

Research Article

# An Efficient Electric Energy Consumption Prediction System Using Machine Learning Framework

Miss. Juveria Khan and Prof. Dr. Pramod Patil

Department of Computer Engineering Dr. D. Y. Patil Institute of Technology Savitribai Phule Pune University

Received 10 Nov 2020, Accepted 10 Dec 2020, Available online 01 Feb 2021, **Special Issue-8 (Feb 2021)**

## Abstract

*In the last few years, the expanding energy utilization has imposed the development of solutions to save electricity. One of these arrangements has been, generating an energy saving policies which is based on forecasting of energy in smart environments. The main idea behind building this model is, the residences are instrumented with smart meters to monitor energy consumption and can be managed accordingly. Recent prediction models focuses on performance of the prediction, but for developing an efficient system, it is required to predict energy demand taking into account various conditions. In this paper we propose a model for predicting energy demand according to various situations using advanced machine learning framework. In this model we have an projector that defines proper state for a particular situation and using that defined state a predictor forecasts the energy demand. The proposed model generates utilization predictions for every 2 hours. Demonstrating the electric power consumption data for 5 years, the proposed system achieves a better performance.*

**Keywords:** *Electric energy; energy management system; energy consumption forecasting; energy prediction; machine learning.*

## Introduction

The worldwide exploitation of electricity is growing rapidly due to increasing human population, great use of electronic equipment to improve the standard of living, emphasis on large-scale industrialization in developed countries and the need to maintain positive economic growth. However, electric energy is an important input for the economic development of any country, through planning and predicting consumption. Forecasting consumption of electric charge is one of the most crucial areas of electrical engineering, it plays important role in economic operation and performance of energy system. Studying the load energy demand is necessary in studying and planning future consumption of electricity appropriately.

For rapidly increasing energy, an energy management system has been proposed to manage the demand. Lot of studies have been done by many researchers, and are involved in algorithms to predict future energy trends of various countries using different prediction approach. Electric energy consumption prediction is essential for analyzing the load characteristics and determining the factors affecting it. In electric power systems many different prediction techniques have been used for achieving accuracy. Achieving high prediction speed and accuracy is an important aspect for any power production companies to schedule its

energy resources appropriately and create optimal bidding plans in the market. In last few years, development of electricity demand forecasting models using machine learning have been of great interest. Electric energy consumption with machine learning has been widely used because of its high performance and accuracy.

## Literature Survey

In this paper [1], they proposed a strategy to foresee the energy request in different circumstances utilizing a profound learning model dependent on a programmed encoder. This model consisted of a projector that defined the state for a given situation and a predictor that predicted the energy requirement of that defined state. The proposed model produced forecasts for the consumption for 15, 30, 45, 60 minutes with a 60-minute demand to date. In this paper [2], they proposed a CNN-LSTM hybrid network that extracts Spatio-fleeting data to viably foresee the house power utilization. Analyses have demonstrated that CNN-LSTM cross breed arranges directly joins convolutional neural system (CNN), long momentary memory (LSTM) and profound neural system (DNN), and can remove sporadic highlights of electric force utilization. The CNN layer was used to reduce the range of spatial i.e space information, and the LSTM layer was

useful in modeling temporal i.e time information, and the predicted time series was generated by the DNN layer.

This study [3] utilizes profound learning advancements in the ecological field to anticipate the status of star natural utilization. They anticipated the star natural utilization list dependent on Google search question information, utilizing an intermittent neural system (RNN) model. To confirm the exactness of the record, they likewise analyzed the expectation precision of the RNN model with that of the conventional least square and counterfeit neural system models. The RNN model predicts the professional ecological utilization file superior to some other model.

This investigation [4] consolidates stacked autoencoders (SAEs) with the outrageous learning machine (ELM) exploiting their individual attributes. Right now, the SAE was utilized to remove the highlights of building energy utilization, while the ELM was used as an indicator to acquire exact forecast results. To decide the information factors of the extraordinary profound learning model, the incomplete autocorrelation investigation strategy was embraced.

