Power Demand Forecasting Using ANN and Prophet Models for the Load Despatch Center in Andhra Pradesh, India

Damini Swargam, Mahitha Natte, Durga Aparajitha Javvadi, Vamsi Krishna Chaitanya Aray, Venkata Rama Santosh Rachuri, Sreedhar Reddy Veguru

Abstract*: This paper uses various data variables to develop and analyze ANN and Prophet models for power demand forecasting in Andhra Pradesh, India. The electricity power consumption in Andhra Pradesh was about 51,756.000 GWh in 2021. Currently, there is a great emphasis on saving power. Power Demand Forecasting is creating much interest, and many models, such as artificial neural networks combined with other techniques based on real-life phenomena, are used and tested. These models have become an essential part of the power and energy sector. This paper considered specific time-series analysis methods and deep-learning techniques for short-term power demand forecasting. This paper also analyzes and compares results between the prophet and ANN models to predict power demand in Andhra Pradesh, India. Our results comparatively revealed the model's appropriateness for the problem. Both models performed well in three performance metrics: accuracy, generalization, and robustness. However, the AI model exhibits better accuracy than Prophet for the historical data set. The time taken for model fitting is also comparatively less for the AI models. The forecast accuracy of the electricity was in the range of 95 to 97.65.

***Keywords*: Demand Forecasting, Weather, Time Series Analysis, Prophet, Keras, TensorFlow**

I. INTRODUCTION

Power demand forecast plays a predominant role in the electrical industry, enabling the utility to plan well in advance since they understand the future consumption or load demand. It helps the company to plan and make economically viable decisions regarding future generation and transmission investments, thereby minimizing risks. A wide range of methods for predicting electricity demand are being used by electrical companies, which apply to short-term, medium-term, and long-term forecasting. However, electricity consumption mainly arises from complex interactions between meteorological and socio-economic factors. Much work has been reported regarding power demand forecasting models with various assumptions and models. It constitutes different models, especially in machine learning and time series.

Manuscript received on 27 February 2024 | Revised Manuscript received on 09 March 2024 | Manuscript Accepted on 15 March 2024 | Manuscript published on 30 March 2024.

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II. LITERATURE REVIEW

- Deep and classical neural networks are used to predict Australia's long-term electricity demand. It is based on a hybrid forecasting model, created by integrating a stacked autoencoder with a multilayer perceptron (MLP). This model is designed to anticipate nationwide electricity consumption rates for periods ranging from 1 to 24 months in advance. Cascade Forward MLP with one hidden layer, the classical MAPE is 27.68 and Deep MAPE 18.68 [1].
- In the 2001 competition, many different methods and models were proposed to solve the problem of using support vector machines and time series models to improve load forecasting. The paper opined that including unprecise information causes higher variance in prediction, and the time-series attributes give models better information to forecast load demand [2].
- The review article by researchers, different models on energy forecasting, summarizes research trends, discusses the importance of reproducible research and open data sources, makes recommendations about publishing high-quality research papers, and offers an outlook into the future of energy forecasting [3][21][22].
- The Prophet model is compared with the well-established Holt–Winters model to evaluate its feasibility and accuracy in forecasting long-term peak loads of Kuwait power plants from 2010 to 2020. However, the Prophet model in these values indicates higher accuracy when compared to the Holt–Winters model. Prophet MAPE is 1.75%, and Holt–Winters is 4.17% [4].

