Annals of R.S.C.B., ISSN:1583-6258, Vol. 24, Issue 2, 2020, Pages. 19 - 34
Received 20 October 2020; Accepted 04 December 2020.

An Efficient Energy Utilization Analysis using Novel Chess Optimization Algorithm

[1a]S. Dhivya, *[1b]R. Arul, [2]S. Ramesh and [3]Padmanathan Kasinathan

[1]School of Electrical Engineering, Vellore Institute of Technology, Chennai 600127, Tamilnadu, India.
[a]E-mail: dhivya.s2019@vitstudent.ac.in * [b]E-mail: arulphd@yahoo.co.in
[2]Department of Computer Science & Engineering, Krishnasamy College of Engineering & Technology, S.Kumarapuram, Cuddalore 607109. Tamilnadu, India. E-mail: swami.itraj@gmail.com
[3]Department of Electrical and Electronics Engineering, Agni College of Technology, Thalambur, Chennai 600130, Tamilnadu, India. E-mail: padmanathanindia@gmail.com
****Corresponding Author***

Abstract:

The demand for the power distribution to the residential buildings is a non consistent form that depends on the inhabitant requirement, occupancy dynamism and the appliances that were working in it. The optimization of power consumption and various different building parameters tends to the reduced power consumption and maximize the efficiency of power management integrating with the forecasting of energy demands. The occupancy dynamism in the residential area possess random pattern of energy utilization and needs an efficient optimization algorithm for the maintenance of occupancy centric energy consumption. With an aim of addressing this need, this paper proposes a novel model of Chess Optimization (CO) algorithm with three phase namely preprocessing, feature extraction and classification. The proposed algorithm utilizes the datasets effectively for the comparison of trained and testing phase to fix the global active power and time series data set values. The performance analysis of the proposed chess optimization algorithm is done at multiple levels of global active with time and smart meters with respect to time. The dataset related to the hourly energy consumption has been effectively used for prediction of high power and low power consumption meters in which the appliances were classified under various levels of smart meters. The experimental results proves that the proposed optimization algorithm possess minimal energy difference (with a standard deviation of 0.1) between the user set parameters and the real time measured parameters, also proves to be an effective energy utilization management with a minimal power consumption.

Keywords: Power Distribution, Building optimization, Chess Optimization algorithm, Minimal energy difference, energy utilization management.

Annals of R.S.C.B., ISSN:1583-6258, Vol. 24, Issue 2, 2020, Pages. 19 - 34
Received 20 October 2020; Accepted 04 December 2020.

1. Introduction

Energy is the backbone of the economy of any country and a major part of energy generated is consumed for the household appliances. The residential buildings occupy about 40 to 50% of the earth area, whereas those residential buildings consume 40% of the total power generated in the world. The analysis of the power generation and consumption is considered to more vital process for the purpose of energy preservation and effective usage and distribution of energy. The analysis of energy consumption in the building depends on multiple parameters like structure of the building, lighting systems employed in the building, parameters of lighting, pump motor for water flow, washing machine, dish washers, kitchen appliances, refrigeration and et more appliances consumes a predefined units of energy per operation time. The energy consumption will not be unique from one residential building to another as it varies with the building population and electrical appliances in the targeted building that is considered for analysis. The analysis of the energy consumption in the residential buildings is not an easier task and the usage of mathematical tools and algorithms makes it simpler to perform the quantitative analysis of the energy consumption. The incorporation of mathematical tools and methods, not only makes the analysis process easier but also attracts plentiful researchers to involve in the analysis of power consumption in a particular targeted area. It is essential to develop a building energy modeling which is considered to be the vital tool for development of decisions on the power concern for the new and existing buildings. The Building energy modeling can be classified into two types namely forward modeling and inverse modeling. The forward energy modeling is a traditional method incorporated by most researchers and energy modeling software designers in their software products. The modeling parameters utilized by the traditional forward method are the geometry of the building, climatic conditions, lighting parameters etc. Whereas the inverse modeling employs mathematical relationship among the given inputs such as temperature to the derived output such as energy consumption. The inverse modeling has become more popular, as the derived relationship between the input temperature and output energy consumption are based on the engineering domain. Based on the forward approach, certain familiarized program tools were created like EnergyPlus, Blast, APACHE etc and these program packages requires training of input datasets like building parameters inclusive of construction and system of the building. In turn, based on the inverse approach, engineering technologies like machine learning, Artificial Neural

Annals of R.S.C.B., ISSN:1583-6258, Vol. 24, Issue 2, 2020, Pages. 19 - 34
Received 20 October 2020; Accepted 04 December 2020.

