Journal of Computational Analysis and Applications VOL. 33, NO. 4, 2024

10.48047/jocaaa.2024.33.04.25

Enhanced Deep Learning Based Predictive Analysis of Electricity Power Consumption Forecasting for Maharashtra State Electricity Distribution Company Ltd. (MSEDCL)

Kanchan A. Khedikar
Research Scholar(USN: 1NT20PCS09) , Nitte Meenakshi Institute of Technology
Bengaluru affiliated to Visvesvaraya Technological University , Belgavi
Assistant Professor, Walchand Institute of Technology, Solapur,
Maharashtra, India
Email : kakhedikar@witsolapur.org

Dr.Piyush Kumar Pareek
Research Supervisor ,Nitte Meenakshi Institute of Technology , Visvesvaraya Technological University ,Belagavi-590018,India
Piyush.kumar@nmit.ac.in

Abstract *- Accurate forecasting of electricity power consumption is vital for efficient grid operation, optimal resource management, and sustainable energy planning. Energy consumption analysis involves gathering, evaluating, and interpreting data on energy usage—particularly electricity. Our research centers on forecasting energy demand for Maharashtra State Electricity Distribution Company Ltd. (MSEDCL) using real-world power consumption datasets. Accurate power consumption forecasts are vital for the reliable management of electrical systems and for optimizing costs for both utilities and end users. The existing researchers have mostly focused on traditional machine learning methods for electricity power consumption prediction. However, these methods have not improved predictive accuracy and therefore do not help in identifying the losses in the electricity power sectors. Three sophisticated forecasting methods—Prophet, Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU)—are examined, and their performances are compared in this study using an interactive computational environment. The ability of each model to depict changes in electricity demand over time is assessed. Although each model has unique benefits, the analysis shows that a hybrid strategy that combines the best features of deep learning and statistics greatly improves predicted accuracy and robustness. The findings highlight how combination modeling approaches may be used to produce accurate and flexible forecasts of electricity usage over a range of time scales. The intelligent decision-making of efficient demand and supply management of electrical power among various locations at various scales is aided by this predictive hybrid modeling technique. This strategy will also lessen the likelihood of theft and losses in the distribution of electricity.*

Keywords *– electricity power consumption forecasting, Gated Recurrent Unit, Long Short-Term Memory, prophet, prediction analysis, sustainable energy planning, MSEDCL*

1. Introduction

Perfect forecasting of electricity power consumption is a foundational element of modern energy management systems, enabling efficient resource allocation, infrastructure development, and implementation of demand-response strategies. As power grids become increasingly complex due to the integration of renewable energy sources and rapidly evolving consumption behaviors. The demand for robust and adaptable forecasting models has grown significantly. Traditionally, statistical models such as Autoregressive Integrated Moving Average (ARIMA) have been widely used for their ability to capture linear trends and seasonal patterns in time-series data. However, the multifaceted nature of electricity usage, influenced by climatic, economic, and behavioral factors, often exceeds the modeling capacity of such linear approaches [1]. Recent advances in machine learning, particularly deep learning, have introduced powerful alternatives capable of uncovering intricate non-linear temporal dependencies. Models like Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks have shown strong performance in handling complex time-series data due to their ability to retain long-term contextual information [2]. Additionally, Prophet, a decomposable time-series model developed by Facebook, offers an intuitive and effective means of capturing trend, seasonality, and holiday effects. This study investigates and compares the effectiveness of these three forecasting techniques in predicting electricity consumption patterns, aiming to identify a more accurate and resilient modeling strategy [3].

2. Literature Review

For identifying the research gap in the electricity power consumption prediction, the literature review of existing approaches is carried out. “Smart Energy Forecast: Machine Learning Model to Predict Electricity Power Consumption,” the study applied three machine learning models-linear regression, random forest, and XGBoost-to predict electricity consumption using a publicly available Kaggle dataset. Data were split into training, validation, and test sets, with performance evaluated using MAE, MSE, RMSE, and R^2 metrics. Among the models tested, Random Forest delivered the most accurate energy consumption forecasts [6]. “An Overview of Machine Learning”: This paper presents a comprehensive overview of machine learning (ML), covering its core definitions, major categories, operational mechanisms, and practical applications. It begins by distinguishing ML [7]. Namrata Lotia, R.L. Shrivastava, Sachin Bagde, and Pushkar Pandit, “Maharashtra State’s Electricity Supply and Demand Forecasting for 2030 and 2050 Using LEAP.” In this paper, LEAP software has been utilized for electricity requirement (demand) and electricity generation (supply) projections using various scenarios for Maharashtra state in 2030 and 2050 [8]. Sarab Shanan Swide, Ali F. Marhoon, et al., “Energy Demand Prediction Based on Deep Learning Techniques” (2023). This study developed a model for estimating Denmark's power consumption using a model that combines LSTM and RNN. The results are compared with random forest model results. Authors analyze 3 years of data from 2016 to 2018, which was taken from the Kaggle dataset [9].

