Electricity Consumption & Prediction using Machine Learning Models

Tapas Ranjan Jena
Regn. No.-180303110001, Department of Computer Science and Engineering,
Centurion University of Technology and Management, Odisha, India

Swati Sucharita Barik
Assistant Professor, Department of Computer Science and Engineering,
Centurion University of Technology and Management, Odisha, India

Sasmita Kumari Nayak
Assistant Professor, Department of Computer Science and Engineering,
Centurion University of Technology and Management, Odisha, India

Abstract:

Electricity Consumption is one among widely studied section of computer architecture for more than decades. Electricity Adoption is one of the parameter in Machine Learning. It is one of the emerging field in the research. It keeps an eye on high accuracy without any kind of computation constraint. The paper has the objectivity to analyze Machine Learning algorithms effectiveness, after being applied to the electricity consumption prediction. Load management and demand response, high dimensional data sets are much effective variable selection, accurate prediction for electricity market pricing. It retains economic mechanisms to the largest. Our goal is about important guidelines offering to the Machine Learning community and provide basic knowledge of building specific electricity consumption estimation methods for machine learning algorithms. This Paper reviews about the Conventional Machine Learning Models as well as the recent models, allowing predicting electricity consumption. A number of research works are concerned with the set of structural models and its corresponding applicabilities are introduced. The predictions are proposed for the research reference, depending upon previous work analogy.

Keyword: Electricity Consumption, Electricity Prediction, Conventional Machine Learning, Adaptive Network based Fuzzy Inference System (ANFIS), Extreme Learning Machine (ELM)

I. Introduction

Now a days, consumption of electricity is increasing along with the financial growth and it is also essential in our day to day life [1], [3], [4]. In recent years, the participants confronted many challenges in the electricity market with the concept of deregulation in the power industry

[1] [5]. The excessive electricity produce is a difficult task, as extra electricity storage is found to be difficult and challenging too. So, the generation of a system is necessary, which accurately predict the electricity consumption and minimize production and storage of the electricity issue. Such system can help for the production and the utilization of electricity optimization. This decreases the electricity usage costs for each individual household with help of improved production scheduling and electricity purchase in advance [5].

In today's era, the software industry gradually moves forward to Machine Intelligence. Machine Learning and Artificial Intelligence becomes essential at each sector for making intelligent machines. In a simple Process, Machine Learning is a set of algorithms, which parses data, get from them, and apply the learning to make intelligent decisions. ML algorithms may be conventional ML model or recent trend models. Here, we have discussed all these models. The Traditional or Conventional **Machine Learning** algorithms are complex. Domain expertise are required for it with the help of human intervention.

One of the major disciplines in Artificial Intelligence (AI) is Machine Learning (ML) .It creates systems, which learns automatically [2]. Learning is understood by identifying the difficult prototypes in large amount of data. The Machine is able to learn the procedure of data review. It is able to forecast the future behavior. It implies improved autonomous systems exist without any human interference [2].

Machine Intelligence allows energy producing companies to foretell, in case, more electricity is going to be consumed by the consumers. The objective of it is to adapt tariffs and supervise the energy supply. In further terms, it's said to go from being reactive to being proactive with Machine Learning [2], [6], [7], [8].

This article has the scope to review ML Models, used in the forecast of electricity utilization. The main input of this toil is to present the better machine learning model producing a better forecast with varied data sets.

The structure of this Paper is arranged as follows:

Section-II depicts the latest ML Models, used for energy predictions and Point-III describes the proposal. Point-IV presents the outcome and conclusions.

II. Literature Reviews

The majority of the methodologies for prediction of the consumption of the electrical energy are categorized into two, i.e conventional statistical methods and ML methods [5]. In this Paper, basically centers around on Neural Networks (NN), Linear Regression (LR), Support Vector Regression (SVR), K-Nearest Neighbors (KNN), Random Forests (RF), Gaussian Process Regression (GPR) to predict the electricity consumption [2]. In addition to these a recent model such as an adaptive network-based fuzzy inference system (ANFIS) and Gray relational analysis (GRA) utilized to get a calculation of the electricity consumption of a building based on human exercises and climate conditions [1].

