

Energy Load Forecasting Based on the Load Consumption Factors and Techniques Employed: A Review

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Abstract

Due to the contradiction between energy production and demand in the current energy crisis, power consumption (PC) is crucial to the world economy. Energy industry can improve power system control and energy usage by using machine learning (ML) models, which are widely acknowledged as a precise and computationally efficient prediction solution. For the purpose of projecting energy consumption and performance, machine learning (ML) techniques and artificial intelligence (AI) have been suggested recently. The various machine learning (ML) techniques i.e. artificial neural networks (ANN), support vector machines (SVM), Gaussian-based regressions and Fuzzy logic etc. that have been frequently used in predicting and enhancing energy performance are reviewed in-depth in this research.

Keywords: Artificial Intelligence; Energy Consumptions; Machine Learning

1. Introduction

A nation's economic development depends heavily on the electric power sector, which also significantly improves society through its effective functioning. The need for power has recently reached unfathomable heights as technology has advanced in cities all over the world. Global warming issues will worsen if national governments on a global scale are unable to meet this energy needs. Energy demand in India continues to rise at over 3% per year in the Stated Policies Scenario from 2021 to 2030. [1] According to the International Energy Agency's 2023 report, the average annual growth rate of total energy demand through 2030 is 0.7%. Demand is expected to rise until 2050. India is predicted to have the fastest-growing energy consumption globally over the next thirty years. By 2030, peak electricity demand has increased by almost 60% from 2022 [2]. Because of the growing population, the comfort levels of buildings, and people spending more time inside of them, the energy demand will therefore climb significantly in the near future. Peak consumption can present significant difficulties for electricity providers since they have to over-dimension the grid to accommodate the unusually

high load of consumption. In order to prevent serious consequences like power outages, energy scarcity must be managed by the providers. An alternative strategy is to balance the grid by introducing intelligent methods for controlling these peaks, which will help prevent overreach and lower the costs associated with over-dimensioning and enormity. There are several ways to control the peaks, including load balancing and the development of dynamic and intelligent pricing strategies that take into account the fact that end users are price sensitive and may cut back on consumption when electricity prices are high. Therefore, it is necessary to forecast energy consumption in order to support national production and consumption balance. This review paper focuses on the different methods that are employed to forecast energy usage. There are three types of load forecasts: short-term forecasts, which are typically from one hour to one week; medium-term forecasts, which are typically from a week to a year; and long-term forecasts, which are typically more than a year. For the scheduling and control of power systems, short-term forecasting is crucial. [3] However, predicting daily load is a difficult process since it depends on

other factors, such as temperature and the calendar effect, in addition to the load from the previous days. As a result, anyone looking to save energy should focus on improving energy usage and the effectiveness of energy in buildings. We highlight a machine learning-based methodology for predicting energy usage in this review. [4] To make the most accurate prediction, it is crucial to identify the optimal strategy and model. Finding the answers to the following questions is the basis of this research:

1. What are the key elements that have a significant impact on how much energy is consumed?
2. How do the daily patterns of electric energy use in winter, rainy and summer differ?

3. Which machine learning techniques have the highest forecast accuracy limitations?
4. What advantages do various models have for accurately estimating how much electricity is used?

Accordingly, Figure 1 depicts the information flow. Apart from above information, the rest of the paper is divided into the following categories: [7-9] Second section discusses the factors affecting for load forecasting, and third section the performance metrics of the models, last section discusses shows the comparative study of the load forecasting techniques. Prediction category and duration shown in Table 1.