Paula Bastida-Molina et al., “A detailed analysis of electricity consumption at the University of Castilla-La Mancha (Spain),” In this, researchers analyze 16 electricity supply points of the UCLM-AB campus. Presents the seasonal and daily patterns identified for the four selected buildings in the UCLM-AB case study. Represent hourly electricity consumption over the complete year of 2021 for the selected buildings in UCLM-AB. The method is based on three clear steps: data collection, electricity consumption study, and parameterization. 1 year of data from 2021 was taken for analysis [10].The authors introduce a hybrid EMD–LSTM framework to forecast electricity demand by season, day, and time interval. First, the Empirical Mode Decomposition (EMD) algorithm splits the load time series into multiple Intrinsic Mode Functions (IMFs) and a residual. Next, individual LSTM models are trained on each IMF and the residual. Finally, the separate forecasts are summed to generate the aggregated electricity demand prediction [11].The paper presents the first application of the Prophet forecasting model for long-term peak load prediction in Kuwait, comparing its performance to the traditional Holt–Winters method. The analysis utilizes historical daily peak load data from Kuwaiti power plants spanning 2010 to 2020 to forecast peak demand for the decade 2020–2030 [13]. The research paper by Das, A., et al. (2020) [16] focuses on using deep learning techniques to predict long-term energy load in buildings, specifically by incorporating building occupancy forecasting. [21].

The proposed model exhibits optimal performance with improved precision and accuracy. Specifically, the proposed LSTM model achieved a decrease in MAE by 30%, RMSE by 25%, and MAPE by 20% compared to the LSTM method [22]. The research employed a Genetic Algorithm (GA) to fine-tune key LSTM hyper parameters-namely, the number of past time steps and the network depth-to maximize forecasting accuracy. By methodically adjusting these settings, the model aimed to outperform conventional machine learning approaches for short- and medium-term predictions of energy consumption [23]. Though the existing methods have shown good accuracy, there is still a requirement for more improved accuracy across diverse datasets with different regions.

2.1. Research Objectives

This research investigates the implementation and comparative performance of Prophet, LSTM, and GRU models for electricity consumption forecasting through an interactive computational framework. The primary objectives include

1. Analyzing the strengths and limitations of each forecasting methodology
2. Evaluating performance across different temporal horizons and consumption patterns
3. Identifying optimal model configurations for specific forecasting contexts
4. Exploring the potential of hybrid approaches to enhance prediction accuracy

2.2. Literature-Based Framework

A literature-based study is required, as outlined below:

2.2.1. Time Series Decomposition and Prophet Methodology:

The Prophet model conceptualizes time series data as a composition of three fundamental components: trend, seasonality, and holidays. This decomposition approach allows for individual modeling of each component, facilitating interpretable forecasts that capture both long-term trends and recurring patterns. The model can be represented mathematically as [12][17]:

$$y(t) = g(t) + s(t) + h(t) + \epsilon t$$

Where g(t) represents the trend component (non-periodic changes), s(t) represents the seasonality component (periodic changes), h(t) represents the holiday effect, and ϵt represents the error term. Prophet employs Bayesian inference through Markov Chain Monte Carlo (MCMC) methods for parameter estimation, providing not only point forecasts but also uncertainty intervals [12]. This probabilistic approach enhances the model's applicability in scenarios requiring risk assessment and decision-making under uncertainty.

2.2.2. Deep Learning Approaches: LSTM and GRU

LSTM and GRU networks represent specialized architectures within the broader category of recurrent neural networks, designed specifically to address the vanishing gradient problem that impedes the modeling of long-term dependencies in sequential data [4][19].

2.2.3. LSTM Architecture

The LSTM architecture introduces a memory cell with three regulatory gates—input, forget, and output—that control information flow within the network. This mechanism enables the selective retention of relevant historical information while discarding irrelevant signals, making LSTM particularly effective for capturing complex temporal patterns. The implemented LSTM model incorporates multiple layers:

```
model=Sequential([
LSTM(units=50,return_sequences=True,input_shape=(X.
shape[^1],1)),Dropout(0.2),
    LSTM(units=50),
    Dropout(0.2),
    Dense(units=1)
])
```

The above code snippet employs two LSTM layers for hierarchical feature extraction, dropout regularization (20%) to prevent overfitting, and a dense output layer for final prediction.

2.2.4. GRU Architecture

The GRU represents a more streamlined variant of LSTM, employing update and reset gates to regulate information flow while omitting the separate memory cell. This simplified structure reduces computational complexity while maintaining comparable performance in many forecasting applications [4]. The implemented GRU model features a similar structure but with reduced complexity:

```
model = Sequential([
    GRU(units=32, return_sequences=True,
input_shape=(X.shape[^1], 1)),
Dropout(0.1),
GRU(units=32),
Dropout(0.1),
Dense(units=1)
])
```

Both architectures employ sequence-to-sequence learning, where historical consumption patterns are processed to predict future values. This approach allows the models to learn complex temporal dependencies that may span various time scales, from short-term fluctuations to long-term trends [3].