- The article provides a view on medium- and long-term electrical generation. The impact of fuel cost is examined based on the many forecasting models to provide an understanding for Kuwait's policymakers [5].
- The Deep learning-based framework can effectively handle non-linear complexities and short-term and long-term dependencies of the electricity consumption time series data. The researchers suggested that this framework can be easily generalized to estimate demand for other demographic locations as it depends purely on historical data. For this purpose, use per-day energy demand data of UT Chandigarh, India [6][23][24].
- The review article by researchers described a wide range of different methodologies applied to load forecasting. The study expressed new hopes in forecasting electricity demand as new methods like fuzzy logic, neural networks, etc., evolve due to rapid technology change [7].
- A flexible architecture incorporating multiple input features, where the inputs are processed using different types of neural network components, is developed and evaluated on a data set consisting of hourly loads of North China city for about three years. The results revealed that more training data is usually required to achieve better performance, and we also need more relevant features, for example, the hourly temperature and humidity [8].
- A linear regression and support vector machine model approach can be useful in energy policies since accurate energy consumption predictions affect capital investment, environmental quality, revenue analysis, and market research management for the long-term prediction of Greek energy consumption [9].
- The tutorial reviewed by Suganthi and Anand raised various energy demand forecasting models such as time series, regression, econometrics, and ARIMA, as well as soft computing techniques such as fuzzy logic genetic algorithm, etc., which can help energy planners to accurately plan for the future and utilize the sustainable and renewable energy resources [10][25].
- Several regression tools are analyzed using a large data set for the urban area of Sydney region electrical load forecasting, such as random forest regressor, k-Nearest Neighbor Regressor, etc., to develop new methods for a technology change [11].
- A quantitative method of parallel neural networks (PNN) is applied for robust monitoring and forecasting of power demand. They generalized the implementation using simulated data and real data from Australia. The PNN can be improved by introducing a more sophisticated decision function in the algorithm [12].
- The authors proposed a hybrid forecast strategy including a feature selection technique, and a complex forecast engine based on a combination of Ridgelet and Elman neural networks is used to predict the electricity load demand. This hybrid method outperformed the conventional neural network methods. Precise load prediction plays a vital role in ensuring the efficient functioning of power systems. The challenge is that the electricity load consumption is non-linear with high volatility. To predict the signals accurately, precision tools are required. Ghadimi et al. (2018) studied a two-stage forecast engine with a feature selection technique and an improved meta-heuristic algorithm for electricity load forecasting. These authors compared various forecasting scenarios and concluded that the new two-stage forecast engine is based on RNN and ENN. The first block consists of pre-forecasting, and ENN predicts the RNN output. Both blocks were improved using a new intelligent algorithm [13].
- The relationship between electricity consumption and an important factor in energy demand and weather patterns in rural households of Uttar Pradesh, India. Weather is a significant determinant of electricity consumption. Though the rural electricity demand remained steady in the collected sample data, it is positively related to temperature. Conevsak and Urpelainen (2021) studied the weathering electric city demand in rural India and how the seasonal variations influence the Market for off-grid households in rural India. These authors investigated the relationship between energy consumption from standalone PV systems and a factor widely understood as critical to general energy use: household data was collected between Jan 2016 and Jan 2017 from seven habitations in Uttar Pradesh, India. Linear regression models incorporating quadratic time polynomials were employed to analyze the data and assess the impact of various essential weather factors on electricity usage. These authors found that with a single degree increase in temperature, electricity consumption increases by 5.2Wh per week on average. The data indicated a considerable influence of seasonal variation on the energy demand. These authors found a positive relationship between electricity consumption and temperature [14]. The study mainly deals with skepticism surrounding using ANN in load forecasting. In this study, explicated neural networks were used to predict load forecasts. Before concluding, more rigorous standards should be adopted in reporting the experiments and analyzing the results so that the scientific community could have more solid results on which to base the discussion about the role played by NNs in load forecasting.
- Hippert et al. (2001) reviewed the application of neural networks for short-term load forecasting. This review found that load forecasting has become critical with huge variability in electricity demand, and many researchers have used traditional forecasting and artificial neural networks. Artificial neural networks (NNs) have received much attention as the predictability of neural networks is close to actual demand. However, even though ANN accurately predicts the electricity demand, some authors are still skeptical about applying it. Based on the review, these authors concluded that most of the proposed models, especially those designed to forecast profiles, are overparameterized, and many were single-model multivariate forecasting using NN. This approach led to very large NNs, with hundreds of parameters to be estimated from minimal data sets. Therefore, this approach has to lead to overfitting the NN. However, these authors also concluded that some of the proposed NN models were successful in everyday use [15].

Retrieval Number: 100.1/ijsce.A362314010324
DOI: 10.35940/ijsce.A3623.14010324
Journal Website: www.ijsce.org