Network (ANN), Genetic Algorithm, Decision Tree Method were used to forecast and measure and energy consumption of residential buildings. The need for the energy consumption analysis and the development of software tools for the analysis rise to meet the expectation of energy preservation, to predict the energy demands, Energy researchers tried with the integration of the forward approach with the inverse approach to obtain better efficient power consumption analysis using sensor based energy consumption modeling. The sensor modeling approach produce output data based on the input datasets applied to the program and computes the energy consumption on executing the appropriate mathematical tools.

The existence of forward and inverse approach holds good in energy consumption analysis and experience a setback among the residential and commercial sites due to the lack of granularity in residential sites. This paper proposes a novel Chess Optimization (CO) algorithm to vanish the aforementioned gap. The Chess Optimization algorithm compares the testing input value with the predetermined datasets and the resulting output is optimized to determine the optimal consumption of the energy in the household purposes.

The remaining section of the research manuscript is progressed as follows. Section 2 describes the related research work of the energy consumption analysis followed by the Section 3 which narrates the process and mathematical foundation of the novel Chess Optimization algorithm in household energy consumption analysis. The results of the proposed work were analyzed in Section 4 whereas the research manuscript is concluded in Section 5.

2. Related Works

The incorporation of mathematical tools in energy consumption analysis attracts plentiful researchers in this domain with multiple types of analysis models. This section narrates the highlighted research outputs and the methodology implemented in the energy utilization analysis.

Minglei Shao and et.al [1] analyzed the energy consumption in hotel buildings by employing support vector machine energy consumption prediction model which considers the weather condition and air conditioning systems of the hotel buildings as the predominant parameters. In this model, the support vector machine is employed for energy utilization analysis

Annals of R.S.C.B., ISSN:1583-6258, Vol. 24, Issue 2, 2020, Pages. 19 - 34
Received 20 October 2020; Accepted 04 December 2020.

and the performance results were recorded with 2.22% of MSE and 0.94 of R^2 and the results were in the satisfactory level.

Richard E.Edwards and et.al [2] has presented a research review on the role of Machine Learning in energy utilization analysis. The analytical study was performed on seven different machine learning algorithms that were utilized to analyze the residential energy consumption datasets which were measured using sensor for every constant time interval.

Bing Dong and et.al [3] proposed a model based on Neural Network (NN) for modeling the energy consumption monitoring and analysis to apply in the commercial buildings of Singapore city. The author performed analysis on five selective buildings which possesses different parameters like temperature, humidity, Global Solar Radiation. The analysis of the proposed model is performed on the basis of coefficient of variance (CV) and is proved to be efficient in computing the energy consumption by the commercial buildings in the city of Singapore.

Radisa Z. Jovanovic and et.al [4] designed a model for the prediction of heat energy due to energy consumption in the buildings of the university. The author employed Feed Forward back propagatin Neural Network (FFNN), Radial Basis Function Network (RBFN), and Adaptive Neuro-Fuzzy Interferene System (ANFIS). The author measured the actual data and compared with the test datasets to predict the vital parameters like accuracy in prediction, energy consumption and heat energy consumption and exhibited better results.

Gamze Ogcu and et.al [5] presented a analysis report of methodologies of Power consumption analysis using Neural Networks (NN) and Support Vector Regression (SVR). The author concentrated the research work on the building of Turkey and compared the measured values of power consumption with the reference value to prove that the accuracy of the proposed model.

M.Krarti and et.al [6] presented the overview of methodologies of forecasting the energy consumption in targeted areas by Neural Networks to determine the energy consumption and the demand by the building retrofits. The author utilized building parameters like structure of building for determining the energy demands in the buildings.

Annals of R.S.C.B., ISSN:1583-6258, Vol. 24, Issue 2, 2020, Pages. 19 - 34
Received 20 October 2020; Accepted 04 December 2020.

Saleh Seyedzadeh and et. al [7] proposed the Machine Learning (ML) methodology to determine the energy demands of the building and to analyze the energy consumption of the targeted areas or buildings. In addition to analysis of energy consumption, the proposed model has analyzed the quantity of emission of CO_2 from the electrical appliances in the buildings.

Hossein Sadeghi and et.al [8] designed an energy analysis model based on Genetic Algorithm (GA) for the evaluation of per capita energy consumption in the residential areas of Iran. The authors developed a model named Genetic Algorithm Electricity Demand Model (GAEDM) and the model relies on the previous data related to the energy consumption using Genetic Algorithm Approach (GAA).