3. Methodology

The methodology of electricity power consumption prediction consists of data collection, data preprocessing, feature engineering, model selection, model training, model predictive performance evaluation, and result visualization. Figure 1 shows the structural block diagram of the general framework of electricity power consumption prediction.

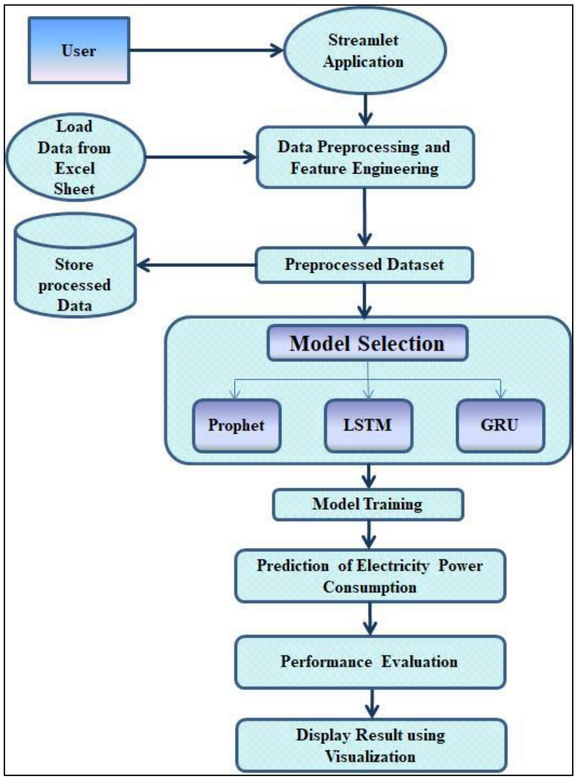


Fig. 1 Structural block diagram of electricity power consumption prediction framework

The diagram presents the structural framework for electricity power consumption prediction. It begins with a user interacting through a Streamlit application, which loads data from an Excel sheet. The data undergoes preprocessing and feature engineering to create a refined dataset, which is then stored. The system allows for model selection among Prophet, LSTM, and GRU models. The selected model is trained to predict electricity consumption. The predictions are evaluated for performance, and the final results are displayed using visualization tools for user interpretation.

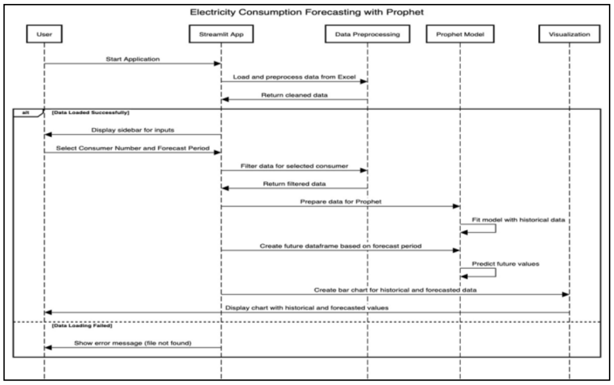


Fig. 2 Electricity consumption forecasting with Prophet

Figure 2 illustrates the process of forecasting electricity consumption using the Prophet model within a Streamlit application. The user starts the app, which loads and preprocesses Excel data. If successful, the app displays a sidebar for the user to select a consumer number and forecast period. The selected data is filtered, cleaned, and prepared for the Prophet model, which is then trained with historical data. Based on the forecast period, future data is generated, predictions are made, and an interactive bar chart is created. This chart, displaying both historical and forecasted values, is shown to the user. If data loading fails, an error message is displayed.

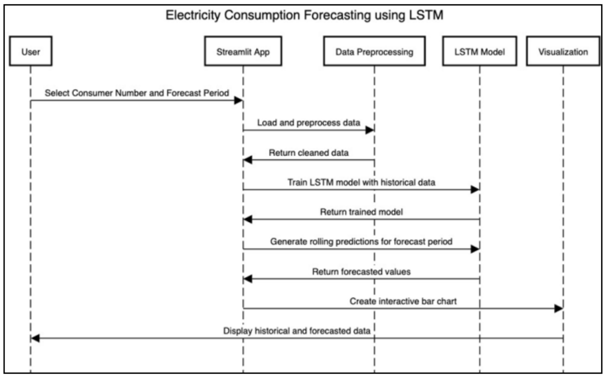
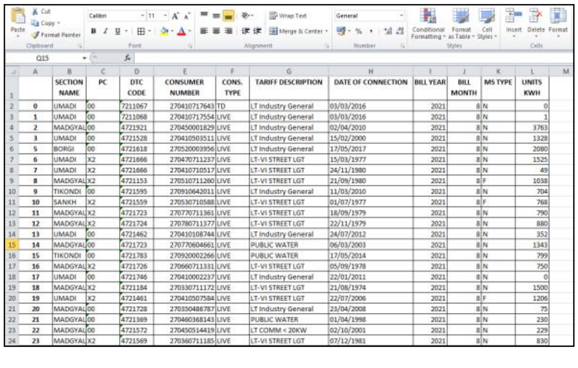