Published By:
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- The tutorial review by Tao Hong and Shu Fan covered probabilistic load forecasting, which can take advantage of developments from multiple fields, such as statistics, electrical engineering, computer science, etc., and can be used for electric load forecasting. Hong and Fan (2015) reviewed the probabilistic electric load forecasting. According to these authors, load forecasting has been a fundamental business problem since the inception of the electric power industry. However, over the last 100 years, research efforts and the industry have primarily focused on point load forecasting. In recent decades, the increased market competition, aging infrastructure, and renewable integration requirements mean that probabilistic load forecasting has become increasingly important to energy systems planning and operations. Therefore, these authors have suggested probabilistic electric load forecasting, a new branch of the load forecasting problem. According to these authors, probabilistic load forecasting can use statistics, electrical engineering, computer science, and meteorological science to forecast electricity demand accurately [16].
- In a review of various methods for forecasting building energy consumption, ANN and SVM methods have fairly high accuracy and speed compared to conventional statistical methods. Zhao and Magoules (2012) reviewed the prediction of building energy consumption and concluded that many factors influence building energy performance. Some factors identified are ambient weather conditions, building structure and characteristics, the operation of sub-level components like lighting and HVAC systems, occupancy, and their behavior. The complexity of the building's energy consumption makes it very difficult to predict it accurately. Recently, models developed to solve this problem include elaborate and simplified engineering methods, statistical methods, and artificial intelligence. Most of the current research is focused on developing and applying the models to new predicting problems, optimizing model parameters or input samples for better performance, simplifying the issues or model development, and comparing different models under certain conditions. These authors also concluded that each model developed has its advantages and disadvantages. It is challenging to figure out which one is better without a complete comparison of the circumstances. These authors have also concluded that artificial intelligence is developing rapidly. Many new and more powerful technologies developed in this field may bring alternatives or even breakthroughs in predicting building energy consumption [17].
- A new systematic methodology is proposed to forecast the peak electricity demand with density and probabilistic uncertainty of annual demand for South Australia. The model captures the non-linear effects of temperature, seasonal effects, economic growth, etc. The model performed well on historical data and stressed the need for more temperature sites in data according to the region under study [18].
- The use of novel Pooling based Deep Recurrent Neural Networks (PDRNN) is explored for household load forecasting to address the overfitting issues in conventional Neural Network models. The dataset utilized in this study originates from the Customer Behaviour Trials (CBTs) of Smart Metering Electricity, which were launched by the Commission for Energy Regulation (CER) in Ireland. The model's performance surpasses ARIMA by 19.5%, SVR by 13.1%, and traditional deep RNN by 6.5% in Root Mean Square Error (RMSE), while demonstrating comparable performance across other evaluation metrics [19].
- The study, mainly in numerical simulations, is performed on the University of Texas's two-year weather and hourly load data. The Q-learning technique is used in two stages of the short-term load forecasting model. i.e., DLF and PLF model selections to effectively select the optimal models. It is suggested that the model selection is influential in accurate load forecasting [20].

III. OBJECTIVE

The main purpose of Demand forecasting is to meet future requirements and to reduce unexpected costs. Accurate prediction of the day-ahead electricity demand is crucial for power utilities, enabling strategic decisions regarding the procurement of cost-effective power from the Market, optimal utilization of low-cost power sources, and facilitating consumer access to affordable energy resources. Electricity consumption depends on factors like local meteorological conditions, holidays, agricultural shifts, cyclones, seasonality, lockdowns, and others. More sophisticated Artificial Intelligence methods are necessary to forecast electricity requirements, especially in a dynamic environment. The objective is to effectively maintain the grid frequency and voltage profile in line with Demand and Generation matching, duly observing merit order dispatch and IEGC regulations in an efficient, cost-effective manner to ensure uninterrupted power supply and the lowest operational disturbances in the state of Andhra Pradesh. Accurate load forecasting results in maximum power-generating plant utilization without any under- or over-generation. By understanding the demand, the distribution company can schedule the maintenance and ensure that it has the minimum impact on the consumers. For example, they may decide to plan the maintenance of residential areas during the day when most people are at work and demand is very low.

IV. METHODOLOGY

A. Study Variables

Firstly, all the important factors affecting the Power requirement of the AP state, such as

- Seasons
- Holidays
- Climatic conditions (temperature, humidity, rainfall, etc.,)
- Agricultural seasons (Kharif & Rabi)
- Industrial growth
- Sudden change in temperature, rainfall
- Schedule maintenances

- Unforeseen conditions like Lockdowns due to COVID, natural disasters, equipment breakdowns, etc., have been listed.

The datasets used as input primarily consist of five years of electricity consumption recorded in 15-minute block wise and historical weather data. All the listed variables affecting the demand are added to the dataset.

B. Data Sources

Observed temperature, humidity, and rainfall data is received from the Andhra Pradesh State Development Planning Society (APSDPS). Weather forecasts are received from the Real Time Governance System (RTGS) and Disaster Management (DM). The data so received gets automatically uploaded to the database of the (Transmission Corporation of Andhra Pradesh Limited) APTRANSCO server. The agricultural shift timings are received from Distribution Companies.

C. Data Analysis

The hourly observed weather data received from APSDPS is converted block-wise by using the same value for four-time blocks in an hour. The weather forecasted data is three hours of data received from the Real Time Governance System (RTGS). A total of 8 values per day is received, i.e., at 02:30, 05:30, 08:30, 11:30, 14:30, 17:30, 20:30, and 23:30. To get the hourly data, each value is used for the remaining two hours. To get the 96-block-wise data, each hourly value is used for four-time blocks in an hour. The observed rainfall data is converted non-cumulative and used for demand forecasting. Before passing the data to the model, the data is cleaned, and validated, and missing data is handled properly. The data set format is tabulated in Table I.

