Journal of Information & Optimization Sciences
ISSN 0252-2667 (Print), ISSN 2169-0103 (Online)
Vol. 45 (2024), No. 2, pp. 605–612
DOI : 10.47974/JIOS-1598

Modelling for forecasting energy consumption using SBO optimization and machine learning

Kalpana D. Vidhate *
Department of Electrical Engineering
Dr. Vithalrao Vikhe Patil College of Engineering
Savitribai Phule Pune University
Ahmednagar 414111
Maharashtra
India

Pragya Nema †
Department of Electrical Engineering
Oriental University
Indore 453555
Madhya Pradesh
India

Totappa Hasarmani §
Department of Electrical Engineering
Savitribai Phule Pune University
Narhe 411041
Pune
Maharashtra
India

Abstract

Forecasting the future electrical load of a single apartment, a grid, an area, or even an entire country is known as load forecasting, which aims to predict future load demand. Using residential data for model training and a School-Based Optimization approach for optimising

---

This research was conducted during the PhD Study at Oriental University, Indore India.

---

* *E-mail:* ghadge.kalpana@gmail.com (Corresponding Author)
† *E-mail:* dr.pragyanema@ymail.com
§ *E-mail:* tshasarmani_elec@tssm.edu.in

© Taru Publications

the process and computing energy consumption and occupant comfort, the proposed approach has 3 components: (1) machine learning model for low energy consumption; (2) occupant behaviour models; and (3) occupant comfort models. The experimental findings indicated that behavioural energy savings were possible, with occupant comfort significantly increased. Machine learning (ML) methods have recently contributed very well in the advancement of the prediction models used for energy consumption. AdaBoost models highly improve the accuracy, robustness, and precision and the generalization ability of the conventional forecasting which is utilized in models.

Subject Classification: *93-XX, 94-XX.*

Keywords: *Mathematical modeling, Energy consumption, SBO optimization, Prediction, Machine learning, Occupant behaviour.*

1. Introduction

The construction industry is responsible for a significant portion of global warming using up 40% of all supplied energy and producing 30% of all CO2 emissions. More energy can be saved in this area than in transportation or manufacturing. People spend the vast majority of their time inside buildings, making it difficult to reduce energy use without sacrificing comfort, health, or productivity. According to estimates, the amount of energy consumed worldwide will rise from 505 quadrillion Btu in 2008 to 700 quadrillion Btu in 2035. A substantial literature is available on load forecasting in power sector using deep learning techniques. Mashael M Asiri et al. [1] suggested Short term load forecasting in grids using deep learning method. Authors have designed and developed Short-Load Forecasting scheme using a Hybrid Deep Learning and Beluga Whale Optimization (LFS-HDLBWO) approach on smart grid environment. Furthermore, short term load forecasting (STLF) using artificial neural network (ANN) methods are suggested by authors [2]. Various neural network models are studied and compared for power generation using solar photovoltaic systems at amazon basin [3]. Short term multi-load energy forecasting using multi-stack Temporal Convolutional Network and Time-Series Transformer (TCN-TST) model is suggested for smart buildings [4]. Similarly various machine learning models, like unidirectional long short-term memory, bidirectional gated recurrent unit, bidirectional long short-term memory, and simple bidirectional recurrent neural network are studied for predicting power generation at solar farms. The results of the study were highly significant for energy management strategies at both residential and industrial sectors that contributed to more accurate and efficient solar energy forecasting [5]. Authors addressed missing solar PV power data using various models like linear imputation, k-nearest neighbour's imputation, Generative Adversarial Imputation and direct deletion. Furthermore, impact of weather variability on the imputation performance were studied [6]. Various direct load control (DLC) technologies in the context of a smart grids are studied and compared [7]. Energy consumption forecasting and optimum sizing and generation scheduling by integrated renewable energy resources for agriculture based isolated grids are studied by authors. Optimally sized Solar PV-DG powered hybrid system is designed and developed to provide uninterrupted power supply to jaggery units those are located in remote rural areas. Additionally, Programmable Logic Controller (PLC) based power generation controller is developed [8-11]. The paper is organized as follows. In section 2, we construct and analyze a simple mathematical model including School Based Optimization (SBO) approach and AdaBoost Regressor. Section 3 discusses a Results and Discussion and provides numerical analysis of a more sophisticated model. Finally, in section 4 we draw conclusions and consider future work followed by references.

2. Proposed Algorithm

In the proposed approach we take real time data for energy minimization from Kaggle. The residential data is considered for training the model. We build a model by training it using the data and finally we test the AR model. The entire process is optimized by School Based Optimization approach.

2.1 *School Based Optimization Algorithm*

Met heuristic optimisation often involves generating a random population of candidate solutions and then systematically increasing the fitness of that population. This strategy is exemplified by algorithms like the eagle strategy and multiclass teaching-learning-based optimisation, which use multiple met heuristics in order to search the entire search space (in the first stage) and zero in on the sub-region containing the most promising solutions (in the second stage) (MC-TLBO). Selecting and enacting the first stage termination criteria presents a difficulty in the use of two-stage algorithms. The complexity of the method rises because the termination criteria adds new, problem-specific tuning parameters. School-based optimisation (SBO), was presented to address this problem.