Fig. 3 Electricity consumption forecasting with LSTM

Figure 3 displays the process of forecasting electricity consumption using an LSTM model within a Streamlit app. The user selects a consumer number and forecast period, after which the app loads and preprocesses the data. The cleaned data is used to train the LSTM model, which then generates future consumption predictions. These predictions are visualized as an interactive bar chart and displayed alongside historical data for user analysis.

3.1. Data Preprocessing and Feature *Engineering*

The electricity consumption forecasting framework implements comprehensive data preprocessing procedures to ensure optimal model performance. The dataset used for model training and evaluation is collected from MSEB, Sangali region of Maharashtra, India. This dataset includes 5 lakhs consumer records from the year 2021 to 2023 with different features such as section name, processing cycle, DTC code, consumer number, tariff description, date of connection, bill month, bill year, MS type and units KWH. The screenshot of the processed dataset is shown in Figure 4.



	A	B	C	D	E	F	G	H	I	J	K	L	M
1		SECTION NAME	PC	DTC CODE	CONSUMER NUMBER	CONS. TYPE	TARIFF DESCRIPTION	DATE OF CONNECTION	BILL YEAR	BILL MONTH	MS TYPE	UNITS KWH	
2	0	UMADI	00	7211067	270410717643	TD	LT Industry General	03/03/2016	2021	8	N	0	
3	1	UMADI	00	7211068	270410717554	LIVE	LT Industry General	03/03/2016	2021	8	N	1	
4	2	MADGYAL	00	4721921	270450001829	LIVE	LT Industry General	02/04/2010	2021	8	N	3763	
5	3	UMADI	00	4721528	270410503511	LIVE	LT Industry General	15/02/2000	2021	8	N	1328	
6	5	BORGI	00	4721618	270520003956	LIVE	LT Industry General	17/05/2017	2021	8	N	2080	
7	6	UMADI	X2	4721666	270470711237	LIVE	LT-VI STREET LGT	15/03/1977	2021	8	N	1525	
8	7	UMADI	X2	4721666	270410710517	LIVE	LT-VI STREET LGT	24/11/1980	2021	8	N	49	
9	8	MADGYAL	X2	4721153	270510711260	LIVE	LT-VI STREET LGT	21/09/1980	2021	8	F	1038	
10	9	TIKONDI	00	4721595	270910642011	LIVE	LT Industry General	11/03/2010	2021	8	N	704	
11	10	SANKH	X2	4721559	270530710588	LIVE	LT-VI STREET LGT	01/07/1977	2021	8	F	768	
12	11	MADGYAL	X2	4721723	270770711361	LIVE	LT-VI STREET LGT	18/09/1979	2021	8	N	790	
13	12	MADGYAL	X2	4721724	270780711377	LIVE	LT-VI STREET LGT	22/11/1979	2021	8	N	880	
14	13	UMADI	00	4721462	270410108744	LIVE	LT Industry General	24/07/2012	2021	8	N	352	
15	14	MADGYAL	00	4721723	270770604661	LIVE	PUBLIC WATER	06/03/2003	2021	8	N	1343	
16	15	TIKONDI	00	4721783	270920002266	LIVE	PUBLIC WATER	17/05/2014	2021	8	N	799	
17	16	MADGYAL	X2	4721726	270660711331	LIVE	LT-VI STREET LGT	05/09/1978	2021	8	N	750	
18	17	UMADI	00	4721746	270410002237	LIVE	LT Industry General	22/01/2011	2021	8	N	0	
19	18	MADGYAL	X2	4721184	270330711172	LIVE	LT-VI STREET LGT	21/08/1974	2021	8	N	1500	
20	19	UMADI	X2	4721461	270410507584	LIVE	LT-VI STREET LGT	22/07/2006	2021	8	F	1206	
21	20	MADGYAL	00	4721728	270350486787	LIVE	LT Industry General	23/04/2008	2021	8	N	75	
22	21	MADGYAL	00	4721369	270460368143	LIVE	PUBLIC WATER	01/04/1998	2021	8	N	230	
23	22	MADGYAL	00	4721572	270450514419	LIVE	LT COMM < 20KW	02/10/2001	2021	8	N	229	
24	23	MADGYAL	X2	4721569	270360711185	LIVE	LT-VI STREET LGT	07/12/1981	2021	8	N	830	