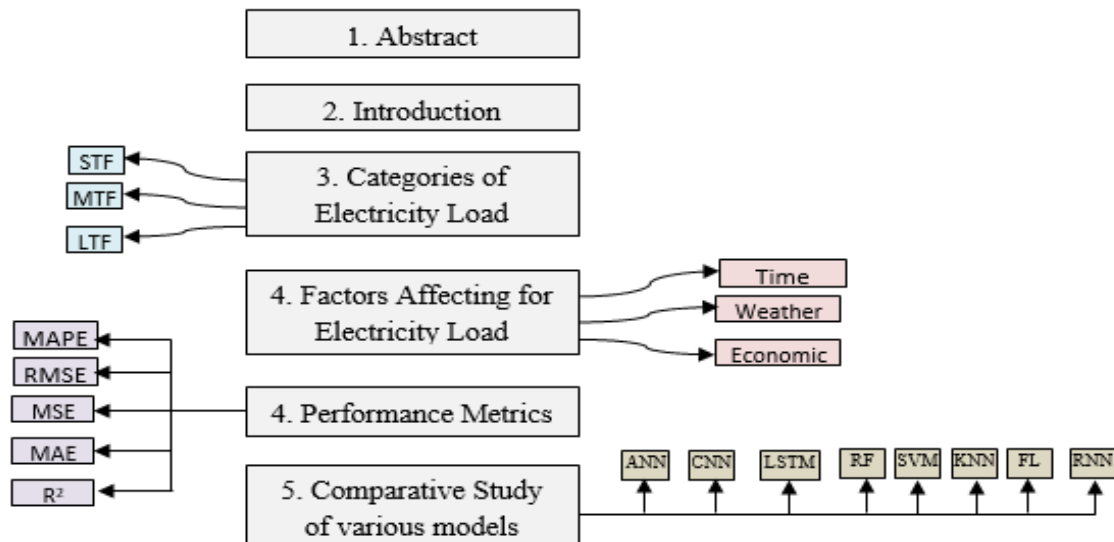


Figure 1 Flow of Information in the Review Paper for Electricity Load Forecasting

1.1. Categories of Electricity Load Forecasting

There are three categories into which electrical load forecasting can be divided, they are Long-term (1–20 years), Medium Term (a week or month), Short term (one week to one hour). [10] The short term forecasting (STF) is used to provide the essential data for scheduling generator start-up and shutdown, and performing a complete examination of gearbox constraints. System security is also assessed using the STF. In order to economically prepare for future additions to the generation system and additional transmission planning, long-term forecasting (LTF) \

Is essential. The medium-term forecasting (MTF) is useful for other elements, primarily for determining tariffs, planning maintenance and repairs, scheduling fuel supply, and financial management. [5][6].

Table 1 Prediction Category and Duration

Sr. No	Prediction Category	Duration
1	Long Term	months to year
2	Mid Term	weeks to a month
3	Short Term	Hours to week

2. Factors Affecting on Load Forecasting

To get a reliable forecast from the system, researchers must carefully choose the dependent components. Each component has a varied impact on load forecasting in varying degrees, and each model may take a variety of factors into account, some of which are listed below. [11-15] though other major and small aspects influence every phase of forecasting, time, weather, and economic considerations may be thought of as the main influences to take into account. Some of the factors are discussed as follows.

Time Factor:

In order to anticipate loads, time is the most crucial aspect. The load curve contains "time of the day" property together with "day of week", "week of month", and "month of season" properties, according to [16] observations of the load curves of many distinct grid stations.

Weather Factors:

According to seasonal patterns, winter months (October–February) accounted for 20% of overall consumption, while the summer months (May–August) contributed 50% to the total. [17] According to a study, demand rose 1.5% in tropical Indian towns for every 1°C increase in summertime temperatures. [18]

Economic Factor:

System average load and maximum demand are significantly impacted by economic factors including power pricing, load management, and industrialization level. [19-23] the accuracy of forecasting is also greatly influenced by factors such as customer behavior, tariff changes, appliance descriptions, population density, and equipment age and employment levels.

2.1. Performance Analysis of Different Models used in Prediction

Each machine learning pipeline includes performance metrics. As per previous study, various distinct metrics are employed to evaluate the models' performance, shown in the equations below.

Mean Absolute Error:

$$MAE = \frac{1}{n} \sum_{i=1}^n |x_i - x|$$

Where:

n = the number of errors,

Σ = summation symbol (which means "add them all up"),

$|x_i - x|$ = the absolute errors.

Mean Absolute Percentage Error:

$$M = \frac{1}{n} \sum_{t=1}^n \left| \frac{A_t - F_t}{A_t} \right|$$

Where:

N is the number of fitted points,

A_t is the actual value,

F_t is the forecast value.

Σ is summation notation (the absolute value is summed for every forecasted point in time).

Root Mean Squared Error:

$$RSME = \sqrt{\frac{\sum (y_i - \hat{y}_i)^2}{N - P}}$$

Where:

Y_i is the actual value for the ith observation.

\hat{Y}_i is the predicted value for the ith observation.

N is the number of observations.

P is the number of parameter estimates, including the constant.

2.2. Comparative Analysis of Error Metrics of Different Forecasting Models

To demonstrate how accurate the load forecasting approaches are at predicting the actual load values, a number of criteria are employed as evaluation indices. [24-27] to measure the precision of their models, different researchers have relied on various statistical metrics. The most common static measurements used by academics around the world are shown in Table 2. According to the study, each of these measurements has benefits and drawbacks of its own. [28-32] mostly used metrics are MAPE, RMSE. The second-degree loss function provided by RMSE prioritizes larger errors rather than minor ones. It can measure average error naturally and is unambiguous. MAPE is simply applied to both large volume and low volume items and is not scale dependent. Figure 2 shows Prediction Matrices Studies.

