Implementation of a Hybrid Technique for the Predictive Control of the Residential Heating Ventilation and Air Conditioning Systems

Mitali Ray
School of Electrical Engineering
KIIT Deemed to be University
Bhubaneswar, Odisha, India
mitaliray87@gmail.com

Padarbinda Samal
School of Electrical Engineering
KIIT Deemed to be University
Bhubaneswar, Odisha, India
padarbindasamal87@gmail.com

Chinmoy Kumar Panigrahi
School of Electrical Engineering
KIIT Deemed to be University
Bhubaneswar, Odisha, India
panigrahichinmoy@gmail.com

Received: 29 April 2022 | Accepted: 15 May 2022

Abstract-Since daily energy needs are increasing, it is imperative to find ways to save energy, such as improving the energy consumption of buildings. Heating Ventilating and Air-Conditioning (HVAC) loads account for the majority of a building's energy use. The accurate estimation of energy consumption and the examination of various ways to improve the energy efficiency of buildings are very important. This paper presents an analysis of HVAC loads in a residential building by examining three Neural Networks (NNs): Feed-Forward (FF), Cascaded Forward Backpropagation (CFBP), and Elman Backpropagation (EBP) networks, based on Mean Absolute Error (MAE), Mean Square Error (MSE), and Mean Relative Error (MRE). Furthermore, these networks were combined in hybrid NNs to obtain more optimized results. These results were also compared with other approaches and showed better prediction performance.

Keywords-HVAC loads; neural networks; energy management; hybrid networks

I. INTRODUCTION

The building sector, which includes both residential and commercial structures, is responsible for up to 36% of global energy use, according to the Energy Information Administration (EIA) [1]. Since 2015, worldwide energy consumption in the residential sector and transportation has climbed at a pace of 1.1% per year according to the International Energy Agency. According to EIA, global energy consumption in the commercial sector is predicted to grow at a pace of 1.2% per year from 2015 to 2040. The rise in energy consumption due to buildings is predicted to be bigger in developing than in developed countries. To reduce energy consumption in buildings, a nation's main objective in terms of the policy is to make them more energy-efficient. Factors that influence energy efficiency management in a building include occupancy levels, heating and cooling loads, the climatic zone, and the exterior envelope of the building.

The prediction and study of energy consumption in buildings are carried out using energy simulation tools, which are frequently used in the construction industry and assist in the design of buildings and efficient management of their energy use [2]. These tools have limitations such as long computational times and the requirement of programming expertise [3]. There are also applications using machine learning tools that are comparatively faster and more convenient [3]. Once a model is properly trained, obtaining answers by modifying a few parameters of the building's design becomes quite simple. The use of Support Vector Machine (SVM) to predict the energy consumption of buildings in a tropical environment was examined in [4]. An SVM was used to forecast the cooling demand of a building on an hourly basis in [5]. Several regression models were created and validated to anticipate the heating demand of residential buildings in [3]. The use of Artificial Neural Networks (ANNs) has been explored in different diversified areas [6-8].

In residential buildings, ANNs are used to forecast Heating Load (HL) and Cooling Load (CL) based on various characteristics of the buildings [6, 10-12]. Although it is a substantial characteristic, the glazing area does not appear to be connected to HL or CL, which is an important limitation of [6]. This paper presents a comparative analysis and hybridization of NNs for forecasting the heating and cooling loads of an HVAC system. MAE, MSE, and MRE were taken as performance indicators, considering eight input variables.

Corresponding author: Mitali Ray

II. NEURAL NETWORKS

An ANN is a series of algorithms that aspires to establish a correlation among a set of data through a certain procedure that replicates the human brain operation. An ANN refers to a system of neurons, either organic or artificial. ANNs are used as problem-solving methods, with the capability of developing solutions to extremely difficult problems and uncovering hidden patterns in large datasets. This results in a collection of approaches that can be employed to provide a fast and cost-effective solution to a complex real-world challenge. Moreover, ANNs have self-learning abilities to produce the output, which is not limited to the inputs provided to them. ANNs were used in [8, 9] to predict thermal loads and in [10] to analyze the energy consumption of a building. In this work, the implementation of hybrid ANNs was performed by considering the sequential combination of any two ANNs among FeedForward (FF), Cascaded Forward Back-Propagation (CFBP), and Elman Back-Propagation (EBP) to estimate the thermal loads of a residential building. Furthermore, a comparative analysis was conducted with other approaches to validate the results.

A. Feedforward Network

FF ANNs are used to learn the mapping between the independent (inputs) and dependent (outputs) variables and predict the outputs. FF networks consist of a series of connected layers. The first layer is connected to the network input. Each subsequent layer is connected to the layer above it via the previous layer's connection. The output of the network is produced by the final layer, as shown in Figure 1. The network is simpler than other recurrent networks and can be used efficiently in pattern recognition. The network does not have feedback, so the output of each layer does not affect the same layer. In this study, a 3-hidden layer network with 20–20–20 neurons was considered with tansig as the transfer function and purelin as the output layer activation function.