In paper [1], predicted the electricity consumption using a simplified and meaningful method using multi-ANFISs. Multiple data sources influence electricity consumption, but the corresponding impact level of each factor is obscure. Therefore, gray relational analysis (GRA) is used to evaluate the correlation between electricity consumption and the input factors. ANFIS is chosen as the relationship between the input variables and the output can be shown by If-Then standards, which are more meaningful than the weights and biases in other machine learning tools. Moreover, the problem considered does not need a deep learning innovation. In this paper, multi-ANFISs is applied in distinct states for the building for reference. The parameters taken as input fall outside of the climate conditions. These conditions include sunshine duration, temperature, solar radiation, precipitation, humidity and cloud covering. A number of ANFIS Structures are selected for running days, offdays in public and private institutions and enterprises buildings. At the end, the results were compared to obtain, this methodology, along with the Levenberg–Marquardt proposed Back Propagation Neural Network approach [3][4], Single ANFIS Model, Linear Regression, and Nonlinear Regression methods. With the help of multi ANFISs, the electricity consumption can be predicted and the relationship between the input factors and the output. As per the observations made, the electricity usage consumptions of different human activities including working day and school day are different even though the climate conditions are identical. In these perceptions, the dataset contains three days having similar weather conditions. Different combinations of working day and school day conditions result in different electricity consumption. In this manner, all are considered as binary coding of working day and school day dates. These are not reasonable to use ANFIS straightforwardly. Henceforth the association between each factor is acclimated to transform the given problem into a consistent circulation. Along these lines, these two parameters are utilized to choose the relating model and the other factors are considered as inputs of the multi ANFISs. The anticipated multi ANFISs method is shown in Figure 1.

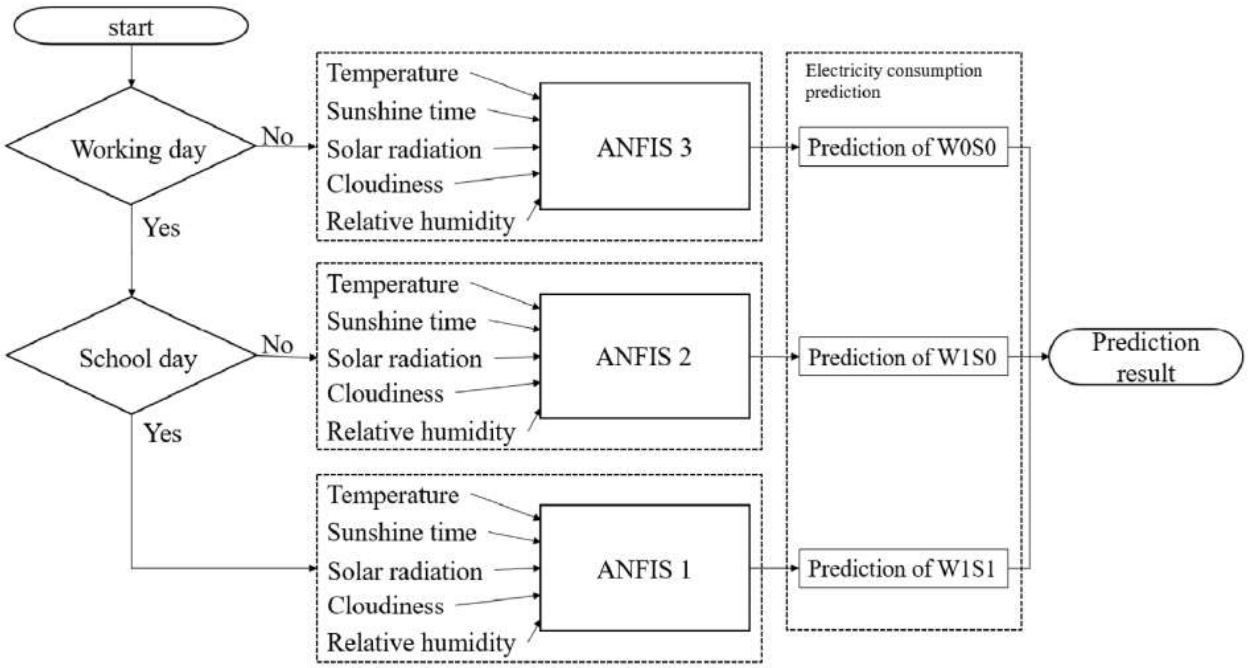


Figure 1: Multi-ANFISs Prediction scheme [1]

In paper [2], prediction of electricity consumption is done using conventional machine learning model. This paper presents the comparison of accuracy of all conventional models with and without the parameter selection as shown in Table 1.

Table 1. Machine Learning Methods Score Without and With the Parameter Selection to Train [2].

Machine learning method	**Accuracy Without Parameters Selection**	**Accuracy With Parameters Selection**
Decision Tree	0.641	0.83
Random Forest	0.798	0.799
K-Nearest Neighbors (KNN)	0.843	0.854
Support Vector Regression	0.844	0.857
Linear Regression	0.857	0.857

This describes, both LR and SVR have yielded 85.7% of precision [2]. Random Forest model has the worst result of 79.9%. It does not conclude SVR, LR are far improved version than that of the rest models, as the variables are fitted with the dataset (i.e day, week, weekday, presence) [1] [2].