Table- I: Format of the Dataset

Ds	Demand	Temp	Hum	Rain	Day	Week	Month	Sec Sat	Ag Season	Holiday	Covid Lockdown/ Unlock	MU	Cyclone	Lift Load	Ag MW
Jan 01, 2021	7000	25	80	0.5	1	0	1	0	1	0	0	180	0	100	200

V. MODEL DEVELOPMENT

A. Prophet Model

Prophet is a library in 'R' for forecasting time series data based on an additive model where non-linear trends are fit with yearly, weekly, and daily seasonality, plus holiday effects. This model is most effective when applied to time series data exhibiting prominent seasonal patterns and a substantial historical record encompassing multiple seasons. Prophet is robust to missing data and shifts in the trend and typically handles outliers as well. The time series model contains three main model components: trend, Seasonality, and Holidays. $y(t) = g(t) + s(t) + h(t) + \text{error}$. Here g(t) represents the trend function, which captures the non-cyclical fluctuations in the time series data. s(t) represents periodic changes (e.g., weekly and yearly seasonality). h(t) denotes the impact of holidays on the time series data, which may occur irregularly and span one or more days. The error term represents any changes that the model does not accommodate.

Two data frames are created in Prophet, one for history (training) and another for the future (for forecasting). The data frame consists of weather, seasons, agricultural shifts, second saturdays, day duration, lockdown, etc.; different models are developed by varying the regressors, such as one model built with average weather data, another model built with ten regressors of weather data (using principal component analysis). Using these developed models, demand was forecasted and error was found. Further, another model was developed to improve the accuracy by varying the priority of regressors.

B. Keras Model

Deep learning, a subset of machine learning, comprises a collection of algorithms inspired by the architecture and functionality of the human brain, often referred to as Artificial Neural Networks. This package is an R interface to the Python deep learning package Keras, a high-level neural networks API capable of running on top of TensorFlow. TensorFlow is the open-source library for various machine learning tasks, i.e., data Pre-processing and constructing a multilayer model. Compile and fit the model to training data and visualize the training history. Predict target values based on test data. Evaluate the model, interpret the results, and fine-tune the model so that it performs better. In the data pre-processing, the history data frame created using demand/energy data and weather data after adding all regressors and seasons are partitioned into two datasets, i.e., the Train and Test datasets with an 80:20 ratio. A simple stack of fully connected layers. Dense layers stand out as one of the prevailing and widely adopted types of layers within neural networks. They operate as standard neural network layers, with interconnections between every neuron in the layer and those in both the preceding and subsequent layers. Each dense layer has an activation function that determines its neurons' output based on the layers' inputs (Table II). and weights. The dropout layers are just regularization layers that randomly drop some of the input units to 0. This helps in reducing the chance of overfitting the neural network. Then, the model is compiled and fitted using a training dataset. Fig. 1. is an example model.

To compile the model, we need to choose the Loss Function, Optimizer, and Metrics (Table III). After compiling the model, it is trained using our train dataset. Learning is an iterative process; the Number of iterations, batch size, and data are given as input while fitting the model (Table IV).

Retrieval Number: 100.1/ijsce.A362314010324
DOI: 10.35940/ijsce.A3623.14010324
Journal Website: www.ijsce.org

Published By:
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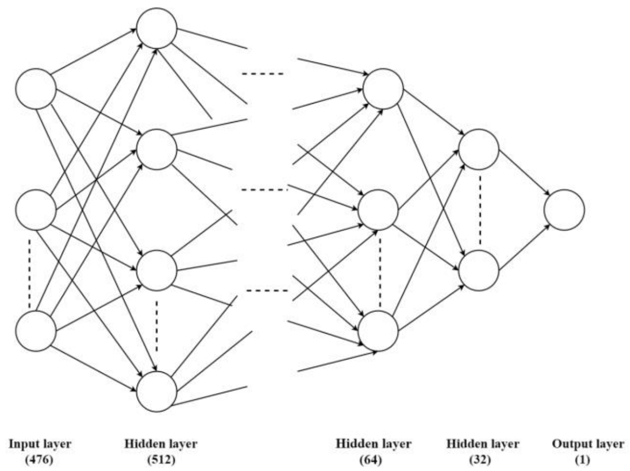

Fig. 1. The Schematic Diagram Representation

After the model is fitted, it is evaluated by predicting the target values on the test dataset.