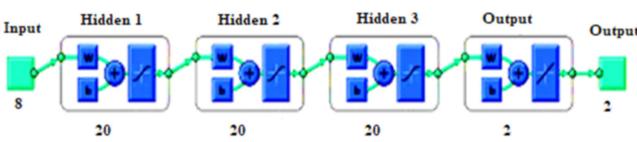

Fig. 1. Feedforward network.

B. Cascaded Forward Backpropagation Network

The CFBP network model includes a connection from the input and every previous layer to the following layers, as shown in Figure 2. This network can accommodate the nonlinear relationship between input and output without eliminating their linear relationship. A 3-hidden layer network with 20–20–20 neurons was considered, where tansig was considered as the transfer and the output layer activation function, as it provided better results than other combinations.

C. Elman Backpropagation Network

The EBP network is a two-layer backpropagation network where a recurrent connection exists from the output of the hidden layer to its input with a tap delay. The recurrent connection allows the network to both detect and generate time-varying patterns, as shown in Figure 3. In this study, a 3-hidden layer network with 20–20–20 neurons per layer was considered, where tansig is considered as both the transfer and the output layer activation function, as it provided better results than other combinations.

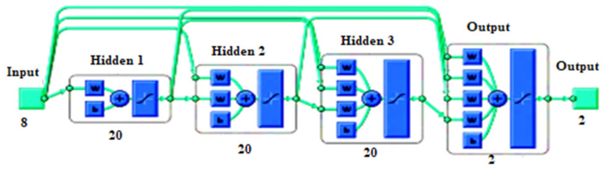

Fig. 2. Cascaded Forward Backpropagation Network.

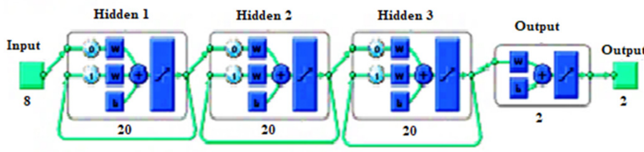

Fig. 3. Elman backpropagation network.

III. PROPOSED MODEL AND INPUT-OUTPUT DATASET

A. The Proposed Model

Performance analysis was based on the prediction of heating and cooling loads in a residential building using hybrid neural networks. Initially, three different ANNs were trained, tested, and validated by considering 10-fold cross-validation. Then, a sequential combination of ANNs was performed to model hybrid networks. The output generated by an input from the input training pattern was then compared with the targeted output, aiming to minimize the error function, as shown in (1):

$$min(E) = \frac{1}{2}\sum_{i=1}^{u} ||b_i - t_i||^2 \quad (1)$$

where u is the number of sets of the training ordered pairs, which depends on the number of samples being taken, b_i is the network output, t_i is the target output, and E is the error function.

B. Input-Output Database

The proposed method was experimentally validated using a dataset collected from the UCI machine learning repository [6, 11]. The Ecotect software was used to simulate 12 distinct building shapes and generate 768 possible building shapes. Relative compactness, surface area, wall area, roof area, overall height, orientation, glazing area, and glazing area distribution (*X1*,…,*X8*) were the input variables of the dataset, and heating and cooling loads (*Y1* and *Y2*) were the output variables. More information on the simulation experiments can be found in [6]. The output variables have a substantial correlation with the first five input variables in the examined dataset. As the volumes of the buildings are assumed to be constant, the values of *X1* (relative compactness) and *X2* (surface area) are inversely proportional. The input variables *X4* (roof area) and *X5* (height) are highly correlated. The correlation coefficient (-0.937) shows that these two variables are roughly inversely proportional.

IV. PERFORMANCE ANALYSIS OF THE ANN MODEL

The trainlm algorithm was used for training. Tansig was considered as the output layer activation function for the CFBP and the EBP networks, as it provided smaller errors for these two networks. Similarly, purelin was considered as the output layer activation function for the FF network. The comparative analysis was obtained by changing the performance goal and learning rate in a step-by-step manner. The weight initialization with arbitrary values and bias updates was performed. The accuracy of these models was measured by the MAE, MSE, and MRE performance indicators:

$$MAE = \frac{\sum_{i=1}^{n}|y_i - x_i|}{n} \quad (2)$$

$$MSE = \frac{\sum_{i=1}^{n}|y_i - x_i|^2}{n} \quad (3)$$

$$MRE = \frac{\sum_{i=1}^{n}|y_i - x_i|}{n x_i} \quad (4)$$

where y_i is the predicted value, x_i is the true value, and n is the number of samples.

Performance analysis was conducted on these three networks. Three hidden layers were used in all networks, with 20 neurons in each layer. The trainlm function updates weights and biases as per Levenberg-Marquardt optimization and is the fastest backpropagation algorithm. Therefore, the trainlm was used as a common training algorithm for all networks. The performance goal was set to 10e-5, and the learning rate was taken as 0.01 for all three networks. Analysis was conducted based on MAE, MSE, and MRE performance evaluators. As purelin is a linear transfer function that gave an accurate result in the FF network, it was used as an output layer activation function in FF. Similarly, as tansig is a hyperbolic tangent sigmoid transfer function, and is preferable to be used where speed is important, it was used as the output layer activation function for both CFBP and EBP. The behaviors of all three networks are shown in Table I. Then among all CFBP networks with 20-20-20-2 neurons, the tansig-tansig-tansig-tansig transfer function was chosen as the optimal network with fewer errors.