Table 2 Performance Matrices and Comparative Study of Various Models

Model	Reference	MAPE	RMSE	MAE	MSE	R ²
ANN	[20]	3.38	4.51	2.19	-	-
	[21]	3.50		2.10	-	-
	[22]	-	-	-	1.12	-
MLR	[23]	1.82	-	-	-	0.96
	[24]	5.05	-	-	-	0.89
LSTM	[25]	51.45	0.8649	0.6278	0.7480	-
	[26]	-	3.337392	-	-	-
	[27]	6.27	0.0154	0.0107	-	-
RF	[28]	4.60	6.10	-	-	0.92
	[29]	5.45	3.219	-	-	0.576
SVM	[29]	-	4.913	-	-	0.277
	[30]	1.9705	-	1.5438	-	-
	[31]	1.682	12.364	-	-	-
KNN	[30]	3.6082	-	1.4826	-	-
	[32]	3.95	-	-	-	-
FL	[33]	0.99	-	-	-	-
	[34]	1.94	202.1	-	-	-
XGBoost	[29]	-	2.914	-	-	0.711
	[34]	2.95	368.4(kWh)	-	-	-
GBDT	[35]	-	4.748(%)	0.625(KW)	-	0.982
CNN	[36]	0.54	-	59.45	14745.41	-

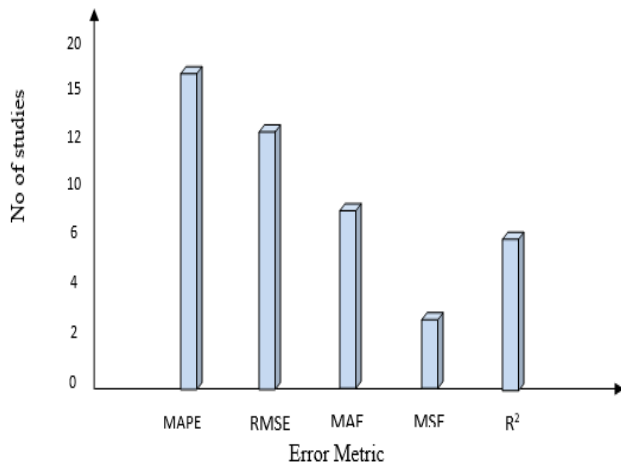


Figure 2 Prediction Matrices Studies

2.3. Models used for Predicting the Electricity Load Consumption

Table 3 shows comparative study of machine learning models for Prediction the review's objective is identifying the most popular algorithms used in electricity forecasting models. The sixty-one (61) article contains eleven (11) of the most frequently used algorithms. [33-37] the results of the study demonstrate how applying AI to different economic sectors can increase productivity and efficiency. According to a study, ANN models are frequently employed for prediction, and fuzzy logic is also growing in favor these days. Figure 3 shows the Comparative Studies.

