on forecasting precision. The agricultural sector in Guilan province demonstrates superior forecasting capability using the hybrid model, while Tehran exhibits commendable outcomes with the LSTM-Randomsearch model; these findings confirm the significant influence of regional factors in this domain.

The commercial sector's forecasts revealed significant disparities among provinces, with Semnan and Bushehr achieving superior results under the hybrid model, while Tehran and Gilan faced more challenging conditions. This effect is ascribed to the increased complexity of expenditure patterns in metropolitan areas. The thorough conclusion reveals that the hybrid model outperforms in 23 of the 36 examined scenarios, exhibiting a 3% error rate in 15 instances, hence emphasizing the model's superiority, in alignment with previous research findings (Jia et al., 2024).The persistent superiority of LSTM-Randomsearch compared to conventional LSTM underscores the significance of hyperparameter optimization, as indicated in (Dhake et al., 2023). The ARIMA model exhibited an average error rate of 14.83 percent, constantly underperforming compared to the other models. This corroborates previous studies that emphasized the constraints of conventional statistical methods relative to machine learning, as cited in (Tarmanini et al., 2023).

Table 6. Regional Comparison of Forecasting Model Accuracy (MAPE %) in Economic Sectors in Iranian Provinces.

Sector	Name of province	Hybrid (LSTM-XGBOOST)	XGBOOST	LSTM-Randomsearch	LSTM	ARIMA
Domestic	Ardebil	2.46	8.60	7.28	15.77	14.76
	Khuzestan	35.86	22.69	10.22	13.79	14.56
	Esfahan	14.78	8.57	14.12	14.60	15.31
	Kurdestan	1.05	7.76	5.75	9.94	15.27
	Bushehr	5.97	9.04	15.61	14.71	14.84
	Semnan	0.75	6.43	21.11	15.99	17.74
	Kerman	3.67	8.55	18.08	13.92	14.56
	Tehran	9.16	7.97	8.92	14.30	15.39
	Gilan	5.23	10.66	7.26	14.05	15.00
General	Ardebil	3.39	6.75	4.26	6.99	13.64
	Khuzestan	26.36	19.46	11.00	7.16	13.71
	Esfahan	10.18	15.95	44.90	58.57	13.42
	Kurdestan	0.74	6.29	2.25	6.47	14.53
	Bushehr	2.77	8.18	10.10	6.82	14.29
	Semnan	1.35	7.14	10.87	7.94	17.19
	Kerman	3.83	5.82	6.66	6.39	14.03
	Tehran	24.28	8.02	4.44	6.08	14.43
	Gilan	3.78	7.18	2.55	4.99	14.54
Industrial	Ardebil	1.92	8.31	4.01	12.68	16.17
	Khuzestan	18.70	24.06	10.58	14.94	16.30
	Esfahan	16.00	9.60	13.64	13.74	16.73
	Kurdestan	1.84	8.34	8.58	12.85	16.17
	Bushehr	0.78	8.34	6.22	13.25	15.61
	Semnan	4.03	7.73	13.30	18.73	18.84
	Kerman	35.69	9.30	12.66	13.39	14.84
	Tehran	8.31	7.96	12.45	13.27	16.73
	Gilan	2.11	9.96	18.02	13.33	16.82
Agriculture	Ardebil	2.84	8.00	9.14	12.13	13.14
	Khuzestan	11.68	14.79	15.07	13.14	12.51
	Esfahan	10.27	6.83	5.57	11.83	13.66
	Kurdestan	2.22	7.68	9.19	12.03	12.86
	Bushehr	3.00	15.59	8.46	12.88	12.16

	Semnan	7.31	6.66	19.34	14.83	15.37
	Kerman	10.36	6.66	5.26	10.57	13.73
	Tehran	18.33	9.05	4.14	11.39	13.70
	Gilan	1.67	7.44	16.17	9.83	13.84
Commercial	Ardebil	2.47	5.82	6.57	11.78	14.65
	Khuzestan	7.81	10.20	19.24	24.07	18.24
	Esfahan	10.49	5.46	5.76	9.41	15.24
	Kurdestan	6.82	5.66	4.10	8.65	15.12
	Bushehr	2.01	10.20	14.37	12.17	15.43
	Semnan	1.05	6.14	24.21	13.91	17.61
	Kerman	2.22	7.34	6.11	11.90	14.89
	Tehran	25.24	5.55	9.40	12.39	15.31
	Gilan	39.00	14.18	12.93	12.10	14.81

The study demonstrates the comparative effectiveness of five forecasting models (Hybrid LSTM-XGBOOST, XGBOOST, LSTM-Randomsearch, LSTM, and ARIMA) across five economic sectors in Iran, supplemented by an extensive analysis featuring multiple figures that illustrate daily and weekly consumption patterns, the impact of climate scenarios, and usage discrepancies between holidays and weekdays. The hybrid model consistently surpasses other models in most scenarios, attaining superior accuracy with the lowest MAPE values (4.20% to 10.79%) and the highest R^2 values across various sectors, whereas XGBOOST demonstrates notable efficacy in the commercial and public sectors on a weekly basis. Regional disparities markedly influence model efficacy, with provinces such as Bushehr and Semnan exhibiting remarkable accuracy (as low as 0.78% MAPE for the industrial sector), whereas urban regions like Tehran and Gilan pose more intricate forecasting challenges due to convoluted consumption patterns. The established performance hierarchy (Hybrid > XGBOOST > LSTM-RandomSearch > LSTM > ARIMA) demonstrates that deep learning models significantly surpass traditional statistical methods, with hyperparameter adjustment being essential for improving prediction accuracy.