Fig. 4 Snapshot of the electricity power consumption dataset with selected features

The initial data loading and transformation processes include

1. Conversion of consumer identification numbers to standardized string format
2. Temporal formatting and validation of billing dates
3. Standardization of measurement units (KWH)
4. Removal of missing or invalid entries

```
data['CONSUMER NUMBER'] = data['CONSUMER
NUMBER'].astype(str)
data['BILL_MONTH_STR'] = data['BILL
MONTH'].astype(str).str.zfill(2)
data['BILL_DATE'] = '01-' + data['BILL_MONTH_STR']
+ '-' + data['BILL YEAR'].astype(str)
data['BILL_DATE'] = pd.to_datetime(data['BILL_DATE'],
format='%d-%m-%Y', dayfirst=True, errors='coerce')
```

Feature engineering for the deep learning models employs a sequence-based approach, where historical consumption values are organized into input-output pairs for supervised learning.

```
def create_sequences(data, seq_length):
    X, y = [], []
    for i in range(len(data) - seq_length):
        X.append(data[i:i + seq_length])
        y.append(data[i + seq_length])
    return np.array(X), np.array(y)
```

This procedure transforms the original time series into a supervised learning problem, where sequences of length n are used to predict the subsequent value. Additionally, the framework implements normalization through MinMaxScaler to standardize input features within the range [5], enhancing training stability and convergence [5][18].

3.2. Outlier Detection and Treatment

The framework incorporates optional outlier detection based on interquartile range (IQR) analysis, which identifies and removes anomalous consumption values that could potentially distort model training. This approach enhances model robustness by mitigating the impact of exceptional consumption events or measurement errors that do not represent typical usage patterns [15].

3.3. Model Selection

In this step, three models-Prophet, LSTM, and GRU-are used for training and prediction of power consumption.

3.4. Seasonality Modeling

The framework provides configurable seasonality modeling options, allowing for the explicit incorporation of yearly and monthly seasonal patterns. This customizable approach acknowledges the diverse seasonal patterns that may influence electricity consumption across different consumer segments and geographical regions.

4. Results and Performance Analysis

4.1. Performance Metrics

The framework evaluates model performance through multiple complementary metrics, providing a comprehensive assessment of prediction accuracy [6]:

1. Coefficient of Determination (R^2): Measures the proportion of variance explained by the model.
2. Mean Absolute Error (MAE): Quantifies the average magnitude of errors without considering direction.
3. Mean Squared Error (MSE): Emphasizes larger errors through squared differences.
4. Root Mean Squared Error (RMSE): Provides error measurement in the original scale of the data

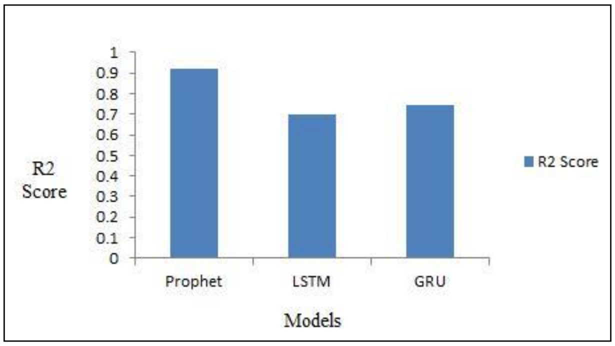
The implementation calculates these metrics for each model to facilitate direct comparison, which shown in Table 1.

Table 1. Performance Analysis of Prophet, LSTM and GRU Models

Metrics	R2 Score	MAE	MSE	RMSE
Prophet	0.922	0.06	0.01	0.11
LSTM	0.701	4.17	38.59	6.21
GRU	0.741	3.89	30.45	4.87

The bar chart in Figure 5 demonstrates the R2 score comparison of Prophet, LSTM, and GRU models. Prophet performs best overall with the lowest MSE and RMSE. LSTM has the lowest MAE, indicating good accuracy, while GRU shows higher errors across most metrics. Prophet demonstrates superior prediction performance among the three models.

Fig. 5 R2 Score evaluation of Prophet, LSTM, and GRU



4.2. Comparative Model Performance

Distinct performance characteristics across various forecasting contexts are revealed by an analysis of the applied forecasting models. In situations when there is enough historical data, the LSTM model achieves competitive R^2 scores of 0.922%, demonstrating superior ability in capturing intricate non-linear patterns and long-term dependencies. This is consistent with results from outside studies that show that in grid-level load forecasting applications, LSTM implementations have produced Mean Absolute Percentage Error (MAPE) values as low as 0.06%.

Due to its lower computing requirements and similar performance to LSTM, the GRU model [20] is especially well-suited for implementation in contexts with limited resources. According to results from hybrid GRU implementations that have attained MAPE values of 1.69% in energy consumption forecasting, this efficiency benefit comes with little loss in predictive accuracy.