Another machine learning model is Random Forests (RF). It predicts with broad set of data producing classifier, which has a higher success rate [1],[2], [31]. The variables provide the temporal value and get advancement in the prediction. This used to happen in KNN. One among the studies have applied RF with maximum percentage of success. It predicts the electricity usage in the zone of Tucumán, Argentina. These were performed by Diego F. Lizondo et al. [1], [2], [30].

Support Vector Regression performs classifications in continuous variable datasets. It vacillates within a subset of IR. Support Vector Regressions is playing an important aspect for yielding the prediction of electrical consumption [2], [32], [33].

One of the reference algorithms is K-Nearest Neighbors (KNN), in terms of making predictions. This algorithm has been widely used to get the analogous cases in multivariate and large dimensional feature spaces of arbitrary attribute scales [1]. This methodology identifies old reasons of the same dependent variable, which corresponds with the future realizations. It is not treated as a causal approach of forecasting [1]. For this reason, the methodology is to be complemented with temporal information as variables. The variables find the day of the week, the day within the year or the week within the year in a manner to facilitate the exploration in some analogous neighbors [1] [2] [34].

Saab et al. [2], [35], found different modeling approaches for forecasting electric energy consumption in Lebanon on month basis.

Bianco et al. enquired about the electricity consumption forecast in Italy with help of a linear regression model [1],[2], [37]. They have compared with the other countries forecasting consumption. They depend upon difficult econometric models, like Markal-Time. It demonstrates consistencies of developed regressions with official projections.

Followings are the observations :-

Mohamed and Bodger [2], [36] had researched and found a representation and formation for electricity usability forecasting at places of New Zealand. This Model depends on a set of many number of linear regression analysis, with respect to demography and economic variables.

ML algorithms have been proposed by P. Shine et al. [9]. It predicted the electricity consumption. It worked on farm direct water consumption. The approach used in this paper is recommendation from [9],[10] to regard multiple Machine Learning techniques and variable collection methods for the reason to raise the prospect of maximizing the accuracy with the forecast of the absolute model. Electricity consumption as well as Consumption of water data were accomplished through the utilization of an isolated monitoring system. It was earlier installed with study sample of 58 number of pasture based, commercial Irish dairy farms between year 2014 and 2016. As a sum of dairy farm variables of count 15 and 20 were analyzed for their predictive power of monthly electricity and water consumption respectively. Milk production, stock numbers, infrastructural equipment, managerial procedures and environmental conditions were selected as the variables. The CART decision tree algorithm, random forest ensemble algorithm, artificial neural network (ANN) and Support Vector Machine (SVM) algorithm were the ones, which had helped in predicting the water consumption and electricity consumption. The developed Machine Learning models provide key decision support information to the dairy farmers as well as policy makers. Energy & Water usage details were collected from 58 Irish commercial dairy farms and the corresponding data related to milk production, stock, farm infrastructure, managerial processes and environmental conditions were useful for developing Multiple Linear Regression Models [9], [11]. This paper assessed the accuracy prediction of four (4) Machine Learning Algorithms for improving the monthly E&W (energy and water) consumption on Irish dairy farms over MLR modeling. The CART Decision Tree algorithm (CDT), Random Forest ensemble Algorithm (RF), Artificial Neural Network (ANN) or Neural Network and Support Vector Machine Regression (SVR) algorithm were the ones in helping predicting forecast accuracies.

The details of the objectives of this work presented in this article were to:

1.Calculate precision of four ML models for dairy ranch E&W forecast from aunique dataset of indicator factors using a scope of data mining techniques. These data mining techniques included: variable choicetechniques to remove high prescient yield factors, grid search hyper-parameter tuning to improve the forecast exhibition of each ML model, and defined settled cross-approval compute the expectation execution properlyusing information not utilized for model preparing or approval.

2. Dissect the month to month forecast inclination of every ML algorithm to decide factors, which may impact model execution.Like to [12] the presentation of every ML algorithm was benchmarked against that of the MLR model. Forecastprecision and inclination of the ML models were benchmarked against results from recentlycreated MLR models utilizing basic model approvalrulesutilized in horticultural research [9], [13]. These recently created MLR models for dairy ranch E&W utilization were created utilizing similar information utilized for this investigation and determined model correctnesses utilizing concealed information.

3. Analyse the absolute prediction accuracy for the most accurate ML model for both E&W (selected from section one) according to the number of dairy cows.

Electricity consumption was most accurately predicted using a support vector machine algorithm with an acceptable relative prediction error (RPE) value of 11.9% and excellent concordance correlation coefficient of 0.97. Compared to a MLR approach previously applied to this problem, the support vector machine model improved electricity prediction accuracy by 54% with respect to RPE. On the other hand, the RF algorithm provided the most accurate prediction of water consumption with poor prediction accuracy of 38.3% (RPE) and moderate correlation coefficient value of 0.76. Compared to the MLR approach, the ANN model improved water prediction accuracy by 23% relative to RPE [9].