In this paper [5], the author tried to put into context the magnitude of increasing consumption of energy in various growth scenarios of human and economic development. While it is said that the scenarios reflect excessively optimistic hypotheses, they represents the growth levels to reduce the level of bias among its citizens. However, studies showed that to get upto the assumed growth levels, the energy consumption levels required were beyond the capacity of available conventional energy sources. Considering the amount of the population increase in developing countries, the increase in energy is much less than the demand. Therefore, there is a need for international awareness and commitment about increasing energy use and implementation of realistic plans to address this problem.

The goal of the work [6] is to define the users of residential energy consumption in Lithuania and compare energy saving techniques in terms of potential of energy savings and cost in residential buildings of Lithuania. Trying to reach the goal of the main work activities they must analyze the theoretical questions of the main users of residential energy usage, analyzing residential energy, using trends in Lithuania and compare these trends with that of other States. They defined the main drivers with the use of residential energy by applying correlation analysis; analyze policies to reduce the consumption in residential buildings and their impact on reducing greenhouse gas emissions.

This study [7] accounts a review of body of research knowledge linked to green construction. Common research themes and various methods have been identified. The themes of these municipalities are the denotation and extent of green building, assessment of the benefits of ecological buildings compared to non-ecological buildings, and different perspective of

constructing an ecological building. There exist studies carried out, focusing mainly on the environmental aspect of green building. Future research opportunities have been identified such as the effects of climatic conditions on the efficiency of green building, quantification tools, verification of the performance of ecological buildings.

This examination [8] sets up the forecast model of yearly energy utilization of private structures utilizing four distinctive demonstrating techniques, for example, bolster vector machine (SVM), conventional back proliferation neural system (BPNN), spiral premise work neural system (RBFNN) and general relapse neural system (GRNN). The reenactment results demonstrated that SVM and GRNN strategies accomplished preferable precision and speculation over BPNN and RBFNN techniques, and are viable for expectation of yearly structure energy utilization.

In this study [9], the primary target is to foresee the structure's energy needs profiting by direction, protection thickness and straightforwardness proportion by utilizing fake neural systems. A back engendering neural system has been utilized and the information have been exhibited in standardized structure to the system. The numerical applications were done with a limited contrast approach for block dividers with and without protection of transient state one-dimensional warmth conduction. Three distinctive structure tests with various structure factors (FF) were chosen for experimentation.

This paper [10] presents support vector machines (SVM), another neural system calculation, to figure building energy utilization in the tropical locale. The goal of this paper was to inspect the possibility and pertinence of SVM in building load guaging. Four business structures in Singapore were chosen arbitrarily as contextual analyses. Climate information including month to month mean open air dry-bulb temperature, relative dampness and worldwide sun oriented radiation were taken as three information highlights. Mean month to month landowner service bills were gathered for creating and testing models.

This paper [11] introduced an approach based on human dynamics analysis derived from aggregated and anonymized data i.e telecom data, to predict the energy consumption of next week, which is calculated from network CDR(call data records). They analyzed the consistency in the source data, provided a perception on the feature extraction method and discuss about the anomaly or abnormality of the regression models appropriate for this big data problem. This proposed model was able to act on energy producers and energy distributors as an necessary help to smart meter data for decision making to reduce the total primary consumption of energy, by restricting the production of energy when demand is not known and to reduce the cost of energy distribution by systematic planning on buy side and provide an insight into geographical space for maximum load planning.

In this paper [12], feature recognition was applied to determine the factors that affect energy efficiency. In view of the component acknowledgment calculation, information mining techniques were utilized to get information from a dataset of 24 territories or urban areas in China. During the time spent information mining, the accompanying three issues were tended to: the ideal element subset was chosen from the first list of capabilities that influences the energy proficiency, the energy effectiveness dependent on the ideal element subset was assessed and, the energy productivity in China was anticipated by seven great fitted arrangement models, whose precision rates were higher than 90%. Consolidating the aftereffects of highlight determination and energy productivity expectation, the system and approach to improve the energy proficiency in China were recommended.