Prophet excels in scenarios characterized by strong seasonality and trend components, providing interpretable decomposition that facilitates insight into underlying consumption patterns. The model's robustness to missing values and outliers enhances its practical utility in real-world forecasting applications.

The framework's automated model selection identifies the optimal approach based on quantitative performance metrics:

```
best_r2 = max(prophet_r2, lstm_r2, gru_r2)
if best_r2 == prophet_r2:
best_model = "Prophet"
elif best_r2 == lstm_r2:
best_model = "LSTM"
else:
best_model="GRU"
```

This data-driven selection process ensures that the most appropriate model is utilized for each specific forecasting context.

Fig. 6 UI of Electricity power consumption framework

Figure 6 displays a user interface for forecasting electricity power consumption. Consumer numbers can be chosen by users via an input field or dropdown menu. Months 1 through 12 can be selected as the forecast period. Toggles for applying yearly seasonality, permitting monthly seasonality and eliminating outliers are additional choices.

Forecasts of power consumption for user 270220000181 using Prophet, LSTM, and GRU models-without outlier removal-are shown in Figures 7, 8, and 9.

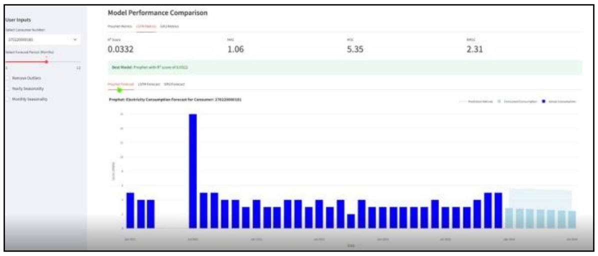


Fig. 7 Electricity consumption forecast for consumer: 270220000181 using Prophet model

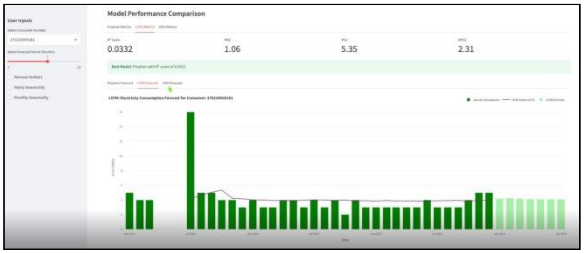


Fig. 8 Electricity consumption forecast for consumer: 270220000181 using LSTM model

Fig. 9 Electricity consumption forecast for consumer: 270220000181 using GRU model

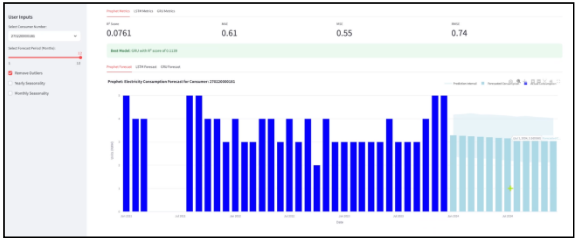


Fig. 10 Electricity consumption forecast for consumer: 270220000181 for 12 months

Fig. 11 Electricity consumption forecast for consumer: 270220000181 with removed outliers and yearly seasonality.

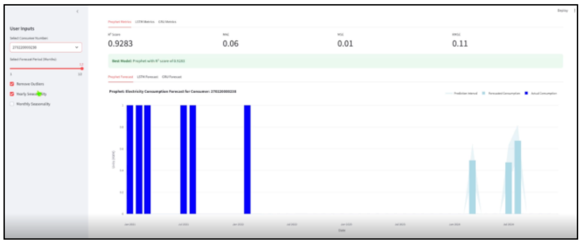


Fig. 12 Electricity consumption forecast for consumer: 270220000238 with removed outliers and yearly seasonality.

Figure 7, 8, and 9 display forecasts that include outliers. After removing the outliers, the Prophet model was reapplied to consumer ID 270220000181, extending the forecast period from 7 to 12 months. This adjustment led to revised performance metrics: an R² score of 0.0761, MAE of 0.61, MSE of 0.55, and RMSE of 0.74, as shown in Figure 10. In the corresponding bar chart, the dark blue bars represent historical electricity consumption data from 2021 to 2023, while the light blue bars indicate forecasted consumption for the year 2024. Figure 11 presents the electricity consumption forecast for consumer 270220000181 using the Prophet model with outliers removed and yearly seasonality enabled. The interface displays model performance metrics: R² score 0.7334, MAE 0.30, MSE 0.16, and RMSE 0.40, indicating a strong predictive performance. Figure 12 depicts the electricity power consumption forecast for consumer number 270220000238 with removed outliers and Yearly seasonality. For this forecast the prophet model has R2 score of 0.9283, MAE 0.06, MSE 0.01, and RMSE 0.11.