Table- II: Model Parameters Used in Forecasting (for Construction of Model)

Layer	Type of Layer	Activation Function	Number of Neurons
Input layer	Dense	ReLU(Rectifiied Linear Unit)	476
Hidden layer 1	Dense	ReLU(Rectifiied Linear Unit)	512
Hidden layer 2	Dense	ReLU(Rectifiied Linear Unit)	256
Hidden layer 3	Dense	ReLU(Rectifiied Linear Unit)	128
Hidden layer 4	Dense	ReLU(Rectifiied Linear Unit)	64
Hidden layer 5	Dense	ReLU(Rectifiied Linear Unit)	32
Output layer	Dense	ReLU(Rectifiied Linear Unit)	1

Table- III: Model Parameters Used in Forecasting (for Compilation of Model)

Compile	
Loss function	MAPE
Optimiser	adam
metrics	MAPE

Table- IV: Model Parameters Used in Forecasting (For Fitting the Model)

Fit	
Epochs(iterations)	500
Batch size	96

The first layer (Input layer) of neural network architecture should be equal to the number of Regressions in the model. The number of neurons in the first hidden layer should be the next second power of the number of neurons in the input layer so that no data is lost during model compilation. All the above model parameters are carefully selected after running heavy trial and error runs, and these parameters are finalized for forecasting the day-ahead demand as the model is not overfitting and error is much less. For developing this model, we considered huge real-time(actual) data from Andhra Pradesh state. The model is trained using history data of 157600 rows. (4.5 years block-wise data).

Train and test data frames are created for demand forecasting in Keras. Regressors and seasonality used in Prophet are added in Keras as columns in training and testing data frames. Different models are built using various combinations of layers and neurons in the artificial neural network.

Table- V: MAPEs for Different Demand Forecasting Models in Prophet

Model No	MAPE	Holidays	Seasonality	Regressors
Dove1	5.09%	Holidays(20, priority(avg): 30)	Daily seasonality:50 Rabi:50 Summer:50 Kharif:50	Sunday:100 Lackodwn1 to Unlcok5:50 Agrishifts: 200
Dove2	4.23%	Holidays(20, priority(avg): 30)	Daily seasonality:50 Rabi:50 Summer:50 Kharif:50	Average temperature:200 Average rain(continuous data): 200 Average Humidtity: 200 Sunday:100 Lcokdown1 to Unlock5:50 Agrihsifts: 200 Evening peak:200 Winter morning:200
Dove3	3.99%	Holidays(20, priority(avg): 30)	Daily seasonality:50 Rabi:50 Summer:50 Kharif:50	PCA temperature(10 regressors): 200 PCA Rain(10 regressors): 200 PCA Humidity(10 regressors): 200 Sunday:100 Lcokdown1 to Unlock5:50 Agrihsifts: 200 Evening peak:200 Winter morning:200

VI. RESULTS AND DISCUSSION

Firstly, every data model is trained with some part of observed data (Ex: 70% of observed data) and tested for remaining data (30% of observed data). The model is fine-tuned until accurate results are achieved for test data sets. Mean absolute percentage error (MAPE) for different models using Prophet and Keras are tabulated in Table V and Table VI, respectively. Thus, various models are developed using both Prophet and Keras. After fine-tuning, every data model will be given the forecast data set as input.

Prophet demonstrates optimal performance when applied to time series datasets characterized by pronounced seasonal patterns and a significant historical record spanning multiple seasonal cycles. Prophet is robust to missing data and shifts in the trend and typically handles outliers as well. Despite this, the Prophet models need a lot of time to run.

Table- VI: MAPEs for Different Demand Forecasting Models in Keras

Model No	MAPE	Holidays	Seasonality	Regressors	Other Parameters
Dove5	1.21%	Holidays (20); Second Saturday (1);	Daily (1); Weekly (7); Monthly (12); Yearly-Khariff (1), Rabi (1);	Temperature (74); Rainfall (272); Humidity (59); Lockdown (4); Unlock (5); Energy (1); Demandprevious_w/normalization (1); Timeblock(1); Cyclone(1); Lift Irrigation (2); DistrictwiseAgMW (13);	Partition – Random (80:20); Layers – 7; Neurons – 476, 512, 256, 128, 64, 32, 1; Batch Size – 96; Normalization – No;
Dove6	1.05%	Holidays (20); Second Saturday (1);	Daily (1); Weekly (7); Monthly (12); Yearly-Khariff (1), Rabi (1);	Temperature (74); Rainfall (272); Humidity (59); Lockdown (4); Unlock (5); Energy (1); Demandprevious_normalised (1); Time block (1); Cyclone (1); Lift Irrigation (2); DistrictwiseAgMW (13);	Partition - Random (80:20); Layers - 7; Neurons - 476, 512, 256, 128, 64, 32, 1; Batch Size - 96; Normalization - No;

Both Prophet and Keras models performed well in three performance metrics: accuracy, generalization, and robustness. However, the AI model exhibits better accuracy than Prophet for the historical data set taken. The time taken for model fitting is also comparatively less for the AI models. The results also reveal that the accuracy is improving by adding independent variables or regressors to the dataset in both models.

