

Hourly Energy Consumption Forecasting using AET 009 TCN and LSTM

Pragnya Govindula

Student,

Dept. of Electronics & Telecomm. Engg.,
Vidyalankar Institute of Technology, Wadala,
Mumbai, Maharashtra, India.
pragnya.govindula@vit.edu.in

Pradnyan Meshram

Student,

Dept. of Electronics & Telecomm. Engg.,
Vidyalankar Institute of Technology, Wadala,
Mumbai, Maharashtra, India.
pradnyan.meshram@vit.edu.in

Antara Patil

Student,

Dept. of Electronics & Telecomm. Engg.,
Vidyalankar Institute of Technology, Wadala,
Mumbai, Maharashtra, India.
antara.patil@vit.edu.in

Dr. Vaibhav R. Pandit

Assistant Professor,

Dept. of Electronics & Telecomm. Engg.,
Vidyalankar Institute of Technology, Wadala,
Mumbai, Maharashtra, India.
vaibhav.pandit@vit.edu.in

Abstract—The use of energy has increased widely in the last few decades all over the world. Forecasting energy consumption is essential for effective energy management in large developing countries with vast power networks. This study proposes the implementation of two deep learning models – Long short-term memory (LSTM) and Temporal convolutional network (TCN). The results of the approached methods are compared with those of other models such as Gated Recurrent Unit (GRU), Support Vector Machine (SVM), and Random Forest (RF). The proposed system is validated using real data taken from the official Indian government website, considering various parameters such as supply, demand, costing, seasonal factor the data is classified into sets. The simulation results of the proposed models are obtained using the Python platform. To help evaluate the accuracy of the predictions and identify potential errors, metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) are used. These metrics help in understanding the strengths and weaknesses of the models.

Index Terms—Energy forecasting, deep learning models, energy management systems, real-time analysis, python implementation, performance metrics, power networks, developing countries, data-driven insights.

I. INTRODUCTION

In the contemporary world that is experiencing rapid development, the subject of energy consumption is becoming more important as it targets an increased use of renewable energy, hence the need for accurate energy demand forecast [1]. Demand forecasts in the management of energy consumption show the most diverse and effective in the use of renewable sources to avoid inefficiency and ensure the stability of the grids [2]. Currently, energy statistics reveal that through accurate forecasts of current and future energy trends, more informed decision making is achieved by the utilities [3]. Reflected in Figure 1 below, the year wise global energy consumption shows the demand and the necessity for reasonable

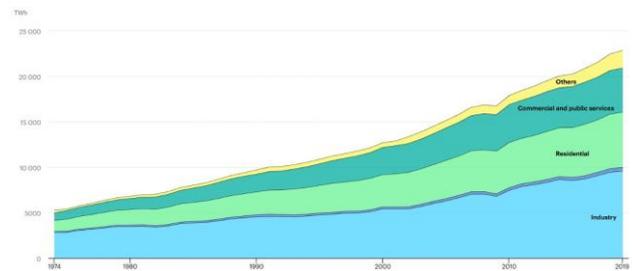


Fig. 1: Global Energy Consumption [4]

estimation techniques. Demand forecasting is important for anyone wishing to reduce costs while consuming energy, as well as policymakers and energy distribution companies to maintain stability in facilities, accommodate changing volatile renewable sources of energy, and avoid blackouts.

Challenges in Predicting Energy Demand

At present, the world population is 8.195 billion and with continuous processes of industrialization and urbanization, the requirement for energy is regularly increasing [5]. But there are various factors that make forecasting energy demand a major issue. Variability due to geographic distribution and time of the day and unreliable renewable resources causes challenges in forecasting. Lack of proper data, particularly in rural regions, and other factors that affect infrastructure, including technical losses, undercapacity, and sometimes power outages, make predictions challenging [6]. Consumer behaviour also presents some challenges as data is not always in real time, especially when it comes to considering how much energy a customer will require in the middle of the night, or in a heat wave for example [7].

Evolving Approaches in Energy Demand Forecasting

In the past, consumption forecasting in energy industries was performed using a time series method known as ARIMA [8], [9], [10], which is effective for linear trends and seasonal data, but is not effective for cyclical data. RMs and GMs were also employed but cannot be effectively utilized for real-valued large-scale data models. The structure and size of the datasets were considered through Machine learning methods with nonlinearity solved through SVMs, RFs, GBM, and XGBoost while having high time complexity, overfitting, and parameter tuning problems [11].