In paper [14], proposed an Extreme Learning Machine (ELM), which is used to predict the multivariate electricity consumption. Power utilization as a type of vitality utilization, with fast expansion of private and business zones, has grown rapidly, which is a danger for practical turn of events. The expectation of power utilization not only improves monitoring and usage application for energy in buildings, but also it plays an important part in improvizing the voltage-current performance. It has an objective of gaining energy utilization conservation and dropping the environmental impact [14], [15]. Additionally, power utilization forecast assumes a critical job in dynamic and future arranging that depend on expectation precision. The exactness of expectation is significant for illuminating the examinations regarding electric forcetrade, exchanging assessment, arrange capacity, security and patterns, and the wellbeing procedure of decrease load [14], [16]. This Paper predicts the electricity consumption at building of institutes, university etc. In this situation, Extreme Learning Machine is utilized for power utilization forecast through investigating the prescient presentation of verifiable power utilization logs alongside power related and natural information. Again a methodology called, Discrete Dynamic Multi Swarm Particle Swarm Optimization (DDMS-PSO) comes into existence. It addresses the optimization problem of discrete values. So that,it will be able to find the subset of all factors, irrespective of feature space of heterogeneous aspect, window sizes and the number of unseen neurons. These direct to the performance of best prediction. The dataset are collected from the smart meters of the buildings in the city campus of the University. The idea is on how to understand the trend of electricity usage consumption under the control of electrical energy correlated and environmental aspects on energy expense. Auxiliary environment data is slowly moved from an online weather station. The weather station transmits periodic findings from each and every 20 minutes of time to an hour. This forecast yield helps to occasion arranging and asset the executives.

The following are the aspects, explored in this paper.

1. Authentic shrewd meter information assesses and figures the structures future power utilization. The outcome viewed as the pattern to assess if the assistant data can help improving the forecast exactness.

2. Power related variables are added to recognize in event that they have impact on improving the expectation execution. Additionally it likewise thinks about which variables can expand the precision the most.

3. In view of the best mix of the power related variables, it investigates if natural elements impact the forecast precision as well as ideal subset of ecological components.

4. Evolutionary algorithm explores that, if a part of environmental factors exist, which are relating to electricity, then relevant dimensions in window and an adequate amount of neurons in hidden state produce the best prediction accuracy in Extreme Learning Machine.

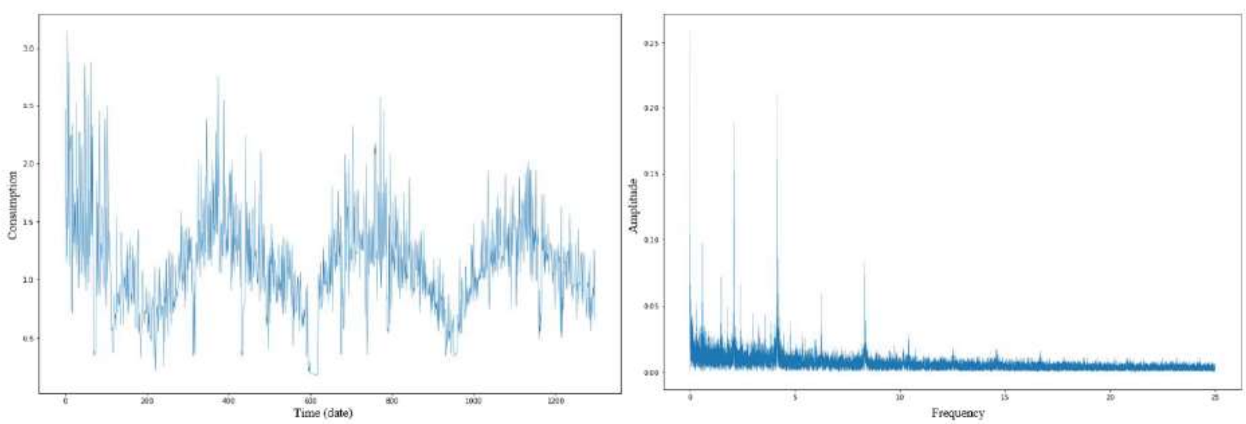
In paper [14], ELM was contrasted with SVR for vitality utilization expectation and demonstrated prevalence over SVR. Additionally, power related and natural components were tentatively exhibited to improve expectation precision acquired by simply utilizing utilization information. With addition to this,

DDMS-PSO proposed with an objective to find the optimal portion of electricity related issues and environmental factors. The individual window dimensions and amount of hidden neurons are available in Extreme Learning Machine. It implies to best prediction accuracy. It concluded, DDMS-PSO found subsets, which lead to the largely taken best predication accuracy.