This paper analyzed the results of around 40 prophet models and 60 ANN demand forecasting models. The developed ANN Forecasting Model gives better results, around 3% MAPE for normal days. The forecast is continually fine-tuned to improve accuracy.

Benefits accrued to the Organization due to the above model:

- Reliable Day-ahead scheduling.
- Economic day ahead purchases from Market.
- Cost savings to DISCOMs.

After continuous improvements made to the model by taking various inputs and suggestions during the development period, the model was deployed in September 2021 for use in day-ahead planning by the SLDC.

A. Case Study I

- The overall energy consumption of the state on 2nd February 2024 was 228.4 MU.
- The APSLDC had forecasted manually an overall energy of 224.28 MU.
- However, the AI-based Machine Learning model had forecasted a load of 230 MU which was much closer to the actual demand, i.e., 228.4 MU (Fig.2.).

B. Case Study II

- The overall energy consumption of the state on 19th December 2023 has increased by 5 MU when compared to the previous day.
- The AI-based Machine Learning model had forecasted a load of 191.7 MU, which was much closer to the actual demand, i.e., 192.9 MU (Fig.3.).

At present, the weather forecast is received for a limited number of locations considering model complexity and runtime, whereas energy consumption is scattered across all the regions throughout the state which depends upon local weather phenomena.

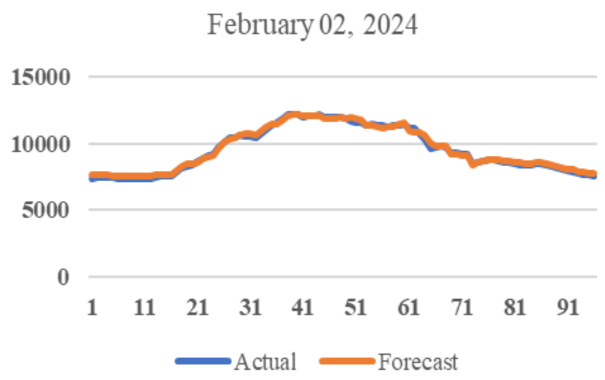

Fig. 2. Actual Demand Vs Forecasted Demand for 2nd February 2024

It is observed that the demand forecast model yields good results using real-time (observed) weather conditions compared to forecast weather data. Therefore, it is imperative to have accurate weather forecasts to get accurate predictions of demand forecasts.

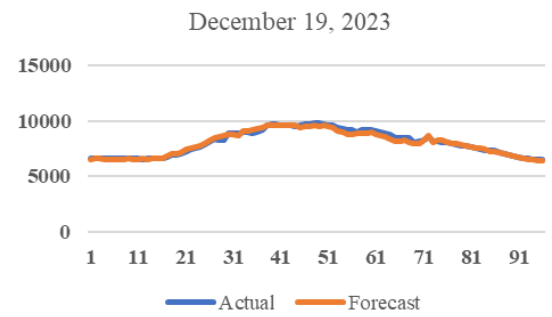

Fig. 3. Actual Demand Vs Forecasted Demand for 19th December 2023

SLDC is currently exploring new demand forecast model for each district using the weather parameters in the area and aggregating them to get the overall state demand.

Retrieval Number: 100.1/ijsce.A362314010324
DOI: 10.35940/ijsce.A3623.14010324
Journal Website: www.ijsce.org

Published By:
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In addition to the above, SLDC is also planning to develop a week-ahead demand forecasting model for the economic scheduling of generators. It is also intended to reduce dependency on RE developers for solar and wind forecasts by setting up the Renewable Energy Management Center (REMC) in SLDC.

C. Limitations

The accuracy of the developed demand forecasting model is majorly dependent on the accuracy of weather forecast data received. Unfortunately, the weather is sometimes unpredictable, and the forecast may not be accurate when the actual weather differs from what is expected. As the data used for training the model is AP state grid demand, the accuracy of the model is confined to the state. The independent variables, such as agricultural loads, and cyclones which are added to the model as the regressors are also in particular to AP state as agricultural load takes a major share in the total state demand.

VII. CONCLUSION

In this paper, we demonstrate an application of deep learning techniques for state aggregate demand forecasting, where the demand is affected by holidays, seasons, summer loads, agriculture shifts, rainfall, temperature and humidity. The Prophet tool is an additive model where non-linear trends are fit with yearly, weekly, daily seasonalities, etc., combined with holiday effects. Additional factors that influence the power demand are unforeseen conditions like bandhs and cyclones. The same model is also developed in Keras, and the accuracy of both the Prophet and Keras demand forecasting models are checked. A good weather forecast additionally improves the accuracy of the forecasting model. An accurate demand forecast allows the utilities to optimize their resources to run the grid system with reliability and in an economical way, which will benefit the consumers.