This paper [13] suggests that feature engineering helps reduce data dimensionality, decrease prediction model complexity, and tackling the problem of corrupted and noisy information. Considering that each building has unique operating characteristics, it is not practical and also not efficient to manually identify features for model developments. Using operation data of real buildings, this paper investigated the performance of different deep learning techniques that automatically derive high quality features for building energy predictions. Three types of deep learning based features were developed: fully-connected autoencoders, convolutional autoencoders, and generative adversarial networks. This study validates the usefulness of deep learning in enhancing the performance of building energy prediction.

In this paper [14], modular recurrent neural network (MRNN), a deep learning algorithm was used for predicting the energy requirements of the electric vehicle from various data available inside the vehicle. This model used various parameters and data from the electric vehicle such as power requirements of electric motor under various driving conditions. Power requirements of other devices in the vehicle were also taken into consideration while modeling the system. Using MRNN, a deep learning algorithm; which was used to train the network to predict the power requirements and providing optimal power, enhanced the driving range. Furthermore, the MRNN algorithm makes the prediction behavior very smooth and avoided jitters in the training phase.

[15] This is a review paper that states, Machine learning methods have recently contributed to a large extent in the advancement of the prediction models used for energy consumption. Machine learning models highly improve the accuracy, robustness, precision and the generalization ability of the conventional time series forecasting tools. Through a novel search and taxonomy, the most relevant literature in the field is classified according to various Machine learning modeling techniques, type of energy, type of perdition, and the application area. Along with the conventional ML methods, like ANNs, MLP, DTs, the application of

hybrid and Ensemble methods have been dramatically increased. Through hybrid and ensemble methods the researchers aim at higher efficiency and accuracy.

## Proposed Methodology

To the field of application, we propose to solve power demand forecasting, using the advanced machine learning algorithm.

### A. System Architecture

The overall architecture of our model consists of raw electric energy data with consumption data and time data. A feature like weather information is also taken into consideration. Also, the time of the day (morning, afternoon or evening) is been taken into account. Proposed work presents, advanced feature selection and prediction algorithm for power consumption prediction, trying to improve the accuracy using this technique. Fig. 1 below shows the overall architecture of our system.

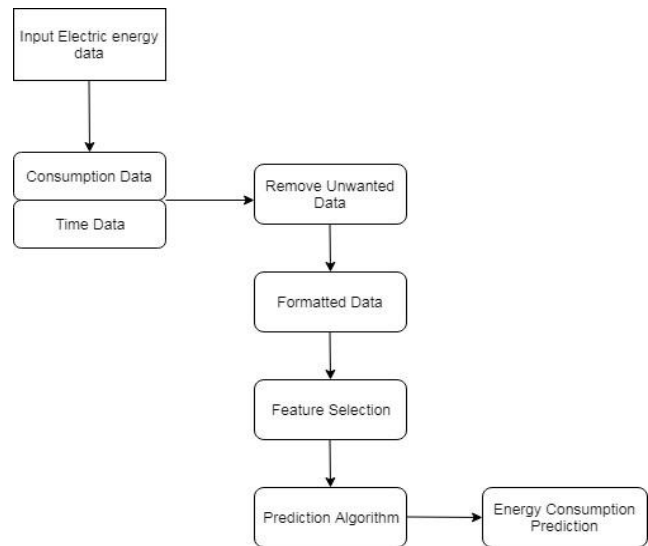


Fig. 1. Proposed System Architecture

### B. Mathematical Model

The Mathematical model for energy prediction system is

$$S = \{I, F, O\}$$

Where,

I = Set of energy dataset

The input consists of a set of features.