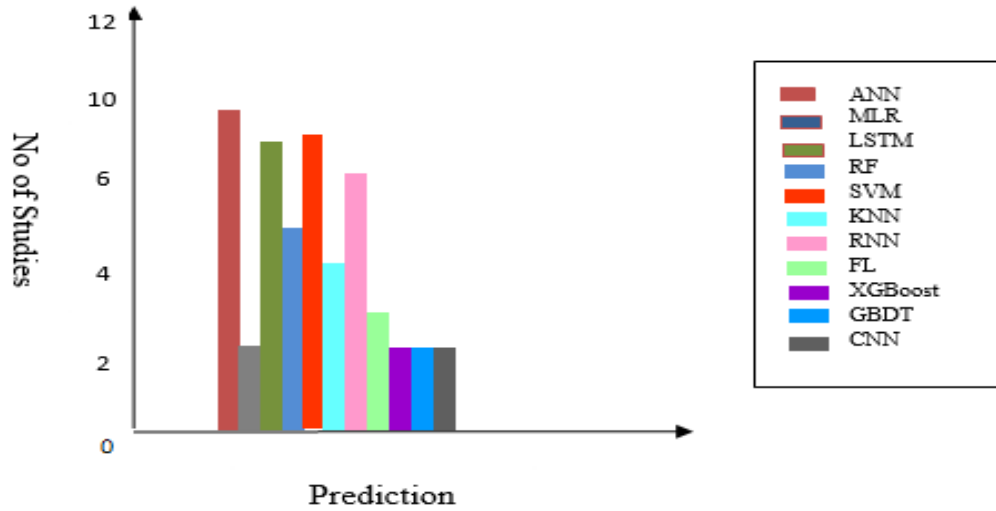


Figure 3 Comparative Studies

Table 3 Comparative Study of Machine Learning Models for Prediction

Categories of model	Reference	Area	Time factor	DataSize	Reason of prediction	Categories of Features	Performance Metric
<u>Fuzzy Logic</u> <u>ANFIS</u>	[46]	Residential	Hourly	4year	Short Term Load Forecasting	Time, day, temperature, season, daylight	<u>3.72%RMSE</u> <u>2.1%MAPE</u> <u>1.85%MAPE</u> <u>3.66%RMSE</u>
<u>ANOVA</u> <u>ANN</u>	[21]	Non Residential	Hourly	24years	Energy consumption in industry sectors	heterogeneity of industries, products, equipment, technologies, processes	3.50MAPE <u>2.10MAE</u>
ANN	[38]	Residential	Hourly	5months	Building Energy Prediction	wind direction, sun radiation, humidity level, and temperature of the outside dry bulb	0.0323(CV)
<u>ANN</u> <u>Time series</u>	[41]	Non residential	Hourly	8years	Accurate peak forecasting	Temperatureandhumidity, windspeed, cloud cover daylight Hours	<u>N/A</u>
<u>ANN</u>	[38]	Residential	Hourly	1year	Sunlight exposure and power usage of the load	sun radiation, surrounding temperature, wind direction, and sampling time stamp	<u>25.50%WMAE</u>
<u>CNN</u> <u>SVM</u>	[45]	Residential	Hourly	2years	Forecasting of residential buildings	The building's size, occupant level, electric appliances, humidity and temperature, and calendar element	<u>0.29MAPE</u> <u>1.32MAE</u> <u>2.99MSE</u> <u>0.23RMSE</u>

<u>FF-DNNR-DNN</u>	[39]	Residential	Hourly	4years	Most dominant factors for power consumption prediction	The distribution of the lagging electrical load across time, weather, time, and holidays, and the price of electricity	<u>1.42%MAPE</u> <u>306(MW/h)RMS</u> <u>E</u> <u>210(MW/h)MAE</u>
<u>ANN</u>	[40]	Non residential	Hourly	4years	Management And Operation of Power System	temperature	<u>44,111.39451MS</u> <u>E</u> <u>160.99752MAE</u> <u>2.72%MAPE</u>
<u>ANN</u>	[22]	Residential	Hourly	1year	cloud-based application for electricity consumption analysis	Sensors,cloudstorage,c lustering	<u>1.12MAE</u>
<u>ANN</u> <u>PCA</u>	[42]	Residential	Hourly	6 Months	Electricity demand of a bio-climatic building and influence of temp and solar radiation	temperature of the dry bulb, sun radiation, humidity ratio, and wind speed	<u>N/A</u>
<u>ANN</u> <u>PSO</u>	[20]	Non-residential	Hourly	3 years	Short term Load prediction	N/A	<u>0.02191MAE</u> <u>1.26268e-003MSE</u> <u>0.03388MAPE</u>
<u>ANN</u>	[43]	Residential	Hourly	One Week	the exact capacity to produce the power and the demand from customers	time factor, historical weather information, customer class, previous load that the region demanded, region growth, and amount of load increased	<u>1.066%MAPE</u>
<u>ANN</u>	[44]	Residential	Hourly	One day	Construction of component load model for house hold	solar radiation, ambient temperature, humidity	<u>N/A</u>

3. Major Findings with Research Gaps

Duration-based model performance analysis

The majority of current models only anticipate loads for the short term, as opposed to long- or mid-term periods. [38-40] this could be due to the fact that a longer forecasting horizon greatly increases the

likelihood that changes that are not yet known to us will have an impact on demand in the future.

The influence of the temporal domain

The prediction capabilities of many models, which rely on either residential or non-residential buildings, are inadequate. Achieving equilibrium between

residential and nonresidential models could be feasible if such a model could be created. [41]

Model Flexibility Issues

The models that have been studied during the research are intended for a certain use case, such as a particular sort of input parameter or geographic area. Throughout the investigation, no model has been discovered that can function with the best accuracy regardless of application changes. [42]

Hybrid Models

Offer greater accuracy than single-method approaches in predicting load consumption.

4. Future Trends

4.1. Model Enhancement

Research evaluation indicates that no model takes into account the customer class and concentrates on year-round peak hour prediction. So need to put further effort on clustering techniques.

4.2. Cloud based Applications

The greatest accuracy is reported for clustering approaches when real-time electricity consumption data is collected using a cloud-based application for electricity consumption analysis. However, additional work on real-time data is required in the future.

Conclusion

A thorough analysis of several load forecasting models covering a range of time periods and sectors has been provided in this paper. We went over the effectiveness and drawbacks of the conventional load forecasting techniques. Lastly, drawing attention to the constraints, patterns, and areas in need of further study will help the readers choose and assess the models in accordance with their needs and obtain guidelines for future work. The goal of future research will be to improve the drawbacks of the current load forecasting models.

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