In paper [17], proposed a deep neural network based model with state explainable auto-encoder to predict the electric energy consumption. The Researchers communities have set experimentations and studies along with different methodologies to predict the energy demand. Previously, Techniques like Support Vector Machine and Linear Regression in Machine Intelligence are utilised. As per the data shown in Figure 2a, the values for energy demand are critical, noisy. It restricts the performance. As rendered in Figure 2(b), the Fourier Transform analyzes the energy demand patterns. Hence it observes and concludes that, it has some difficult traits. For the quantity study, Dataset were used with ANOVA and t-test in this paper as shown in Table 2.

Table 2. Results on Statistical Analysis of Electric Energy Demand by Hour, Date and Month [17]

Statistical Analysis	Hour	Date	Month
p-value (t-test)	0.011	0.152	0.005
p-value (ANOVA)	0.000	6.986×10^{-56}	0.000



(a) (b)

Figure 2. (a) Date wise Electric Energy Demand, (b) Fourier Transform Outcome [17].

In the statistical, mathematical analysis using t-test, two sets are randomly selected and calculated p-values. The average of all likely samples are computed. ANOVA helps in finding the p-value. The p-value is computed from all the samplings taking account of month, date, and hour. The previous work of this article is summarized in Table 3.

III. Machine Learning Models for Prediction

A. Support Vector Regression (SVR)

Support Vector Machine is considered as a regression method. It upholds all important features, characterizing the algorithm with highest margin. The Support Vector Regression Method uses the principles as of the SVM for classification, with little differences. The outcome is a real number. So it is difficult to predict the information with countless possibilities. In regression, tolerance or epsilon is put in an approximation to the SVM, which have been asked for the problem. A more complicated reason too exists. The algorithm is more obscured to be considered. The main objectivity is to diminish the error by individualizing the hyper plane. The hyper plane exceeds the margin by tolerating the part of error.

B. Random Forest (RF)

Another Learning methodology is known as Random Forest i.e RF. Random Forest gets operated by multiple numbers of Decision Trees. The ultimate conclusion is made considering the maximum of the trees. Here it uses the random forest method. The advantage is, it diminishes the threat of over fitting and the training time. Also, it offers a higher level of precision. Random Forest Algorithm runs efficiently and effectively in larger databases and yields highly accurate predictions by estimating the missing data. Random Forest i.e RF is an appreciable algorithm to train before time in the model development process. Its objective is quite sure to check performance measure. building might be treated “bad” by considering its simple approach and it becomes proposed as a bad random forest.

Table 3. Summary of Previous Paper work [17].

Category of Models	Methodology	Objective
Statistical Model	ANN [18]	Forecast buildings energy are taken advantages from insulation, orientation, insulation thickness and transparency ratio using ANN
	Feedback neural network [19]	It Presents a simpler approach for the electric load in buildings to predict
	SVM [20]	Building energy demand can be easily predicted in the tropical region using SVM method
	Statistical model and its physical principles [21]	Applies statistical method of multiple linear regression to real-world trip and energy consumption data

	ARIMA [22]	A set of forecasting methods can be deployed for electricity usage consumption prediction
	K-Means Clustering [23]	Calculates the center value of the cluster and classify the time series into regular and irregular trend
Machine learning model	Deep neural network [24]	Forecasts energy demand with information of climate, date, and building usage rate
	Linear Regression Method [25]	Proposes model based on linear regression that predicts large-scale public building energy demand
	Fuzzy support vector machine, Fuzzy c-means clustering [26]	Presents a novel short-term cooling load forecasting with conjunctive use of fuzzy C-mean clustering to define state and fuzzy SVM for prediction
	SVM [27]	Annual energy demand can be forecastsed using the building’s heat transfer coefficient
Deep learning model	Autoencoder [28]	Extracts the building energy demand and predict future energy consumption
	Recurrent neural network (RNN) [29]	Measures the environmental consumption level for each region in a country with the help of proenvironmental consumption index with the application of big data queries

The algorithm is better to be used for user, who wants its application. It also helps those, who wishes to develop a quick model. Random forests are very hard to beat performance. A model can be used to provide better performance, like a Artificial Neural Network. The only drawback is more time consumption to develop. The only thing to consider is different feature types, numeric, binary, categorical. In a nutshell, Random Forest is considered as the fast yet simple as well as flexible tool. The best part of it is, it’s not restricted with any limitations.

C. Linear regression (LR)

Linear Regression [2], is a model, which finds the relationship between the response variable or energy consumption and the return or other variables. The objective of regression analysis forecasts the demand for energy from one or more independent variables. Linear regression is a method used, when trend in historical forecast data is obvious. For this reason, the application has been used for electricity consumption forecast.