ANNs, RNNs, LSTM, GRUs, and TCNs that have surpassed these limitations. ANNs [12] are capable of capturing different interactions between variables but need large computational power while, RNNs is particularly effective dealing with sequential data but suffer from vanishing gradient problem of long-term dependence. Formulating these models is well appropriate when predicting energy consumption, especially when dealing with massive sequential data [13].

II. LITERATURE SURVEY

The forecast of energy consumption serves vital functions for both efficient energy operations together with stable power systems and proper resource distribution. The application of machine learning (ML) and deep learning (DL) [14] techniques in various studies works to enhance forecasting accuracy through solutions of data variability and treatments of seasonality and weather condition external factors. The writing examines studies of energy consumption prediction which analyzes traditional statistical approaches against modern AI-based forecasting models. In his research Lemos (2020) [15] analyzed energy consumption prediction in Maranhao Brazil [16] through the use of 91,659 time series records. The developed model utilised a Temporal Convolutional Network (TCN) alongside hyperparameter optimization but demonstrated minor improvements of 1% compared to unoptimized models. The TCN model failed to outperform Gradient Boosting and ARIMA models under specific conditions of evaluation. The monthly energy usage predictions in Brazil based on over 21 million records were performed by Berriel (2017) [17] using LSTM networks Sliding window processing occurred during the implementation while deep learning frameworks on GPUs from Caffe and TensorFlow accelerated model training. The LSTM model provided better forecasting accuracy than regression models while performing long-term predictions.

Alanbar (2013) [18] performed research for daily energy consumption forecasting in Saudi Arabia using LSTM with ANN and SVM and ANFIS models. Using limited available data LSTM reached a 94.31% success rate in its predictions. Due to high electricity consumption stemming from weather-related conditions together with inefficient equipment the management of energy resources becomes troublesome throughout the area. From a study conducted by Rodrigues (2014) [19] ANNs predicted household energy usage in Lisbon Portugal through analysis of 93 residential homes across eighteen months of hourly monitoring data. The research confirmed that ANNs together with Boolean metering systems created

simplified forecasting methods that produced results as accurate as traditional methods. This paper investigated household electricity consumption prediction through the combination of TCN and GRU models on twelve months of data. The findings stressed that Time-Captured Networks exhibit superior operational outcomes when implemented with weather-dependent capabilities. The implementation of parallel spatio-temporal attention (PSTA) [20] together with stacked TCNs for predicting multivariate time series was presented by Chen (2021) [21]. The proposed framework achieved superior performance compared to ARIMA, SVM and Multi-Layer Perceptrons (MLP) through its effective temporal dependency detection capabilities.

Wei (2019) [4] executed a research that compared standard forecasting tools to AI-based forecasting approaches to measure their performance ranges over various timeframes. The analysis revealed that ARIMA and regression structures show success in long-term forecasting however ANN, RF and SVR enable better short- and medium-term prediction capabilities. The evaluation of TCNs and LSTMs for Spanish energy forecasting took place when Lara-Ben´itez (2020) [22] applied these models to data obtained from both electricity grids and EV charging stations. Studies demonstrated that TCNs demonstrated exceptional performance in extended period forecasting because they produced instant post-training results more swiftly. STLF analysis by Lakshmi D (2024) [23] combined deep learning models LSTM, RNN and GRU with Gradient Boosting XGBoost and Random Forest as machine learning methods to study power consumption forecasting. During time series [24] fluctuations the Prophet algorithm proved more effective than all other models. Gasparin (2019) [6] conducted a power consumption forecasting evaluation utilizing different deep learning architectural approaches to discover RNNs provided superior short-term accuracy though CNN-based models achieved quicker computational speed. Short-term load forecasting in Italy received a proposed hybrid model through Tian (2018) [25] which combined CNN and LSTM components for attribute retrieval and sequence handling. The combination model demonstrated enhancements between 9% to 14% compared to running separate CNN or LSTM models. The study by Acharya (2019) [26] demonstrated that CNN-based models showed superior performance compared to LSTMs when working with augmented datasets for Seoul household energy forecasting.