The bars of Figure 12 compare historical and forecasted electricity consumption, with forecast values shown in a lighter shade. The user inputs on the left allow selection of consumer number and forecast period and options for handling seasonality and outliers.

5. Discussion

5.1. Complementary Strengths of Forecasting Approaches

The implemented forecasting framework demonstrates the complementary strengths of statistical and deep learning approaches. While Prophet excels in decomposing time series into interpretable components, LSTM and GRU networks demonstrate superior capacity for capturing complex non-linear relationships without explicit feature engineering [3].

This complementarily suggests potential advantages in hybrid approaches that leverage the strengths of multiple methodologies. Research on hybrid forecasting frameworks combining Prophet and LSTM has demonstrated significant performance improvements relative to individual models, particularly in scenarios characterized by both strong seasonality and complex nonlinear patterns [3].

5.2. Contextual Performance Variability

The comparative analysis reveals significant context-dependency in model performance, with forecasting efficacy varying based on:

5.2.1. *Time horizon:* LSTM models typically outperform statistical approaches in short-term forecasting (hours to days), while Prophet demonstrates advantages in medium-term horizons (weeks to months) [6]

5.2.2. *Data availability:* Deep learning approaches require substantial historical data for optimal performance, while statistical methods can produce reasonable forecasts with limited historical data [7]

5.2.3. *Consumption patterns:* The presence of strong seasonality, trends, or irregular patterns influences the relative performance of different forecasting approaches [1]

This context-dependency underscores the importance of adaptive model selection based on specific forecasting requirements and data characteristics.

5.3. Practical Implementation Considerations

The interactive implementation facilitates practical application by incorporating several user-centric features:

1. Consumer-specific forecasting: The framework allows selection of individual consumers from available data, enabling targeted analysis of specific consumption patterns.
2. Configurable forecast horizon: Users can adjust the prediction timeframe based on specific planning requirements.
3. Outlier treatment options: The optional removal of anomalous data points enhances model robustness.
4. Seasonal component configuration: Users can selectively incorporate yearly and monthly seasonality based on domain knowledge.

These features enhance the frameworks practical utility across diverse forecasting scenarios, from operational planning to strategic infrastructure development.

6. Conclusion

Using an interactive computational framework, this research work presents the implementation of Prophet, LSTM, and GRU models for forecasting electricity power consumption. The comparison analysis shows that although each approach has unique advantages in various forecasting situations, when combined, they offer a strong basis for precise consumption prediction in a range of situations. The results emphasize how crucial it is to choose contextual models according to particular forecasting needs, data properties, and computational limitations. Through interactive visualization and setup, the exhibited framework offers a useful implementation that makes such adaptive model selection possible while preserving accessibility.

In order to ensure system sustainability and dependability, advanced forecasting techniques will become more and more important as electrical systems continue to develop toward higher complexity and integration of renewable resources. By improving the deep learning based model's ability to predict and adapt to changing consumption patterns, the approaches and implementations examined in this research support this larger goal. Forecasting performance can be further improved by future research on hybrid architectures, exogenous variable integration, and uncertainty quantification, which will ultimately support more sustainable and efficient electrical systems.

References

[1] Dmitry Brykin, (2024). Sales Forecasting Models: Comparison between ARIMA, LSTM and Prophet. *Journal of Computer Science,* 20(10) 1222-1230, DOI: 10.3844/jcssp.2024.1222.1230, (2024)

[2] Rashmi Bareth, Matushree Kochar, Anamika Yadav, Mohammad Pazoki, “Load Forecasting Model Using LSTM for Indian State Load Dispatch Centre”, in Electrica 2024, DOI: 10.5152/electrica.2024.23158, August 2024, https://electricajournal.org/Content/files/sayilar/85/ELECT_20230158-AOP-1508(1).pdf

[3] Serdar Arslan, “A hybrid forecasting model using LSTM and Prophet for energy consumption with decomposition of time series data”, June 2022, DOI: 10.7717/peerj-cs.1001/supp-1, https://pmc.ncbi.nlm.nih.gov/articles/PMC9202617/

[4] Shaokun Liang, Tao Deng, Anna Huang, Ningxian Liu, Xuchu Jiang, “Energy consumption prediction using the GRU-MMattention-LightGBM model with features of Prophet decomposition”, 2023 Jan 17;18(1):e0277085. doi: 10.1371/journal.pone.0277085, https://pmc.ncbi.nlm.nih.gov/articles/PMC9844920/

[5] https://ppl-ai-file-upload.s3.amazonaws.com/web/direct-files/38946341/9fde2468-b3ad-424f-bd2c-7286d19e93d2/paste.txt

[6] Kanchan A. Khedikar and Dr. Piyush Kumar Pareek, “An overview of Machine Learning”, JAC: A Journal Of Composition Theory, Volume XIII, Issue III, March 2020 ISSN: 0731-6755, pp 587-592. https://jctjournal.com/volume-xiii-issue-3-2020