Seok Ho Yoon and et.al [9] proposed a Multiple Power Based Building Energy Management System (MPBEMS) for the analysis of energy consumption in the buildings. Based on the analysis results the energy consumption of the building is preserved to a level of 5% of average energy consumption. The author suggests the energy utilization factor by prediction model called Adaptive Energy Consumption Prediction (AECP) algorithm.

Zhun Yu and et. al [10] presented a energy demand model that relies on Decision Tree method. The decision tree method is efficient in analyzing and predicting the energy consumption of the building as the method employs Artificial Neural Network (ANN) and regressive method for performing the energy utilization factor of the building. The proposed model has proven to be 93% accurate when comparing the pre measured dataset value and the measured test value.

S.Karatasou and et.al [11] discussed the role of Neural Network (NN) in predicting the energy demand for a particular area or a building and is employed in the analysis of energy utilization. The model performed hypothetical testing process and the performance analysis of the proposed model is performed on the basis of dual databases and the Neural models for the power applications of the targeted building or a specific area.

Jason Runge and et.al [12] applied Artificial Neural Network (ANN) in predicting the energy consumption of the targeted building. The author designed data driven models to compare the measured test value with the datasets to predict with an high level of accuracy.

Annals of R.S.C.B., ISSN:1583-6258, Vol. 24, Issue 2, 2020, Pages. 19 - 34
Received 20 October 2020; Accepted 04 December 2020.

3. Proposed Methodology

The proposed methodology of Chess Optimization (CO) algorithm for the energy utilization analysis in residential buildings comprises of hierarchy of three levels namely preprocessing, feature extraction and classification with two phase namely testing phase and training phase. The testing phase is the actual data which is the measured energy utilization of the residential building whereas the training phase is the predefined set of values stored as a database which is the predicted value to identify the energy demand of the target residential building. The Figure 1 depicts the pictorial representation of the three phases of the proposed methodology.