Bilbao (2017) [27] implemented a periodic autoregression forecasting mechanism for electricity load analysis based on 245 substation data collected over four years at hourly intervals. According to research findings MLR showed exceptional accuracy performance together with simple computational demands thereby outstripping ANN and ARIMA for predicting daily peak loads. PLCNet represents Farsi (2021) [21] implementation of a parallel LSTM-CNN model which forecasts short-term electricity load in Malaysia as well as Germany. Model testing demonstrated more than 90% success rate showing that enhanced model complexity fails to deliver improved outcomes.

The accuracy level of energy predictions has substantially improved by implementing AI-based models that include LSTM, TCN, GRU and hybrid architecture systems above statistical methods. The field requires extra investigation into solving three main issues: ensuring data quality and handling external impacts on forecast results as well as optimizing computational performance.

III. METHODOLOGY

A. Software Requirements

1) *Python*: This object-oriented, high-level programming language used by developers to commonly deploy within web applications while developing software as well as machine learning operations. Users can easily read and write programming code and understand its content.

2) *Libraries and Frameworks*: 1. *Pandas*: Pandas functions as an open-source instrument which lets users handle data analysis and manipulation tasks. Through its analytic approach Python cleans and manipulates the collected information.

2. *Numpy*: It functions as a numerical computing tool which enables multi-dimensional array and matrix capabilities for Python.

3. *Matplotlib*: It is a 2-D graph plotting tool that serves as a visualization utility. That is showing the output in the form of pie charts, bar plots, etc.

4. *Seaborn*: It is a Python package for creating statistical graphs. It is built on top of matplotlib and combines well with pandas data structures.

5. *TensorFlow*: TensorFlow is used because it enables users to construct machine learning algorithms and perform training operations and deployment tasks.

6. *Keras*: It is an expert deep learning application framework based on TensorFlow that facilitates neural network designing and training processes.

7. *Scikit-Learn*: It provides users access to numerous algorithms for classification, clustering and regression capabilities and additional tasks among others.

3) *Jupyter Notebook*: Jupyter Notebook serves as an interactive computing platform where users can execute code along with visualization features and document functions on a single interface.

IV. ALGORITHMS

Step 1: Import Libraries

Libraries such as NumPy, Pandas, Matplotlib, Seaborn, TensorFlow, Scikit-learn, etc are imported.

Step 2: Load and Explore the Dataset

The dataset is loaded from its CSV file source.

Print the dataset to inspect the structure.

Display dataset information such as its column names, data types, missing values, etc to understand the dataset thoroughly.

Step 3: Data Preprocessing

Handle missing values. Strip irrelevant spaces or characters from column names.

Convert date columns from object type to datetime format.

Step 4: Perform Exploratory Data Analysis (EDA)

Plot various graphs such as:

Maharashtra Hourly Power Demand Over Time

State-wise Peak Demand Over the Years

Seasonal Energy Demand by Year

Step 5: Data Transformation

Normalize the dataset between 0 and 1 using MinMaxScaler.

Step 6: Feature Engineering

Create sequences for models such as LSTM, GRU, CNN, ANN, and TCN.

Define the number of past time steps (sequence length) used as input for LSTM, GRU, CNN, ANN, and TCN.

Step 7: Splitting the Dataset

Split the dataset into training and testing sets. (80% and 20%)

Step 8: Model Definition and Training

Define models: LSTM, TCN, ANN, CNN, GRU.