Conclusion and Discussion

This paper offers a thorough assessment of electricity consumption forecasts in Iran, utilizing sophisticated machine learning methodologies to tackle the intricacies of sector-specific and regional energy demand trends. The hybrid LSTM-XGBOOST model proved to be the most efficient forecasting instrument, continuously surpassing standalone models including XGBOOST, LSTM-RandomSearch, LSTM, and ARIMA in all analyzed sectors. The hybrid model achieved the lowest Mean Absolute Percentage Error (MAPE) values (ranging from 4.20% to 10.79%) and the highest R^2 values, demonstrating its remarkable ability to characterize both linear and nonlinear consumption patterns. This aligns with prior research emphasizing the efficacy of integrating deep learning and ensemble methodologies for energy forecasting (Jember et al., 2024; Li et al., 2018(Semmelmann et al., 2022)). The findings underscore the substantial impact of regional attributes on predictive precision. Provinces like Bushehr and Semnan demonstrated outstanding performance, with MAPE values as low as 0.78% in the industrial sector, whereas urban areas such as Tehran and Gilan presented more significant hurdles due to intricate consumption patterns. This underscores the imperative of tailoring forecasting models to regional and sector-specific conditions, as highlighted by Dou et al. (2025) in their analysis of urban electricity consumption patterns in China.

The integration of climate change scenarios (A1B, A1FI, and A1T) into the forecasting framework provided substantial insights into the potential impacts of environmental variables on future energy demand. The hybrid model demonstrated robust performance under these conditions, particularly in capturing seasonal fluctuations and peak demand periods. This discovery corresponds with Salkuti (2018), who emphasized the critical impact of meteorological circumstances on improving short-term load forecasting accuracy.

The study emphasized the inadequacies of traditional statistical methods, such as ARIMA, which consistently produced subpar outcomes in comparison to machine learning models. This corroborates previous research (Elhadj et al., 2024; Nepal et al., 2020) that highlighted the challenges of utilizing conventional time series models to effectively depict complex, nonlinear consumption patterns.The research identified the limitations of conventional statistical techniques, including ARIMA, which consistently yielded inferior results relative to machine learning models.This supports prior studies (Elhadj et al., 2024; Nepal et al., 2020) emphasizing the difficulties of employing conventional time series models to accurately represent intricate, nonlinear consumption patterns. The efficacy of LSTM-RandomSearch compared to the conventional LSTM model highlights the significance of hyperparameter optimization in improving forecasting precision. The established performance hierarchy (Hybrid > XGBOOST > LSTM-RandomSearch > LSTM > ARIMA) clearly demonstrates the superiority of deep learning models compared to traditional statistical approaches. This research advances the understanding of energy forecasting by introducing a comprehensive and flexible hybrid model that tackles the specific challenges posed by Iran's varied climatic and economic factors. The findings provide essential insights for policymakers and energy system operators, especially regarding Iran's shift to renewable energy sources. Future research may investigate the incorporation of other external variables, including socioeconomic factors and technological innovations, to enhance predictive accuracy and facilitate sustainable energy planning.

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The authors used the AI system [https://quillbot.com/]" paraphrase several passage of the manuscript" to refine the presentation of key information.

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Appendix 1: Definition of meteorological and calendar variables with units.

Variable		Unit
tmin	Minimum Temperature	(°C)
tmax	Maximum Temperature	(°C)
sshn	Sunshine Hours	(h)
rrr24	Total Daily Precipitation	(mm)
evt	Evaporation	(mm)
twet	Wet Temperature	(°C)
ff_max	Maximum Wind Speed	(m/s)
dd_max	Direction of Maximum Wind	(°)
ew	Vapor Pressure	(hPa)
tsea	Sea Surface Temperature	(°C)
u	Relative Humidity	(%)
vv	Horizontal Visibility	(m)
dd	Wind Direction	(°)
ff	Wind Speed	(m/s)
P0	Synoptic Station Pressure	(hPa)
ss	Snowfall Amount	(mm)
h	Lowest Observable Cloud	(m)
n	Cloudiness	Okta
radglo24	Radiation	j/cm2/day

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t	Temperature	(°C)
td	Dew Point	(°C)
p	Sea Level Pressure	(hPa)
Working day	Work Day	day
holiday	Weekend.	day
Consumption		kwh