The SBO algorithm may take use of several teachers to direct the optimisation process thanks to the teacher assignment mechanism.

2.2 *AdaBoost Regressor*

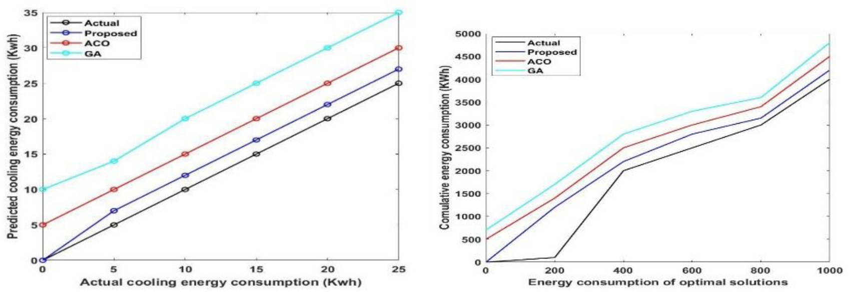
Since Freund and Schapire originally introduced the ensemble modelling technique known as "boosting" in 1997, it has been a popular method for solving binary classification issues. Boosting methods work on the basis of building a framework on the data set used for training first, then building a second model to correct any flaws in the primary model. AdaBoost functions by giving harder-to-classify examples more weight and less weight to instances that have previously been handled effectively. AdaBoost techniques are applicable to problems involving both regression and classification. A met estimator known as an AdaBoost regressor. AdaBoost is a meta-algorithm, which means it can be used together with other algorithms for performance improvement. Following are the step for AdaBoost Algorithms –

- Give each data point an equal weight.
- Determine which stump classifies the new sample collection the best by calculating its Gini Index and choosing the stump with the smallest Gini index.

3. Results and Discussion

The proposed algorithm is compared with the actual value. Energy-priority, thermal-comfort-priority, visual-comfort-priority, and balanced solutions were all taken into account throughout the optimisation process. Fig.1 (a) displays the relationship between observed and predicted values of energy use. It is seen that the proposed approach makes the prediction which is closes to the actual value. ACO prediction diverts from that of the actual value, and GA has the worst performance. The performance gain of the proposed algorithm is due to better parameter optimization and convergence of SBO.

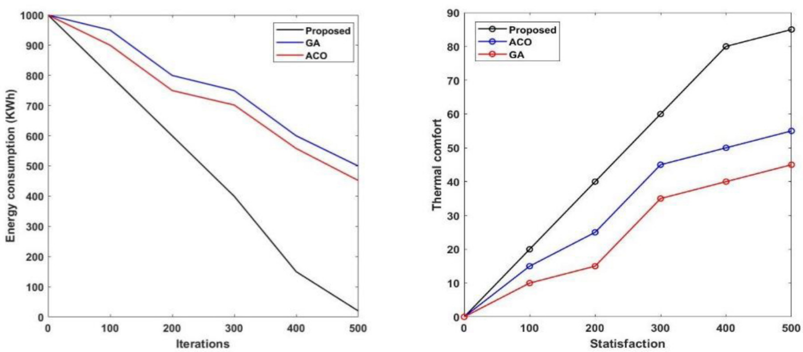
Figure 1 (b) shows the total energy used together with the energy used by the three extreme and the moderate solutions. It can be observed that the suggested method predicts a value that is quite near to the actual value. The ACO model's forecast deviates from the true value, while the GA model performs the poorest. Improved parameter optimization and



(a) (b)

Figure 1

(a) Predicted and actual cooling energy (b) Total Energy Usage



(a) (b)

Figure 2

(a) Convergence performance of SBO (b) Thermal comfort comparison

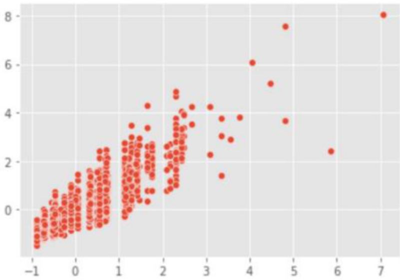
convergence of SBO are responsible for the suggested algorithm's performance boost.

The proposed approach is compared with ACO and GA in terms for convergence. It is evident from Figure 2(a) that the SBO converges better and faster as compared to ACO and GA. Here the convergence is measured in terms of effectiveness of minimizing energy. Figure 2(b) shows that the proposed approach is most effectives in energy minimization.

The proposed framework is compared with the existing approaches in terms of thermal comfort. The suggested method is found to perform best, while GA performs the worst. Better convergence of SBO and parameter optimisation are to credit for the suggested algorithm's performance boost.

Name	Score
Training Accuracy	82.0375%
Testing Accuracy	79.8388%
Mean Squared Error	0.8269
Mean Absolute Error	0.854
Root Mean Square Error	0.9093

(a)



(b)

Figure 3

AdaBoost Regressor: (a) Evaluation Matrix (b) Scatterplot

AdaBoost Regressor

AdaBoost is an algorithm of boosting that also operates on the idea of stage wise addition, which uses several weak learners to produce strong learners. In this scenario, the alpha parameter's value will be incidentally proportional to the learner's mistake. In this case, the value of the alpha parameter will be indirectly proportional to the fallacy of the weak learner, unalike Gradient Boosting in XGBoost where the alpha parameter computed is connected to the mistakes of the weak learner shown in Figure 3.