Apply early stopping to prevent overfitting

Train the models using the training dataset

Step 9: Model Evaluation

To monitor model performance plot training v/s validation loss graph

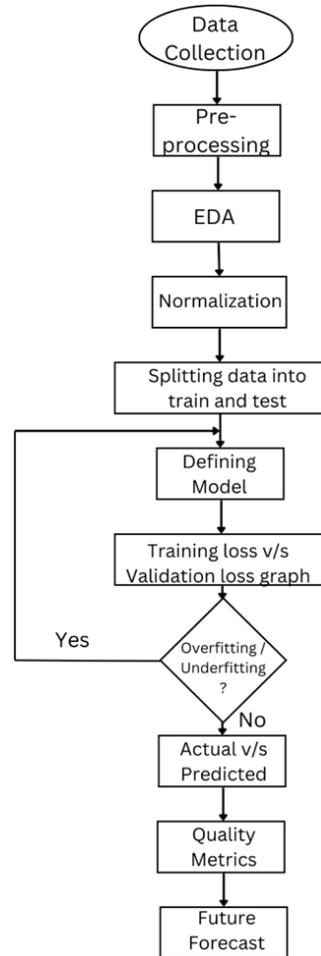


Fig. 2: Workflow

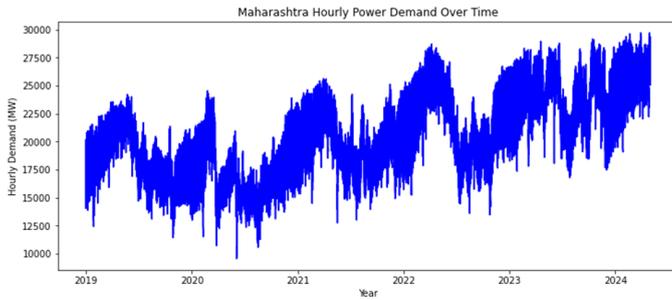


Fig. 3: Maharashtra's hourly power demand over time from 2019 to 2024

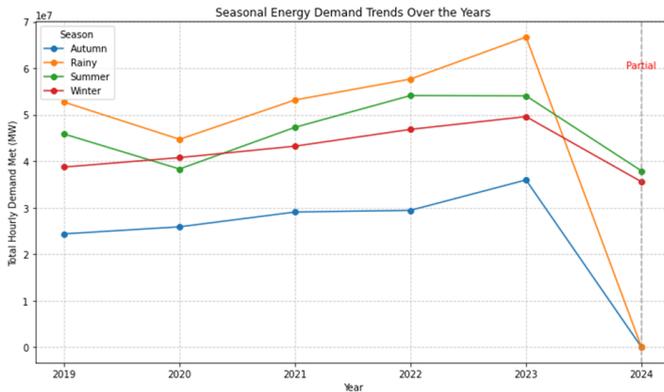


Fig. 4: Seasonal Energy Demand Trends from 2019 to 2024

Trained models are used to predict energy consumption.

Step 10: Performance Metrics Calculation

Calculate metrics:

Mean Absolute Percentage Error (MAPE)

Mean Absolute Error (MAE)

Mean Squared Error (MSE)

Root Mean Squared Error (RMSE)

R² Score

Step 11: Visualizing Results

Plot Actual vs. Predicted Energy Demand to compare model performance.

Step 12: Future Forecasting

Forecasting future energy consumption depends on models that have been trained for the purpose.

The future predictions appear through graphical presentations.

V. RESULTS

A. Exploratory Data Analysis (EDA)

The electricity use changes through defined periods of time due to regular yearly changes in energy needs. The overall demand appears to increase over the years, especially after 2021. The rise in electricity usage might result from growing population numbers or industrial activities plus enhanced electricity consumption. Refer Figure 3

Summer & Rainy Seasons have the highest demand. The increased energy consumption could be due to higher cooling