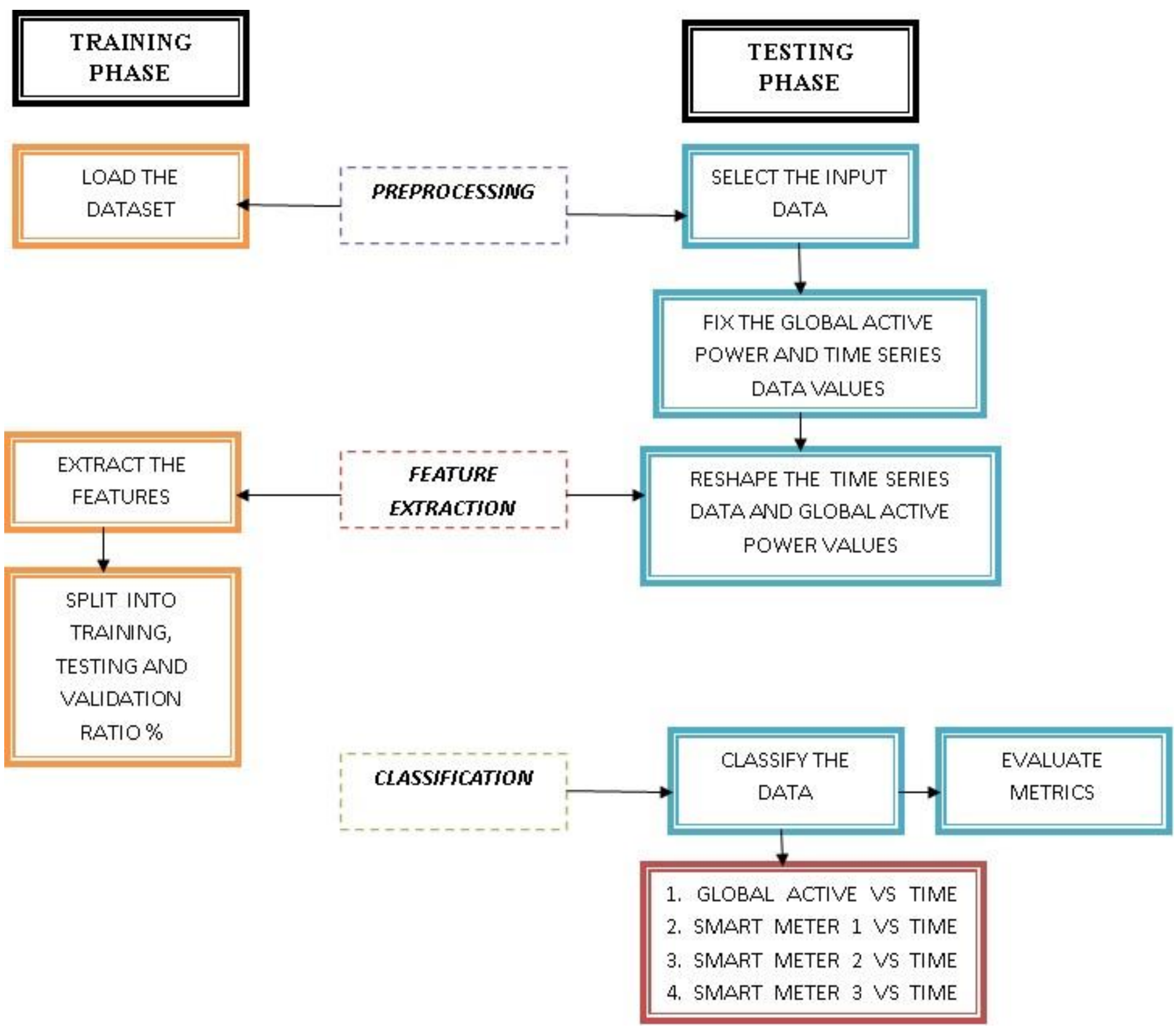

Figure 1: Flow Diagram of the proposed Chess Optimization algorithm

Annals of R.S.C.B., ISSN:1583-6258, Vol. 24, Issue 2, 2020, Pages. 19 - 34
Received 20 October 2020; Accepted 04 December 2020.

3.1 Preprocessing Phase:

The preprocessing phase of the Chess Optimization algorithm is the initial process which is considered to be vital process of the energy consumption analysis in which the dataset is loaded. The data set consist of hourly household energy consumption, which is predicted and is stored in the local database for comparing with the actual measured data. The Data preprocessing phase is composed of various processes namely data cleaning, data transformation, data reduction and data integration. The data cleaning is a process of identifying the missing parameters and filling it with accurate values. The processed data is generalized and is performed normalization function to reduce the redundant values in the data sets. The data stored in the datasets must be dependent each other with necessary logic among those data. On removing the redundant data, the data reduction process is performed so that to increase the speed of the data processing when comparing the trained dataset with the test data measured. The pseudocode for the proposed Chess Optimization (CO) algorithm is illustrated in Table 1.

Table 1: Pseudocode for the Chess Optimization (CO) algorithm

Pseudocode for Chess Optimization Algorithm
Step 1: Let x be no. of players x1, x2, x3,..........xn ---------eqn (1) Step 2: Let t and T be the time and performance time of each player in eqn(1)----eqn(2) consider eqn(1) and (2),------(a) Step 3: initiate the players x and time t, evaluate their performance time 'T' Step 4: Extract T with reshape the values into array form of objects Step 5: Split the training and testing with respect to the size variable value' v' Step 6: clf.fit(x_train,y_train) test=clf.predict(x_test) *confusion_matrix(y_test, pred)* *accuracy = accuracy_score(y_test, pred)* Step 7: Print the values of confusion matrix and accuracy

The Table 1 indicates the step by step process of the Chess Optimization algorithm in the process of energy utilization analysis of the residential buildings. The algorithm is initiated with the x number of player which indicates the number of electrical appliances. The household appliances are categorized as x_1, ….. x_n.

Annals of R.S.C.B., ISSN:1583-6258, Vol. 24, Issue 2, 2020, Pages. 19 - 34
Received 20 October 2020; Accepted 04 December 2020.

$$\text{Let } f(T) = \sum_{n=1}^{\infty} x_n(t)_{a\times b} \quad (1)$$

Where the testing parameters were stored in the matrix format of order a x b.

The training parameters were measured are classified as global active power, global reactive power, voltage, global intensity, and sub-metering values that were measured in the targeted building at the constant time intervals.

The global active and reactive power at any particular time can be measured using the mathematical expression mentioned in equation 2 and 3.

$$P_{GA} = |S|cos\emptyset_A = |I|^2R = \left|\frac{V}{Z}\right|^2 R \quad (2)$$

$$P_{GR} = |S|cos\emptyset_R = |I|^2R = \left|\frac{V}{Z}\right|^2 R \quad (3)$$

Where, $S = |I|^2Z = \left|\frac{V}{Z^*}\right|^2$ (4)

The Equation 2, 3 and 4 were used to measure the initial training data to store in the data base for is utilized for time dependent energy utilization analysis. The time to time utilization of energy by the household appliance were measured and is stores as test data so that to compare with the training data for the determination of accuracy in prediction. The equation 5 and 6 gives the mathematical representation of measured data with respect to time.