F = Set of functions

O = electric energy prediction

$$F = \{F1, F2, F3, F4\}$$

Where,

F1 = Data Collection

F2 = Data Preprocessing

F3 = Feature Selection

F4 = Classification

**C. Algorithm Random Forest:**

**Step 1:** First, start with the selection of random samples i.e. the random subset of feature values (Time and Weather) from a given dataset.

**Step 2:** Next, this algorithm will construct a decision tree for every sample (each subset of energy dataset attributes). One subset of attributes will be taken at a time to construct decision tree. Many decision trees will be formed.

- a. Decision tree uses tree representation for solving the problem, here internal node of the tree contains dataset attributes like date, time etc and each leaf node corresponds to a class label.
- b. At the beginning, we consider the whole training set as the root and construct the decision tree.
- c. Feature values are mostly categorical. Features values are discretized if the values are continuous, before building a model.

**Step 3:** In this step, energy prediction will be performed by each decision tree. Prediction will be according to various conditions, like time of the day, different seasons etc.

**Step 4:** At last, select the most predicted result by all decision trees, as the final prediction result.

**Result and Discussions**

Experiments are done by a personal computer with a configuration: Intel (R) Core (TM) i3-2120 CPU @ 3.30GHz, 4GB memory, Windows 7, MySQL 5.1 backend database and Jdk 1.8. The application is a web application used tool for design code in Eclipse and executes on the Tomcat server. Some functions used in the algorithm are provided by a list of jars like Weka etc. The experimental result evaluation, we have a notation as follows:

- 1. **TP:** True positive (correctly predicted number of instance)
- 2. **FP:** False positive (incorrectly predicted number of instance)
- 3. **TN:** True negative (correctly predicted the number of instances as not required)
- 4. **FN:** False negative (incorrectly predicted the number of instances as not required)

Based on this parameter, we can calculate four measurements.

- I. Accuracy =  $TP+TN \div TP+FP+TN+FN$
- II. Precision =  $TP \div TP+FP$
- III. Recall =  $TP \div TP+FN$
- IV. F1-Measure =  $2 \times Precision \times Recall \div Precision + Recall$ .

Root Mean Square Error (RMSE) is the standard deviation of the residuals (prediction errors). Residuals are a measure of how far from the regression line data points are. RMSE is a measure of, how spread out these residuals are.

The formula for calculating RMSE is

$$RMSE_{f0} = [\sum_{i=1}^N (Z_{fi} - Z_{oi})^2 / N]^{1/2} \tag{1}$$

**Where:**

$\Sigma$  = summation ("add up")

$(Z_{fi} - Z_{oi})^2$  = differences, squared

N = sample size

f = forecasted values (expected values or unknown results) o = observed values (known results)

Below Fig. 2 Shows the expected MAE (Mean Absolute Error) & RMSE (Root Mean Square Error) for small subset of dataset. MAE and RMSE of the dataset for the two hours data are 0.0943 and 0.1266.

Correctly Classified Instances	100	100	%
Incorrectly Classified Instances	0	0	%
Kappa statistic	1		
Mean absolute error	0.0943		
Root mean squared error	0.1266		
Relative absolute error	20.9647	%	
Root relative squared error	26.7192	%	
Total Number of Instances	100		

Fig. 2. Expected MAE & RMSE for a small dataset.

Fig. 3 below shows the graph of the performance of the random forest in comparison with the previous model.

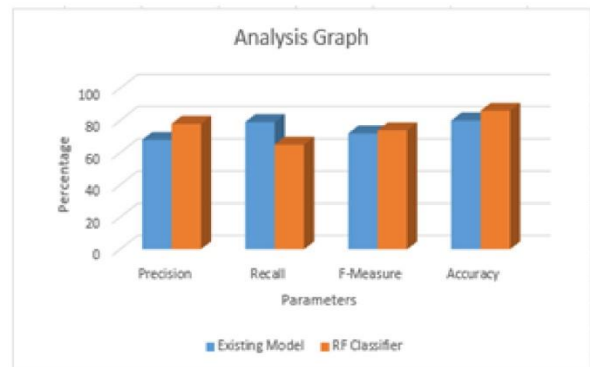


Fig. 3. Performance Analysis Graph

**Dataset Used:**

<https://archive.ics.uci.edu/ml/datasets/individual+household+electric+power+consumption>.