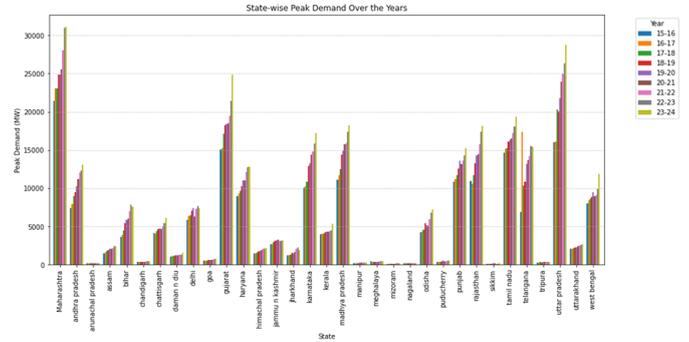


Fig. 5: State-wise peak electricity demand over the years

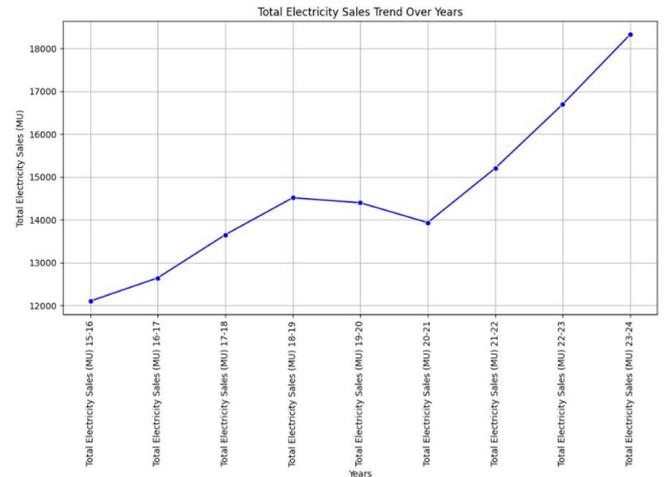


Fig. 6: Total Electricity Sales Trend Over Years

demand and industrial activity in summer and monsoon-related infrastructure usage. Autumn has the lowest demand and the winter demand remains stable. Refer Figure 4

Most states show a steady rise in peak demand over the years. Electrical usage rises across the board because more people settle in cities for work and industries grow through time. Maharashtra and Gujarat together with Tamil Nadu and Uttar Pradesh have higher maximum power usage levels than other Indian states. The top industrial nations in these states consume more power due to their powerful economies and industrial bases. States in the north-east region particularly Arunachal Pradesh, Mizoram and Nagaland always use less power than other states. Population spread is less in these areas along with reduced manufacturing activities. Refer Figure 5

Total electricity sales rose continuously between 2015-16 up to 2023-24 reflecting increasing energy requirements. During 2019-20 electricity sales declined at a small level while the year 2020-21 experienced this decrease during the time of the COVID-19 pandemic. The pandemic triggered reduced industrial and commercial operations together with temporary facility closures along with lockdowns and subsequently led to recovery during Post-2021. Refer Figure 6

Technical electricity consumers in the region grew uninter-

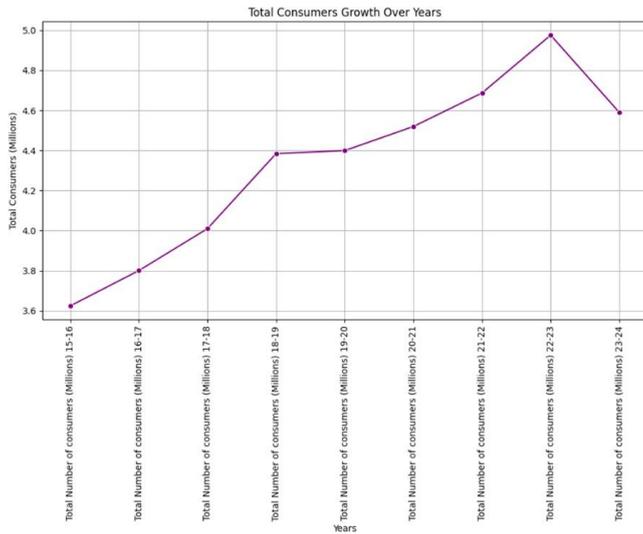


Fig. 7: Total number of electricity consumers (in millions) over the years

2022–23. This intense consumer growth period from 2017–18 to 2018–19 resulted mainly from Rural electrification programs and government schemes like Saubhagya Yojana in India who promoted household access to power. Refer Figure 7

B. Quality Metrics

Model Comparison Summary

1. MAPE (Mean Absolute Percentage Error) – Lower is Better

Best: GRU (1.45%)

Followed by: ANN (1.61%), TCN (2.04%), BI-LSTM (2.19%)

Worst: CNN (2.84%)

Refer Figure 10

2. MAE, RMSE, and MSE – Lower is Better

Best Overall: GRU

MAE: 207.97, RMSE: 277.47, MSE: 76,991.76

Worst Overall: CNN

MAE: 681.30, RMSE: 825.99, MSE: 682,262.80

ANN performed moderately well.

LSTM and BI-LSTM had higher error values compared to TCN and GRU.