Following are the step for AdaBoost Algorithms –

- Allocate equal weights to each data point.
- By calculating each stump's Gini Index and choosing the one with the lowest Gini index, you may determine which one classifies the new set of data the best.
- Make the new sample weights normal.

For our complicated challenges, a single weak model might not be sufficient. In these scenarios, we combine different weak models to generate a strong and correct model for our problem. This process of combining multiple tiny problems to get a strong model is what we call boosting. By merge several weak classifiers, the group modelling approach known as "boosting" aims to generate a powerful classifier. It is accomplished by employing weak models in sequence to develop a model. First, a model is created using the training set of data. The second model is then generated in an attempt to fix the previous model's flaws. Models are added in this way until either the full training data set is appropriately predicted or the maximum number of models has been added.

4. Conclusion

This research offered a genuine data-driven approach to evaluating occupant behaviour's ability to accomplish these two goals (reduce energy consumption and improve comfort) in a single step. The suggested approach has two parts: a genetic algorithm-based optimisation model for optimising occupant behaviour, and a collection of machine learning-based occupant-behaviour-sensitive models for forecasting energy consumption and thermal and visual comfort. The most reliable prediction models were then used to optimise occupant behaviour in the interest of lowering energy use and raising resident satisfaction. The models' results were compared to those of others that lacked occupant-behaviour variables to ensure that the behaviour features are really discriminatory.

References

[1] M. M. Asiri, G. Aldehim, F. Alotaibi, M. M. Alnfiai, M. Assiri and A. Mahmud, "Short-Term Load Forecasting in Smart Grids using Hybrid Deep Learning," in *IEEE Access*, doi: 10.1109/ACCESS.2024.3358182.

[2] T. Panapongpakorn and D. Banjerdpongchai, "Short-Term Load Forecast for Energy Management System Using Neural Networks with Mutual Information Method of Input Selection," 2019 SICE International Symposium on Control Systems (SICE ISCS), Kumamoto, Japan, pp. 9-15 (2019), doi: 10.23919/SICEISCS.2019.8758714.

[3] A. L. F. Marques, M. J. Teixeira, F. V. De Almeida and P. L. P. Corrêa, "Neural networks forecast models comparison for the solar energy generation in Amazon Basin," in *IEEE Access*, doi: 10.1109/ACCESS.2024.3358339.

[4] S. Cen and C. G. Lim, "Multi-task Learning of the PatchTCN-TST Model for Short-term Multi-load Energy Forecasting Considering Indoor Environments in a Smart Building," in *IEEE Access*, doi: 10.1109/ACCESS.2024.3355448.

[5] A. M. Hayajneh, F. Alasali, A. Salama and W. Holderbaum, "Intelligent Solar Forecasts: Modern Machine Learning Models and TinyML

Role for Improved Solar Energy Yield Predictions," in *IEEE Access*, vol. 12, pp. 10846-10864 (2024), doi: 10.1109/ACCESS.2024.3354703.

[6] D. -S. Lee and S. -Y. Son, "PV Forecasting Model Development and Impact Assessment via Imputation of Missing PV Power Data," in *IEEE Access*, vol. 12, pp. 12843-12852 (2024), doi: 10.1109/ACCESS.2024.3352038.

[7] E. Ozkop, "A Survey on Direct Load Control Technologies in the Smart Grid," in *IEEE Access*, vol. 12, pp. 4997-5053 (2024), doi: 10.1109/ACCESS.2024.3349965.

[8] D. Yang, T. Li, Z. Guo and Q. Li, "Multi-scale convolutional echo state network with an effective pre-training strategy for solar irradiance forecasting," in *IEEE Access*, doi: 10.1109/ACCESS.2024.3349661.

[9] T. Hasarmani, R. Holmukhe and N. Ganer, "Techno-Economic Sizing of Renewable Energy Resources for Energy Improvements in Jaggery Making Process," *2018 IEEE Punecon*, Pune, India, pp. 1-5 (2018), doi: 10.1109/PUNECON.2018.8745390.

[10] T. Hasarmani, R. Holmukhe and S. Tamke, "Performance Analysis of Grid Interfaced Photovoltaic Systems for Reliable Agri-Microgrids using PVsyst," 2019 International Conference on Information and Communications Technology (ICOIACT), Yogyakarta, Indonesia, pp. 894-898 (2019), doi: 10.1109/ICOIACT46704.2019.8938561.

[11] T. Hasarmani, R. Holmukhe, A. Gandhar and S. Bhardwaj, "Optimum Sizing and Performance Assessment of Solar PV-DG Hybrid System for Energy Self Sufficiency of Jaggery Making Units," 2020 IEEE Bangalore Humanitarian Technology Conference (B-HTC), Vijiyapur, India, pp. 1-6 (2020), doi: 10.1109/B-HTC50970.2020.9297885.