D. K-Nearest Neighbors (KNN)

The K-Nearest Neighbors algorithm is a simple, supervised Machine Learning algorithm. It solves both classification and regression problems. It’s easy for understanding and implementation. It has a major drawback i.e it becomes slows as the data size grows.

The KNN algorithm assumes, similar things exist in close proximity. This means to imply that, similar things are near to each other. KNN works by finding the distances between a query and all the examples in the data, selecting the specified number examples closest to the query, then opts for the most frequent label in the case of classification or averages the labels in regression.

E. Artificial Neural Network (ANN)

The Artificial Neural Network (ANN) is also known as neural network. It is a Machine Learning Method, evolved from the idea of simulating the human brain [38]. An ANN simulates the network of neurons, making up a human brain, so that the computer will be able to learn things and make decisions in a humanlike manner. ANNs are created by programming the Computer Systems to behave as though they are interconnected brain cells. There are several ways, ANN can be deployed to classify information, predict the outcomes and cluster data. As the networks process and learn from data, they can classify a given data set into a predefined class. It can be trained to predict outputs, from a given input and can identify a special feature of data to then classify the data by that special feature. Computers understand the world around them in a human like manner using ANN.

F. K-Means Clustering

Clustering belongs to unsupervised learning approach, where test dataset are not labeled. Hierarchical Clustering depends on building hierarchy, using two types of a clustering techniques. They are Agglomerative and Divisive. Agglomerative Clustering is paired to create big cluster in bottom up approach. The Divisive Clustering breaks a big cluster into the small clusters in a top down approach. Partitioning Clustering is a technique, which use partitioning the datasets into equal or unequal sets. Each of the set is characterized in cluster form. In K-Means Clustering, Dataset is into set of K-small clusters. Each of the cluster is represented through cluster mean [39], [40].

G. Extreme Learning Machine (ELM)

Extreme Learning Machine (ELM) is a new learning method, proposed by Huang et al. [14], [47]. One major drawback was caused by gradient descent based algorithms and Back Propagation. ELM overcomes out of it. ELM is based on Single hidden Layer Feed Forward Neural Network architecture. Three different layers, input layer, hidden layer and output layer are there [48]. The hidden bias and the weight for connecting input layer and hidden layer are randomly get and maintained through the whole training process. Extreme Learning Machine have no parameters to adjust the hidden neurons. These can easily be applied in regression [46] or classification [45] issues. It yields low computational cost during the process of training. ELM comes into existence for its application in time series prediction. Time sries prediction is used for predicting the sales in fashion retailing [44]. ELM is used for electricity price forecasting with fast computational ability [43]. ELM is also applications with wind power density prediction [42]. It is compared with SVM and ANN. In [41], ELM has been applied for daily dew point temperature prediction.

IV. Conclusion

This paper provides a detailed survey on the prediction of electricity consumption. The literature survey concludes with better results for electricity consumption prediction with the hybrid approach of machine learning techniques. It has been considered to be an attempt to use hybrid approach to combine dimensionality reduction techniques with machine learning techniques. The hybrid model has been used in most of the problems. Performance Improvement for the prediction of electricity consumption is the difficult task. The review of this paper helps in doing so. The accuracy rate has been implemented with those techniques. The above techniques can be implemented to get better results with changes in existing model.

Reference

1. Alfonso Gonzalez-Briones, Guillermo Hernandez, Juan M. Corchado, Sigeru Omatu, Mohd Saberi Mohamad. "Machine Learning Models for Electricity Consumption Forecasting:A Review", 2019 2nd International Conference on Computer Applications & Information Security (ICCAIS), 2019
2. Chen, H. Y., & Lee, C. H. (2019). Electricity consumption prediction for buildings using multiple adaptive network-based fuzzy inference system models and gray relational analysis. Energy Reports, 5, 1509-1524.
3. A. González-Briones, G. Hernández, J. M. Corchado, S. Omatu and M. S. Mohamad, "Machine Learning Models for Electricity Consumption Forecasting: A Review," 2019 2nd International Conference on Computer Applications & Information Security (ICCAIS), Riyadh, Saudi Arabia, 2019, pp. 1-6, doi: 10.1109/CAIS.2019.8769508.
4. Su, Y.-W., (2019). Residential electricity demand in Taiwan: Consumption behavior and rebound effect. Energy Policy 124, 36–45.
5. Shahbaz, M., Sarwar, S., Chen, W., & Malik, M.N., (2017). Dynamics of electricity consumption, oil price and economic growth: Global perspective. Energy Policy 108, 256–270.
6. Stankoski, Simon., Kiprijanovska, Ivana., Ilievski, Igor., Slobodan, Jovanovski., & Gjoreski, Gjoreski. (2019). "Electrical Energy Consumption Prediction Using Machine Learning", In S. Gievska and G. Madjarov (Eds.): ICT Innovations 2019, CCIS 1110, pp. 72–82, 2019. https://doi.org/10.1007/978-3-030-33110-8_7.
7. Coria, J. A. G., Castellanos-Garzón, J. A., & Corchado, J. M. (2014). Intelligent business processes composition based on multi-agent systems. Expert Systems with Applications, 41(4), 1189-1205.
8. Li, T., Sun, S., Bolić, M., & Corchado, J. M. (2016). Algorithm design for parallel implementation of the SMC-PHD filter. Signal Processing, 119, 115-127.