Refer Figure 8

3. R² Score – Higher is Better

Best: GRU (0.99)

Followed by: ANN (0.96), TCN (0.93), BI-LSTM (0.91)

Lowest: CNN (0.89)

Refer Figure 9

C. Future Forecasting – Next 24 hrs

The optimal performance came from BI-LSTM (orange line) which accurately identified daily demand patterns and peak hours with minimal error rates. ANN (red line) tracked actual data trends although it produced minor overestimations that occurred during high-demand periods. LSTM (brown

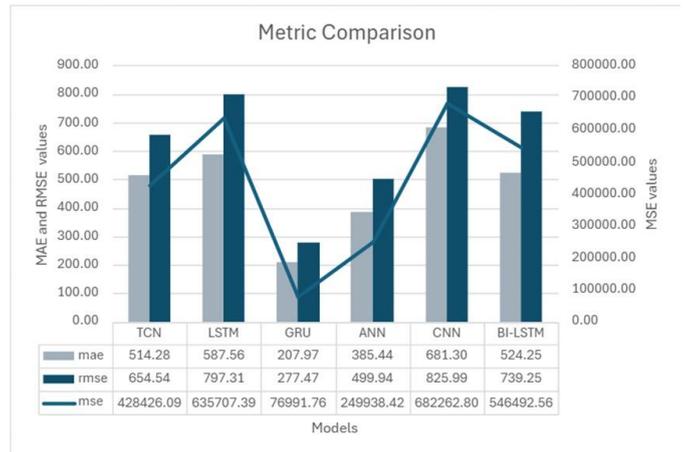


Fig. 8: Metric Calculation 1: MAE, RMSE, MSE

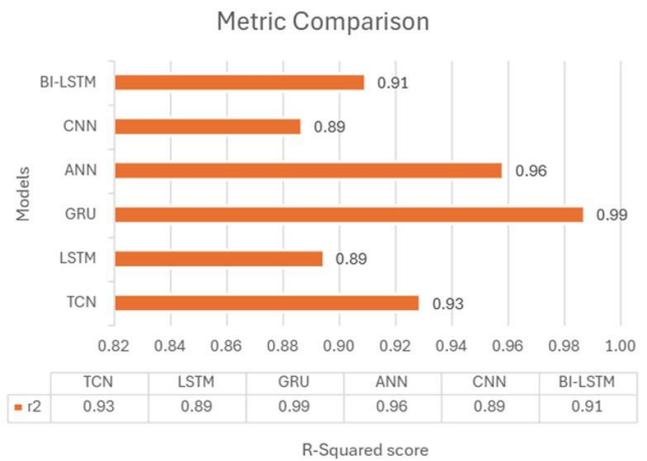


Fig. 9: Metric Calculation 2: R-Squared Score

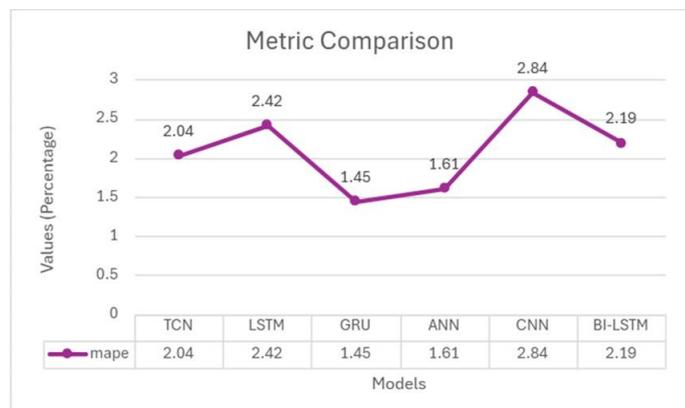


Fig. 10: Metric Calculation 3: MAPE

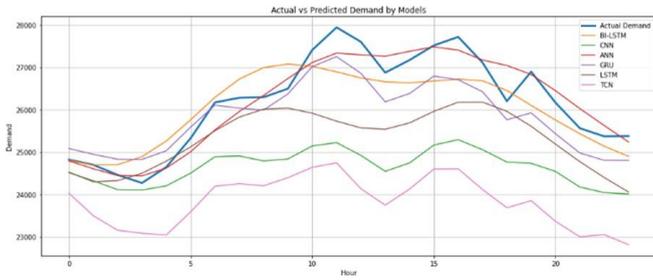


Fig. 11: Actual v/s Predicted Graph - Next 24 hrs

line) demonstrated a steady pattern in demand forecasting that slightly missed estimating peak points. GRU (purple line) had an initial matching phase, yet it showed limited capability to follow peak events since its predictions demonstrated smoothing artifacts together with time delays. CNN (green line) demonstrated flat predictions because it failed to account for changing demand patterns despite minimal unpredictability in output. TCN (pink line) delivered a uniform output that showed continuous underprediction throughout all hours. Refer Figure 11