**Conclusion**

In this paper, we proposed an efficient predictive model that can be described by predicting the energy demand for future, according to various conditions and also defining the state as current energy demand patterns. This model will be able to predict a very complex energy demand value with stability and increased performance, as compared with previous studies. System analyses the state defined by the model

and evaluates a model that predicts the future power requirements. Conditions taken into account are weather and time of the day. The model can be extended for predicting the power demand according to more different conditions like economy etc.

## References

- [1] Jin-Young Kim and Sung-Bae Cho, "Electric Energy Consumption Prediction by Deep Learning with State Explainable Autoencoder" MDPI, 22 February 2019; en12040739.
- [2] Kim, T.Y.; Cho, S.B. "Predicting the Household Power Consumption Using CNN-LSTM Hybrid Networks". In Proceedings of the Int. Conf. on Intelligent Data Engineering and Automated Learning, Madrid, Spain, 21–23 November 2018; pp. 481–490.
- [3] Lee, D.; Kang, S.; Shin, J. Using Deep Learning Techniques to Forecast Environmental Consumption Level. Sustainability 2017, 9, 1894.
- [4] Li, C.; Ding, Z.; Zhao, D.; Yi, J.; Zhang, G. Building Energy Consumption Prediction: An Extreme Deep Learning Approach. Energies 2017, 10, 1525.
- [5] Ugursal, V.I. Energy Consumption, Associated Questions and some Answers. Appl. Energy 2014, 130, 783–792.
- [6] Streimikiene, D. Residential Energy Consumption Trends, Main Drivers and Policies in Lithuania. Renew. Sustain. Energy Rev. 2014, 35, 285–293.
- [7] Zuo, J.; Zhao, Z.Y. Green Building Research-Current Status and Future Agenda: A review. Renew. Sustain. Energy Rev. 2014, 30, 271–281.
- [8] Li, Q.; Ren, P.; Meng, Q. Prediction Model of Annual Energy Consumption of Residential Buildings. In Proceedings of the 2010 International Conference on Advances in Energy Engineering, Beijing, China, 19–20 June 2010; pp. 223–226.
- [9] Ekici, B.B.; Aksoy, U.T. Prediction of Building Energy Consumption by Using Artificial Neural Networks. Adv. Eng. Softw. 2009, 40, 356–362.
- [10] Dong, B.; Cao, C.; Lee, S.E. Applying Support Vector Machines to Predict Building Energy Consumption in Tropical Region. Energy Build. 2005, 37, 545–553.
- [11] Andrey Bogomolov1; Bruno Lepri; Roberto Larcher; Fabrizio Antonelli; Fabio Pianesi and Alex Pentland "Energy consumption prediction using people dynamics derived from cellular network data." Bogomolov et al. EPJ Data Science (2016) 5-13
- [12] Y. Guo, Q. Wang, J. Wan, D. Yang, J. Yu and K. Zeng, "Provincial Energy Efficiency Prediction in China Based on Classification Method," in *IEEE Access*, vol. 7, pp. 91602-91611, 2019.
- [13] Cheng Fan; Yongjun Sun; Yang Zhao; Mengjie Song; Jiayuan Wang" Deep learning-based feature engineering methods for improved building energy prediction"; 7 February 2019; j.apenergy.2019.02.052.
- [14] N. Jinil and S. Reka, "Deep Learning method to predict Electric Vehicle power requirements and optimizing power distribution," 2019 Fifth International Conference on Electrical Energy Systems (ICEES), Chennai, India, 2019, pp. 1-5.
- [15] Mosavi, Amir & Bahmani, Abdullah. (2019). Energy Consumption Prediction Using Machine Learning; A Review.