$$P_{GA}(t) = |S(t)|cos\emptyset_A \quad (5)$$

$$P_{GR}(t) = |S(t)|cos\emptyset_R \quad (6)$$

3.2 Feature Extraction Phase:

The feature extraction is the post process of determining the accuracy in matching the test data with the training data. The measured values of global active reactive powers, voltage, power intensity were considered to be the test value and is compared for the standard deviation. The lower the standard deviation yields high level of accuracy in the feature extraction phase of the proposed Chess Optimized (CO) algorithm. The time series data of the global active and reactive powers

Annals of R.S.C.B., ISSN:1583-6258, Vol. 24, Issue 2, 2020, Pages. 19 - 34
Received 20 October 2020; Accepted 04 December 2020.

were compared with the extracted features. The correlation coefficient among the test and training data is determined using the mathematical equation 7.

$$C(t) = \frac{|\sum_{n=1}^{\infty}(x_n - \bar{x}_n|}{\sqrt{|\sum_{n=1}^{\infty}(x_n - \bar{x}_n|}} \quad (7)$$

The correlation coefficient yields the matching factor on comparing the test and trained values of global active power, global reactive power, power intensity. The Standard Deviation (SD) between the test and trained values were mathematically expressed in equation 8.

$$SD\ (\sigma) = \sqrt{\frac{\sum(x_i - \mu)^2}{N}} \quad (8)$$

The equation 8 represents the mathematical expression of determining the standard deviation of the predicted value and is depends on the total electrical appliances in the test residential building (N) and the mean of electrical appliances in the targeted residential building (μ). The Pseudocode for the feature extraction is illustrated in Table 2.

Table 2: Pseudocode for the Feature Extraction Phase

Pseudocode for the Feature Extraction Phase
def create_data(x, lookback-1) data x, data y = [ ], [ ] for “i" in range (4000) a-x[i:i+lookback+1] data x. append(a) data y.append (x[i+lookback, i] return np.array(data x(, np.array (data y)

3.3 Classification Phase:

The Classification phase is the final steps in the proposed Chess Optimization (CO) algorithm. Plentiful classifier algorithms were evolving over which the Ada boost classifier, SVM classifier and bagging classifier algorithms were implemented for obtaining better comparative results.

Annals of R.S.C.B., ISSN:1583-6258, Vol. 24, Issue 2, 2020, Pages. 19 - 34
Received 20 October 2020; Accepted 04 December 2020.

3.3.1 Ada Boost Classifier:

The Ada boost classifier is an algorithm utilized for training the boosted classifier in the form of weak learner function which is represented in equation 9.

$$F_T(x) = \sum_{i=1}^{I} f_i(x) \qquad (9)$$

The $f_i(x)$ is the function of weak learner and on performing the classification process the result turns be positive if the recorded sample is in positive whereas the result will turn to be negative for the recorded negative samples. The training error of the Ada Boost classifier algorithm can be computed as represented in equation 10.

$$E_i = \sum E|F_{i-1}(x_i) + \alpha_i h(x_i)| \qquad (10)$$

The error function is determined for each iterations at pre-defined time intervals in which the global active powers were measured to compare with the trained datasets.

3.3.2 SVM Classifier:

The Select Vector Machine (SVM) Classifier [13] is contrary in behavior when compared with the Ada Boost algorithm due to its characteristic of model based on supervised learning. The SVM classifier is based on Machine Learning (ML) model and is employed to compare the test data with the trained data. The SVM classifier integrates the test and training points with a decision boundary for a clear level of classification. Let us consider the training database be (x_i, y_i), where the value of "i" ranges from 1 to infinity. The deviation between the trained dataset and the test data is termed to be margin in which the proposed Chess Optimization algorithm possess low level of margin that yields high level of prediction accuracy. The margin between the trained and test data can be computed as mentioned in equation 11.

$$\left[\frac{1}{n}\sum_{i=1}^{n} \max\left(0,1 - x^i(w^{-1}y_i - a)\right)\right] \qquad (11)$$

Where x_i represents the margin between the test and trained dataset. The small margin levels were significantly negligible and is not considered for computation.

Annals of R.S.C.B., ISSN:1583-6258, Vol. 24, Issue 2, 2020, Pages. 19 - 34
Received 20 October 2020; Accepted 04 December 2020.

The Pseudocode for the SVM classifier is illustrated in Table 3. In which the x and y training data were compared for measurement of accuracy in predicted value.