[7] N. Lotia, R. Shrivastava, Pushkar Pandit “Maharashtra State’s Electricity Supply - Demand Forecasting for 2030 and 2050 using LEAP” https://www.semanticscholar.org/paper/Maharashtra-State%E2%80%99s-Electricity-Supply-Demand-for-Lotia-Shrivastava/7e7413d96864c0caac1f6cd53044247476119f86

[8] “Energy_Demand_Prediction_Based_on_Deep_Learning_Techniques”, Iraqi Journal for Electrical and Electronic Engineering Original Article or Review Article or Short Article, DOI: 10.37917/ijeee.19.2.10, December 2023, https://doi.org/10.37917/ijeee.19.2.10, https://www.ijeee.edu.iq

[9] Paula Bastida-Molina a, Juan Torres-Navarro b, Andrés Honrubia-Escribano c, Inmaculada Gallego-Giner d, Emilio Gómez-Lázaro c “A detailed analysis of electricity consumption at the University of Castilla-La Mancha (Spain)”, Published by Elsevier B.V., https://doi.org/10.1016/j.enbuild.2023.1130460378-7788/

[10] Jatin Bedi And Durga Toshniwal, (Member, IEEE) Department of CSE, IIT Roorkee, Roorkee 247667, India,“ Empirical Mode Decomposition Based Deep Learning for Electricity Demand forecasting”, Published in August 29, 2018. Source: https://ieeexplore.ieee.org/document/8449937

[11] Tasarruf Bashir, Chen Haoyong, Muhammad Faizan Tahir, Zhu Liqiang, “Short term electricity load forecasting using hybrid prophet-LSTM model optimized by BPNN”, Energy Reports 8 (2022) 1678–1686, Energy Reports Elsevier. https://www.sciencedirect.com/science/article/pii/S2352484721015067?via%3Dihub

[12] Almazrouee A.I., Almeshal A.M., Almutairi A.S., Alenezi M.R., Alhajeri S.N. “Long-Term Forecasting of Electrical Loads in Kuwait Using Prophet and Holt–Winters Models”, in Appl. Sci., 10 (16) (2020), p. 5627, https://www.mdpi.com/2076-3417/10/16/5627

[13] Maria Jacob , Cláudia Neves, Danica Vukadinović Greetham, “Forecasting and Assessing Risk of Individual Electricity Peaks”, published in Forecasting and Assessing Risk of Individual Electricity Peaks, eBook ISBN978-3-030-28669-9, September 2019, https://doi.org/10.1007/978-3-030-28669-9

[14] Denis Cousineau, Sylvain Chartier, “Outliers detection and treatment: A review”, June 2010, International Journal of Psychological Research, 3(1), DOI:10.21500/20112084.844, License CC BY-NC-ND 4.0 https://www.researchgate.net/publication/50946372 Outliers_detection_and_treatment_A_review

[15] Das, A., et al. (2020). Long-term energy load prediction using deep learning techniques for building occupancy forecasting. *Energy and Buildings*, 225, 110318. https://doi.org/10.1016/j.enbuild.2020.110318

[16] Sreenadh V Movva, “Electrical Energy Consumption Prediction For Schools”, Master Programme in Data Science 2022, Luleå University of Technology, https://www.diva-portal.org/smash/get/diva2:1720589/FULLTEXT01.pdf

[17] Meia Alsup, “Forecasting Electricity Demand in the Data-Poor Indian Context”, Massachusetts Institute Of Technology, September 2020, https://dspace.mit.edu/bitstream/handle/1721.1/129084/1227274035-MIT.pdf?sequence=1&isAllowed=y

[18] Alanbar, M. A., et al. (2020). “Energy Consumption Prediction Using Deep Learning Technique Case Study of Computer College”, LSTM-based energy prediction model for a building at Qassim University https://doi.org/10.3991/ijim.v14i10.14383

[19] Ming-Chuan Chiu, et al. (2023), “A hybrid CNN-GRU based probabilistic model for load forecasting from individual household to commercial building”, A generalized energy prediction model using CNN and GRU deep learning models. https://www.sciencedirect.com/science/article/pii/S2352484723008387?via%3Dihub

[20] Florian Ziel, Rick Steinert (2018), “Probabilistic mid- and long-term electricity price forecasting”, https://www.sciencedirect.com/science/article/abs/pii/S1364032118303885

[21] Tan Ngoc Dinh, et al. (2023), “Predicting Commercial Building Energy Consumption Using a Multivariate Multilayered Long-Short Term Memory Time-Series Model” DOI:10.20944/preprints202306.0135.v1

[22] Almalaq and Zhang (2018), “Genetic algorithm and LSTM deep learning method for building energy consumption prediction: A case study in Sydney”