ACKNOWLEDGEMENT

The authors want to thank Dr. Jaya Shankar Tumuluru, Ph.D., who worked as a distinguished staff engineer at Idaho National Laboratory, Energy and Environment Directorate, Idaho Falls, Idaho, USA, for his valuable support in writing the paper.

The authors also want to thank K Vijayanand IAS, who is Chairman and Managing Director of APTRANSCO, for his unwavering support, guidance, insights, and expertise which has been invaluable to the success of our research. His continuous involvement and profound understanding of the subject matter have significantly contributed to navigating challenges and achieving the objectives of the article.

The authors also want to thank A K V Bhaskar, B.Tech, M.B.A, who worked as a Chief Engineer at Andhra Pradesh State Load Despatch Center, for his invaluable guidance, mentorship, and support throughout this study.

The authors also want to thank Y Anantha Srinivas, B.E, M.B.A, who is a Superintending Engineer at Andhra Pradesh State Load Despatch Center, for his constructive feedback and suggestions, which significantly improved the quality of the study.

DECLARATION STATEMENT

Funding	No, I did not receive it.
Conflicts of Interest	No conflicts of interest to the best of our knowledge.
Ethical Approval and Consent to Participate	No, the article does not require ethical approval and consent to participate with evidence.
Availability of Data and Material	Not relevant.
Authors Contributions	All authors have equal participation in this article.

REFERENCES

1. H. Hamedmoghadam, N. Joorabloo, and M. Jalili, "Australia's long-term electricity demand forecasting.pdf".
2. B. J. Chen, M. W. Chang, and C. J. Lin, "Load forecasting using support vector machines: A study on EUNITE Competition 2001," IEEE Transactions on Power Systems, vol. 19, no. 4, pp. 1821–1830, 2004, doi: 10.1109/TPWRS.2004.835679. https://doi.org/10.1109/TPWRS.2004.835679
3. T. Hong, P. Pinson, Y. Wang, R. Weron, D. Yang, and H. Zareipour, "Energy Forecasting: A Review and Outlook," IEEE Open Access Journal of Power and Energy, vol. 7, no. April, pp. 376–388, 2020, doi: 10.1109/oajpe.2020.3029979. https://doi.org/10.1109/OAJPE.2020.3029979
4. A. I. Almazrouee, A. M. Almeshal, and A. S. Almutairi, "applied sciences Long-Term Forecasting of Electrical Loads in Kuwait," Appliend Science, vol. 5627, no. 10, pp. 2–17, 2020. https://doi.org/10.3390/app10165627
5. A. I. Almazrouee, A. M. Almeshal, A. S. Almutairi, M. R. Alenezi, S. N. Alhajeri, and F. M. Alshammari, "Forecasting of electrical generation using prophet and multiple seasonality of holt–winters models: A case study of Kuwait," Applied Sciences (Switzerland), vol. 10, no. 23, pp. 1–19, 2020, doi: 10.3390/app10238412. https://doi.org/10.3390/app10238412
6. J. Bedi and D. Toshniwal, "Deep learning framework to forecast electricity demand," Applied Energy, vol. 238, no. July 2018, pp. 1312–1326, 2019, doi: 10.1016/j.apenergy.2019.01.113. https://doi.org/10.1016/j.apenergy.2019.01.113
7. H. K. Alfares and M. Nazeeruddin, "Electric load forecasting: Literature survey and classification of methods," International Journal of Systems Science, vol. 33, no. 1, pp. 23–34, 2002, doi: 10.1080/00207720110067421. https://doi.org/10.1080/00207720110067421
8. W. He, "Load Forecasting via Deep Neural Networks," Procedia Computer Science, vol. 122, pp. 308–314, 2017, doi: 10.1016/j.procs.2017.11.374. https://doi.org/10.1016/j.procs.2017.11.374
9. L. Ekonomou, "Greek long-term energy consumption prediction using artificial neural networks," Energy, vol. 35, no. 2, pp. 512–517, 2010, doi: 10.1016/j.energy.2009.10.018. https://doi.org/10.1016/j.energy.2009.10.018
10. L. Suganthi and A. A. Samuel, "Energy models for demand forecasting - A review," Renewable and Sustainable Energy Reviews, vol. 16, no. 2, pp. 1223–1240, 2012, doi: 10.1016/j.rser.2011.08.014. https://doi.org/10.1016/j.rser.2011.08.014
11. J. Johannesen, M. Kolhe, and M. Goodwin, "Relative evaluation of regression tools for urban area electrical energy demand forecasting," Journal of Cleaner Production, vol. 218, pp. 555–564, 2019, doi: 10.1016/j.jclepro.2019.01.108. https://doi.org/10.1016/j.jclepro.2019.01.108
12. Y. T. Chen, E. W. Sun, and Y. B. Lin, "Machine learning with parallel neural networks for analyzing and forecasting electricity demand," Computational Economics, vol. 56, no. 2, pp. 569–597, 2020, doi: 10.1007/s10614-019-09960-5. https://doi.org/10.1007/s10614-019-09960-5
13. N. Ghadimi, A. Akbarimajd, H. Shayeghi, and O. Abedinia, "Two stage forecast engine with feature selection technique and improved meta-heuristic algorithm for electricity load forecasting," Energy, vol. 161, pp. 130–142, 2018, doi: 10.1016/j.energy.2018.07.088. https://doi.org/10.1016/j.energy.2018.07.088