9. Morente-Molinera, J. A., Kou, G., González-Crespo, R., Corchado, J. M., & Herrera-Viedma, E. (2017). Solving multi-criteria group decision making problems under environments with a high number of alternatives using fuzzy ontologies and multi-granular linguistic modelling methods. Knowledge-Based Systems, 137, 54-64.
10. Shine, P., Murphy, M. D., Upton, J., & Scully, T. (2018). Machine-learning algorithms for predicting on-farm direct water and electricity consumption on pasture based dairy farms. Computers and electronics in agriculture, 150, 74-87.
11. Bermúdez-Chacón, R., Gonnet, G.H., Smith, K., 2015. Automatic problem-specific hyperparameter optimization and model selection for supervised machine learning: Technical Report. Zurich. http://dx.doi.org/10.3929/ethz-a-010782581.
12. P. Shine, M.D. Murphy, J. Upton, T. Scully."Machine-learning algorithms for predicting onfarm direct water and electricity consumption on pasture based dairy farms", Computers and Electronics in Agriculture, 2018
13. Hui Song, A. K. Qin, Flora D. Salim."Multivariate electricity consumption prediction with Extreme Learning Machine", 2016 International Joint Conference on Neural Networks (IJCNN), 2016
14. Shine, P., Scully, T., Upton, J., Murphy, M.D., 2018a. Multiple linear regression modeling of on-farm direct water and electricity consumption on pasture based dairy farms. Comput. Chem. Eng. http://dx.doi.org/10.1016/j.compag.2018.02.020 (in press).
15. Song, H., Qin, A. K., & Salim, F. D. (2016, July). Multivariate electricity consumption prediction with extreme learning machine. In 2016 International Joint Conference on Neural Networks (IJCNN) (pp. 2313-2320). IEEE.
16. A. Foucquier, S. Robert, F. Suard, L. St´ephan, and A. Jay, “State of the art in building modelling and energy performances prediction: A review,” Renewable and Sustainable Energy Reviews, vol. 23, pp. 272–288, 2013.
17. X. L. Yuan, X. Wang, and J. Zuo, “Renewable energy in buildings in chinała review,” Renewable and Sustainable Energy Reviews, vol. 24, pp. 1–8, 2013.
18. Kim, J. Y., & Cho, S. B. (2019). Electric energy consumption prediction by deep learning with state explainable autoencoder. Energies, 12(4), 739.
19. Ekici, B.B.; Aksoy, U.T. Prediction of Building Energy Consumption by Using Artificial Neural Networks. Adv. Eng. Softw. 2009, 40, 356–362.
20. Gonzalez, P.A.; Zamarreno, J.M. Prediction of Hourly Energy Consumption in Buildings Based on a Feedback Artificial Neural Network. Energy Build. 2005, 37, 595–601.
21. 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.
22. De Cauwer, C.; Van Mierlo, J.; Coosemans, T. Energy Consumption Prediction for Electric Vehicles based on Real-world Data. Energies 2015, 8, 8573–8593.
23. Kandananond, K. Forecasting Electricity Demand in Thailand with an Artificial Neural Network Approach. Energies 2011, 4, 1246–1257.
24. Munz, G.; Li, S.; Carle, G. Traffic Anomaly Detection Using k-means Clustering. In Proceedings of the GI/ITG Workshop MMBnet, Hamburg, Germany, 13–14 September 2007; pp. 13–14.