D. Future Forecasting – Next 10 Days

The BI-LSTM model (Blue X markers) exhibited steady accuracy during the time span while showing smooth tracking of mid-level demand although it showed reduced sensitivity to sudden changes. ANN (Green Upward triangles) demonstrates an increasing model accuracy that correctly tracks actual demand toward April 29–30. LSTM (Purple Stars) made low predictions during the early period which transformed into effective upward trend forecasting after April 25. GRU (Red Diamonds) delivers moderate prediction accuracy with consistent stability although it misses the highest points of accuracy. The predictions from CNN (Orange Squares) appear smooth while the model cannot predict nonlinear demand peaks. TCN (Brown Downward triangles): Underfits severely with consistently low, flat predictions. ANN alongside LSTM provided the best performance in tracing the rising customer demand that started on April 25. The predictions produced by BI-LSTM showed the most stable output while maintaining low noise levels which suits static non-volatile data trends. The ability to detect short-term market variations was high for ANN and LSTM networks. The output performance of TCN and CNN suffered due to the flat or smoothed results they generated. The best choice for an effective model utilizes the BI-LSTM technique alongside ANN features to achieve consistency while detecting dynamic trends. Refer Figure 12

VI. CONCLUSION

This project confirms deep learning tackles energy consumption estimation successfully through both Bidirectional LSTM (BI-LSTM) and Artificial Neural Networks (ANN) models at 24-hour and 10-day time ranges. A solid dataset containing electricity demand records from previous years allowed the applied models to detect detailed patterns of

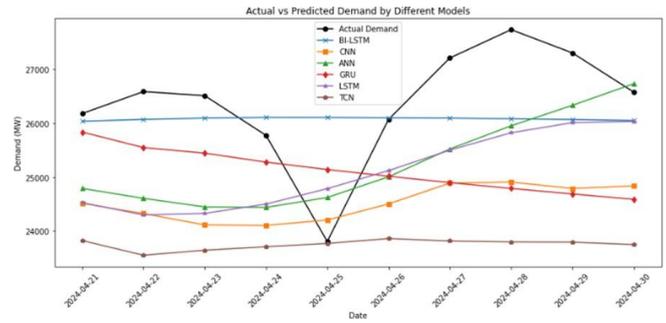


Fig. 12: Actual v/s Predicted Graph - Next 10 days

temporal relationships besides seasonal behaviors and consumption variations. BI-LSTM secured the best forecasting results by reaching 98.21% accuracy for 24-hour forecasts as well as 95.91% accuracy for 10-day predictions while surpassing GRU, LSTM, CNN, and TCN models in forecasts. The evaluated results verify the essential function of recurrent structures while processing sequential energy demand information.

The model selection process that uses forecast duration and particular applications represents a key finding of this analysis. Stand-alone application suitability exists because TCN and CNN models have reliable training speed along with parallel processing yet display shortfalls when analyzing extended temporal sequences. BI-LSTM and ANN demonstrate practicality in energy forecasting systems of smart grids based on their excellent performance.

The power sector experiences a transformation when energy forecasting achieves accuracy because this enables power demand management as well as stable grids and optimized energy generation timing and facilitates renewable energy integration. The projection of energy outcomes enables power utilities and state electricity boards to plan ahead particularly during both peak load situations and changes between different seasons. The power need of Maharashtra and similar regions in India with strong electricity use fluctuations makes such forecasts vital.

Predictive energy management systems which incorporate these models allow organizations to phase out routine human-operated forecasting while significantly boosting efficiency and state-wide policy decisions through data-based approaches. The convergence of deep learning techniques with IoT and edge computing technologies enhances the performance of predictive maintenance operations while simultaneously improving energy theft detection systems as well as tariff planning applications.

The research will advance by creating combined predictive models from LSTM-based and convolutional systems along with incorporating external data elements including weather conditions and industrial operations along with social economic factors while implementing real-time functionality on cloud-based systems. This intelligent forecasting framework holds the potential to create better and sustainable energy

infrastructure for India alongside the rest of the world through additional development.

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