14. A. Conevska and J. Urpelainen, “Weathering electricity demand? Seasonal variation in electricity consumption among off-grid households in rural India,” Energy Research and Social Science, vol. 65, no. June 2019, p. 101444, 2020, doi: 10.1016/j.erss.2020.101444. https://doi.org/10.1016/j.erss.2020.101444
15. H. S. Hippert, C. E. Pedreira, and R. C. Souza, “Neural networks for short-term load forecasting: A review and evaluation,” IEEE Transactions on Power Systems, vol. 16, no. 1, pp. 44–55, 2001, doi: 10.1109/59.910780. https://doi.org/10.1109/59.910780
16. T. Hong and S. Fan, “Probabilistic electric load forecasting: A tutorial review,” International Journal of Forecasting, vol. 32, no. 3, pp. 914–938, 2016, doi: 10.1016/j.ijforecast.2015.11.011. https://doi.org/10.1016/j.ijforecast.2015.11.011
17. H. X. Zhao and F. Magoulès, “A review on the prediction of building energy consumption,” Renewable and Sustainable Energy Reviews, vol. 16, no. 6, pp. 3586–3592, 2012, doi: 10.1016/j.rser.2012.02.049. https://doi.org/10.1016/j.rser.2012.02.049
18. R. J. Hyndman and S. Fan, “Density forecasting for long-term peak electricity demand,” IEEE Transactions on Power Systems, vol. 25, no. 2, pp. 1142–1153, 2010, doi: 10.1109/TPWRS.2009.2036017. https://doi.org/10.1109/TPWRS.2009.2036017
19. H. Shi, M. Xu, and R. Li, “Deep Learning for Household Load Forecasting-A Novel Pooling Deep RNN,” IEEE Transactions on Smart Grid, vol. 9, no. 5, pp. 5271–5280, Sep. 2018, doi: 10.1109/TSG.2017.2686012. https://doi.org/10.1109/TSG.2017.2686012
20. C. Feng, M. Sun, and J. Zhang, “Reinforced Deterministic and Probabilistic Load Forecasting via Q-Learning Dynamic Model Selection,” IEEE Trans. Smart Grid, vol. 11, no. 2, pp. 1377–1386, 2020. https://doi.org/10.1109/TSG.2019.2937338
21. Shahiduzzaman, K. M., Jamal, M. N., & Nawab, Md. R. I. (2021). Renewable Energy Production Forecasting: A Comparative Machine Learning Analysis. In International Journal of Engineering and Advanced Technology (Vol. 10, Issue 6, pp. 11–18). https://doi.org/10.35940/ijeat.e2689.0810621
22. Vendoti, S., Muralidhar, Dr. M., & Kiranmayi, Dr. R. (2019). Performance Analysis of Hybrid Power System Along With Conventional Energy Sources for Sustainable Development in Rural Areas. In International Journal of Recent Technology and Engineering (IJRTE) (Vol. 8, Issue 3, pp. 5971–5977). https://doi.org/10.35940/ijrte.f2567.098319
23. Malyada, C., Keerthana, R., Rao, Dr. P. V. R. D. P., & Keerthana, R. (2020). Prediction of Electricity usage in Industries by Big Data. In International Journal of Innovative Technology and Exploring Engineering (Vol. 9, Issue 3, pp. 3059–3062). https://doi.org/10.35940/ijitee.c8375.019320
24. Das, S., S, S., M, A., & Jayaram, S. (2021). Deep Learning Convolutional Neural Network for Defect Identification and Classification in Woven Fabric. In Indian Journal of Artificial Intelligence and Neural Networking (Vol. 1, Issue 2, pp. 9–13). https://doi.org/10.54105/ijainn.b1011.041221
25. Sharma, T., & Sharma, R. (2024). Smart Grid Monitoring: Enhancing Reliability and Efficiency in Energy Distribution. In Indian Journal of Data Communication and Networking (Vol. 4, Issue 2, pp. 1–4). https://doi.org/10.54105/ijdcn.d7954.04020224

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