Table 3: Pseudocode for the Classifier Phase- SVM Classifier

Pseudocode for the SVM Classifier
clf=svm.SVR ( )
clf.fit(x_train, y_train)
test=clf.predict(x_test)
#print (test)
y_test=[int (float(x)) for x in y _test]
print (y_test)
pred = int(x for x in test)
print (pred)

4. Result and Performance Analysis:

The analysis of the proposed Chess Optimization (CO) algorithm is executed based on the comparison of trained dataset and test datasets. The trained data sets are loaded in advance to compare the real time measured value and to determine the prediction accuracy. The loaded datasets are mentioned in the Table 3

Table 3: Loading Datasets

Date (Random)	Time (Random)	Global Active Power (W)	Global Reactive Power (W)	Voltage (V)
16.12.2006	17.24.00	4.216	0.418	234.84
16.12.2006	17.25.00	5.36	0.436	233.63
16.12.2006	17.26.00	5.374	0.498	233.29
16.12.2006	17.27.00	5.388	0.502	233.74
16.12.2006	17.28.00	3.666	0.528	235.68

The Table 2 mentions the minimized procedure of loading datasets, whereas the data measured for 4 years (i.e from 2006 to 2010) is loaded in the training datasets. The values of Global active

Annals of R.S.C.B., ISSN:1583-6258, Vol. 24, Issue 2, 2020, Pages. 19 - 34
Received 20 October 2020; Accepted 04 December 2020.

power, Global Reactive power and Voltage of vital parameter metrics measured from the aforementioned duration and is loaded in the datasets.

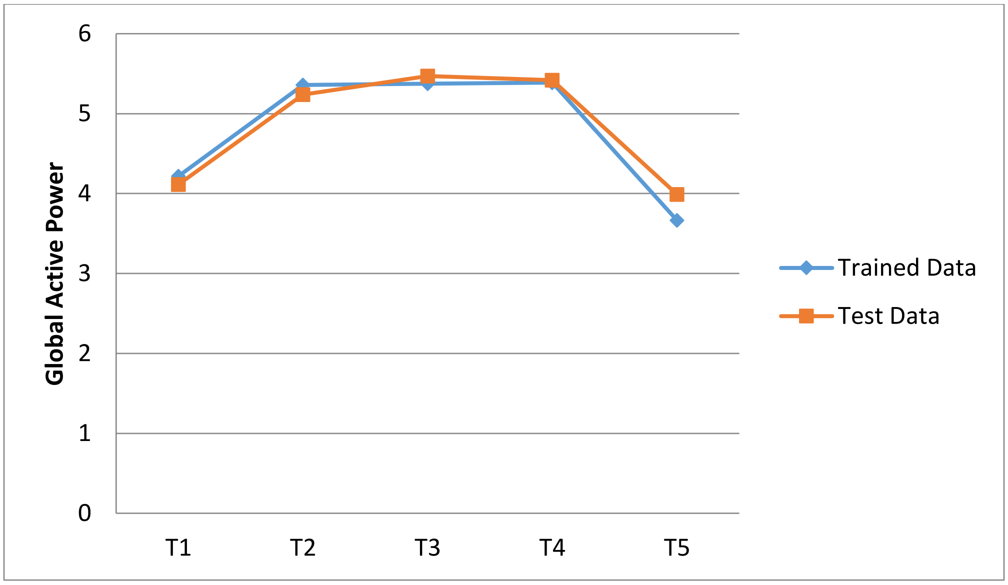

Figure 2: Global Active Power comparison of Test and Trained Data

The Figure 2 depicts the pictorial representation of the comparison of the global active power of measured test data and the trained data. From the Figure 2, it is clearly provable that the accuracy of prediction is of high level as the deviation between the test and the trained data are negligibly low. The association of global active power between the test data and trained data is depicted in Figure 3.

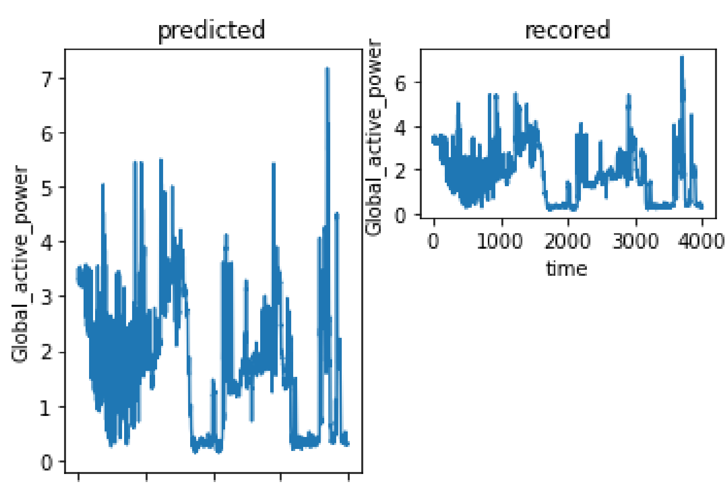

Figure 3: Global Active Power comparison of Predicted and Recorded Data

Annals of R.S.C.B., ISSN:1583-6258, Vol. 24, Issue 2, 2020, Pages. 19 - 34
Received 20 October 2020; Accepted 04 December 2020.