25. Ahmad, M.W.; Mourshed, M.; Rezgui, Y. Trees vs Neurons: Comparison between Random Forest and ANN for High-resolution Prediction of Building Energy Consumption. Energy Build. 2017, 147, 77–89.
26. Ma, Y.; Yu, J.Q.; Yang, C.Y.; Wang, L. Study on Power Energy Consumption Model for Large-scale Public Building. In Proceedings of the 2010 2nd International Workshop on. IEEE Intelligent Systems and Applications, Wuhan, China, 22–23 May 2010; pp. 1–4.
27. Xuemei, L.; Yuyan, D.; Lixing, D.; Liangzhong, J. Building Cooling Load Forecasting Using Fuzzy Support Vector Machine and Fuzzy C-mean Clustering. In Proceedings of the 2010 International Conference on Computer and Communication Technologies in Agriculture Engineering, Chengdu, China,12–13 June 2010 pp. 438–441.
28. 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.
29. Li, C.; Ding, Z.; Zhao, D.; Yi, J.; Zhang, G. Building Energy Consumption Prediction: An Extreme Deep Learning Approach. Energies 2017, 10, 1525.
30. Lee, D.; Kang, S.; Shin, J. Using Deep Learning Techniques to Forecast Environmental Consumption Level. Sustainability 2017, 9, 1894.
31. Aye, S. A., & Heyns, P. S. (2017). An integrated Gaussian process regression for prediction of remaining useful life of slow speed bearings based on acoustic emission. Mechanical Systems and Signal Processing, 84, 485-498.
32. Lahouar, A., & Slama, J. B. H. (2015). Day-ahead load forecast using random forest and expert input selection. Energy Conversion and Management, 103, 1040-1051.
33. Oğcu, G., Demirel, O. F., & Zaim, S. (2012). Forecasting electricity consumption with neural networks and support vector regression. Procedia-Social and Behavioral Sciences, 58, 1576-1585.
34. Magoulès, F., Piliougine, M., & Elizondo, D. (2016, August). Support vector regression for electricity consumption prediction in a building in japan. In Computational Science and Engineering (CSE) and IEEE Intl Conference on Embedded and Ubiquitous Computing (EUC) and 15th Intl Symposium on Distributed Computing and Applications for Business Engineering (DCABES), 2016 IEEE Intl Conference on (pp.189-196). IEEE.
35. Al-Qahtani, F. H., & Crone, S. F. (2013, August). Multivariate k-nearest neighbour regression for time series data—A novel algorithm for forecasting UK electricity demand. In Neural Networks (IJCNN), The 2013 International Joint Conference on (pp. 1-8). IEEE.
36. Saab, S., Badr, E., & Nasr, G. (2001). Univariate modeling and forecasting of energy consumption: the case of electricity in Lebanon. Energy, 26(1), 1-14.
37. Mohamed, Z., & Bodger, P. (2005). Forecasting electricity consumption in New Zealand using economic and demographic variables. Energy, 30(10), 1833-1843.
38. Bianco, V., Manca, O., & Nardini, S. (2009). Electricity consumption forecasting in Italy using linear regression models. Energy, 34(9), 1413-1421.

39. Zou J, Han Y, So SS. Overview of artificial neural networks. Methods in Molecular Biology (Clifton, N.J.). 2008 ;458:15-23. DOI: 10.1007/978-1-60327-101-1_2.
40. Chauhan, N. K., & Singh, K. (2018, September). A review on conventional machine learning vs deep learning. In 2018 International Conference on Computing, Power and Communication Technologies (GUCON) (pp. 347-352). IEEE.
41. K. Alsabati, S. Ranaka, V. Singh, "An efficient k-means clustering algorithm", Electrical Engineering and Computer Science, 1997.
42. K. Mohammadi, S. Shamshirband, S. Motamedi, D. Petkovi´c, R. Hashim, and M. Gocic, "Extreme learning machine based prediction of daily dew point temperature," Computers and Electronics in Agriculture, vol. 117, pp. 214–225, 2015.
43. K. Mohammadi, S. Shamshirband, L. Yee, D. Petkovi´c, M. Zamani, and S. Ch, "Predicting the wind power density based upon extreme learning machine," Energy, vol. 86, pp. 232–239, 2015.
44. X. Chen, Z. Y. Dong, K. Meng, Y. Xu, K. P.Wong, and H. Ngan, "Electricity price forecasting with extreme learning machine and bootstrapping," IEEE Transactions on Power Systems, vol. 27, pp. 2055–2062, 2012.
45. Z. L. Sun, T. M. Choi, K. F. Au, and Y. Yu, "Sales forecasting using extreme learning machine with applications in fashion retailing," Decision Support Systems, vol. 46, pp. 411–419, 2008.
46. G. B. Huang, X. Ding, and H. Zhou, "Optimization method based extreme learning machine for classification," Neurocomputing, vol. 74, pp. 155–163, 2010.
47. R. Zhang, Y. Lan, G. b. Huang, and Z.-B. Xu, "Universal approximation of extreme learning machine with adaptive growth of hidden nodes," IEEE Transactions on Neural Networks and Learning Systems, vol. 23, pp. 365–371, 2012.
48. G. B. Huang, Q. Y. Zhu, and C. K. Siew, "Extreme learning machine: theory and applications," Neuro computing, vol. 70, pp. 489–501, 2006.