The Figure 3 clearly illustrates the predicted data and the lively recorded data related to the global active power is almost equal giving rise to the high level of accuracy. The Figure 4 shows the pictorial representation of smart meter 1 readings with respect to different time intervals. The smart meter 1 readings were the energy utilization of kitchen appliances.

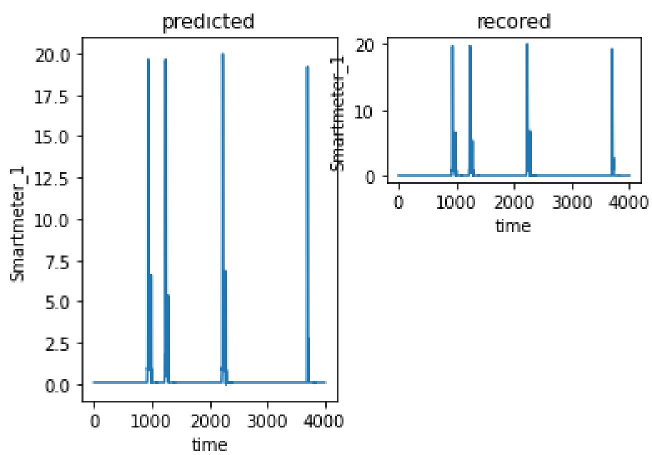

Figure 4: Smart Meter 1 Reading of Predicted and Recorded Data- Comparison

The Figure 4 shows the comparative results of predicted and recorded Smart meter 1 reading which is measured to be alike to each other with negligible level of deviation. This provides high level of accuracy between the predicted and recorded datasets.

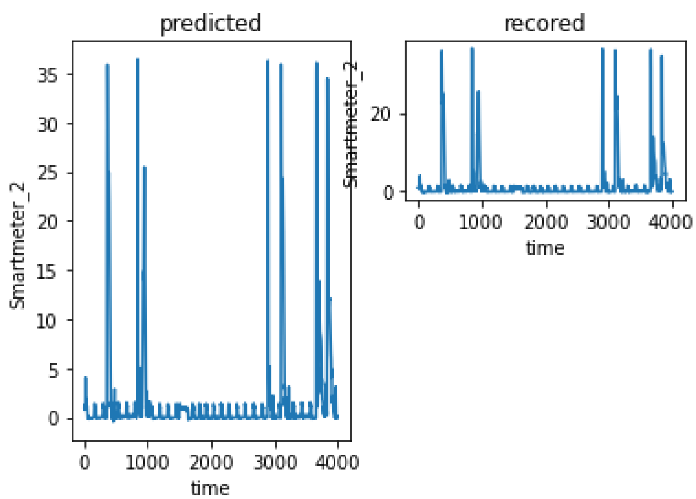

Figure 5: Smart Meter 2 Reading of Predicted and Recorded Data- Comparison

Annals of R.S.C.B., ISSN:1583-6258, Vol. 24, Issue 2, 2020, Pages. 19 - 34
Received 20 October 2020; Accepted 04 December 2020.

The Figure 5 depicts the smart meter 2 reading and the comparative results of predicted and recorded datasets. The smart meter 2 is group of high energy extracting electrical appliances like Refridgerator, Washing machine, Dishwasher, etc. The comparative results of predicted and recorded values of smart meter 2 are analyzed to determine that the values are alike with minor level of deviation which is considered to be negligible.

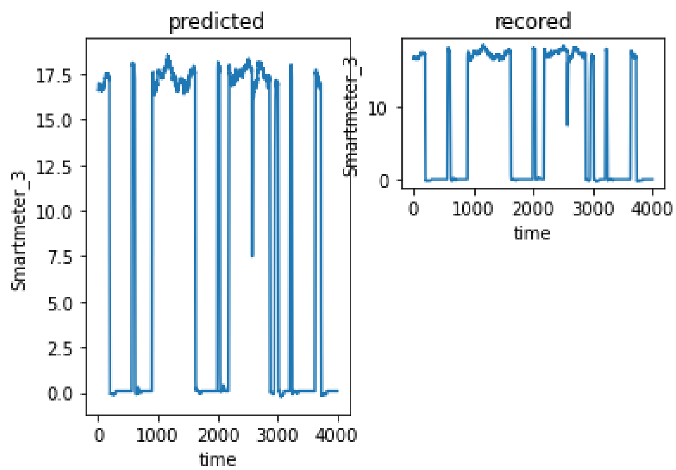

Figure 6: Smart Meter 3 Reading of Predicted and Recorded Data- Comparison

The comparative analysis result of predicted and recorded data of smart meter 3 is graphically plotted for analysis to prove that the values were matching to produce an high level of accuracy. The smart meter 3 incorporates the energy utilized by electrical appliances like Microwave Owen, Electric Iron box, etc.

5. Conclusion

Based on the comparative results of global active power, smart meter 1, smart meter 2 and smart meter 3, were performed and the results were matching with the predicted values. This proves that the proposed Chess Optimization (CO) algorithm possess high level of accuracy in analyzing the energy utilization of household appliances in the residential buildings. Due to the high level of accuracy, the demand for energy can be predicted accurately so that power generation and distribution planning can be performed effectively. The proposed novel Chess Optimization algorithm is well suitable for energy utilization analysis and is applicable for wide range of applications like residential and industrial energy utilization analysis. Depending on the application, the electrical equipments or appliances are categorized under smart meters 1, 2 and 3. Employing the proposed novel Chess Optimization algorithm, the energy demands for the various range of aforementioned applications like residential or industrial areas can be determined and thus provides data for the energy generation and efficient distribution.

References

[1] Shao, Minglei & Wang, Xin & Bu, Zhen & Chen, Xiaobo & Wang, Yuqing. (2020). Prediction of energy consumption in hotel buildings via support vector machines. Sustainable Cities and Society. 57. 102128. 10.1016/j.scs.2020.102128.

[2] Edwards, Richard & New, Joshua & Parker, Lynne. (2012). Predicting Future Hourly Residential Electrical Consumption: A Machine Learning Case Study. Energy and Buildings - ENERG BLDG. 49. 591-603. 10.1016/j.enbuild.2012.03.010.

[3] Bing Dong, Siew Eang Lee (2004), Applying Neural Networks to Model Monthly Energy Consumption of Commercial Buildings in Singapore, ICCAS-2004.

[4] Jovanović, Radiša & Sretenovic, Aleksandra & Živković, Branislav. (2015). Ensemble of various neural networks for prediction of heating energy consumption. Energy and Buildings. 94. 10.1016/j.enbuild.2015.02.052.

[5] Oğcu, Gamze & Demirel, Funda & Zaim, Selim. (2012). Forecasting Electricity Consumption with Neural Networks and Support Vector Regression. Procedia - Social and Behavioral Sciences. 58. 1576-1585. 10.1016/j.sbspro.2012.09.1144.

[6] M.Krarti, J.F.Kreider, “Estimation of Energy Savings for Building Retrofits Using Neural Networks”, Journal of Solar Engineering Energy, Vol 120, August 1998.

[7] Seyedzadeh, Saleh & Pour Rahimian, Farzad & Glesk, Ivan & Roper, Marc. (2018). Machine learning for estimation of building energy consumption and performance: a review. Visualization in Engineering. 6. 10.1186/s40327-018-0064-7.

[8] Sadeghi, H. & Zolfaghari, M. & Heydarizade, M.. (2011). Estimation of Electricity Demand in Residential sector using Genetic Algorithm Approach. International Journal of Industrial Engineering and Production Research. 22. 43-50.

[9] Yoon, Seok-Ho & Kim, Seung-Yeon & Park, Geon-Hee & Kim, Yi-Kang & Cho, Choong-Ho & Park, Byung-Hun. (2018). Multiple Power-Based Building Energy Management System for Efficient Management of Building Energy. Sustainable Cities and Society. 42. 10.1016/j.scs.2018.08.008.

[10] Yu, Zhun & Haghighat, Fariborz & Fung, Benjamin & Yoshino, Hiroshi. (2010). A decision tree method for building energy demand modeling. Energy and Buildings. 42. 1637-1646. 10.1016/j.enbuild.2010.04.006.

[11] Karatasou, Stavroula & Santamouris, Mat & Geros, V.. (2006). Modeling and predicting building's energy use with artificial neural networks: Methods and results. Energy and Buildings. 38. 949-958. 10.1016/j.enbuild.2005.11.005.

[12] Runge, Jason & Zmeureanu, R.. (2019). Forecasting Energy Use in Buildings Using Artificial Neural Networks: A Review. Energies. 12. 3254. 10.3390/en12173254.

[13] Poggio, Tomaso & Cauwenberghs, Gert. (2001). Incremental and decremental support vector machine learning. Advances in Neural Information Processing Systems. 13. 409-412.