TABLE I. PERFORMANCE BY VARYING NEURAL NETWORKS

ANN	Heating load			Cooling load		
	MAE	MSE	MRE	MAE	MSE	MRE
FF	0.1248	0.033	0.0075	0.1686	0.0611	0.0087
CFBP	0.1023	0.0326	0.0058	0.1406	0.0473	0.0072
EBP	0.2023	0.0819	0.0106	0.2471	0.1193	0.0117

V. HYBRID MODEL PERFORMANCE CALCULATION

A hybrid ANN is a valuable learning tool where numerous ANNs are collaboratively used to solve a problem and improve the predicted output of a sequential data set. MAE, MSE, and MRE were used as the performance indicators for each model in order to calculate the best hybrid configuration. Performance indicators were used to select the best algorithm. In this study, a hybrid intelligent model was designed by combining two of the proposed models, which were efficient for network analysis. Two of the mentioned algorithms were considered for each combination. As in the performance analysis of the ANNs, the best results were obtained with 20-20-20-2 neurons, tansig-tansig-tansig-purelin transfer function, trainlm training algorithm, 10e-7 performance goal, and learning rate of 0.01 for the FF network. The best result for the CFBP network was achieved by using 20-20-20-2 neurons, tansig-tansig-tansig-tansig transfer function, trainlm training algorithm, 10e-7 performance goal, and learning rate of 0.01. Similarly, the best result for the EBP network was achieved using 20-20-20-2 neurons, tansig-tansig-tansig-tansig transfer function, trainlm training algorithm, 10e-7 performance goal, and learning rate of 0.01. The block diagram of the hybrid network is shown in Figure 4, and the flow chart of the hybridization is shown in Figure 5.

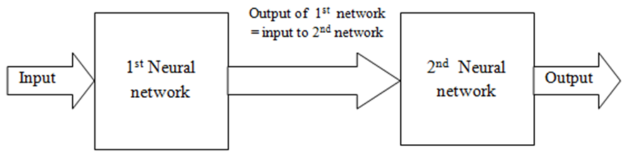

Fig. 4. Block diagram of the hybrid network.

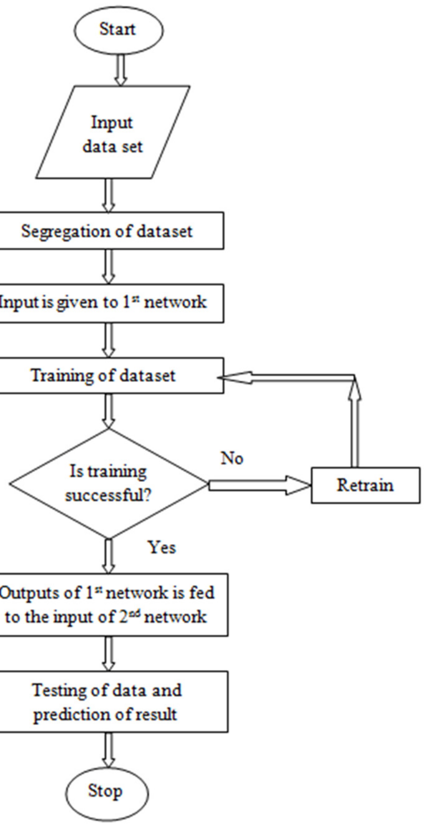

Fig. 5. Flowchart of the hybridization of the neural network.

Six different combinations were considered as hybrid networks: FF and CFBP, FF and EBP, EBP and FF, EBP and CFBP, CFBP and FF, and CFBP and EBP.

VI. Results and Analysis

The performance analysis of these hybrid networks is shown in Table II. It can be observed that the best results were achieved in the FF and CFBP hybrid network, with 0.0466 and 0.0797 for MAE in HL and CL, 0.0071 and 0.0166 for MSE in HL and CL, and 0.0031 and 0.0039 MRE in HL and CL respectively. In this network, the computational time was also very smaller (28s). Its error plot is shown in Figure 6 and the variation between target and actual values is shown in Figure 7. The variation between the target and the actual output of the FF and CFBP hybrid network for 768 sample numbers was very low. This signifies achievements of least error by this hybrid network compared to the others.

TABLE II. PERFORMANCE ANALYSIS OF HYBRID MODELS

Hybrid neural network	Heating load			Cooling load			Time
	MAE	MSE	MRE	MAE	MSE	MRE	(s)
FF and CFBP	0.0466	0.0071	0.0031	0.0797	0.0166	0.0039	28
FF and EBP	0.1097	0.0281	0.0067	0.0775	0.0153	0.0040	100
EBP and FF	0.1002	0.0287	0.0051	0.0932	0.0229	0.0038	172
EBP and CFBP	0.0834	0.0227	0.0046	0.0757	0.0184	0.0035	186
CFBP and FF	0.0202	0.0009	0.0010	0.1368	0.0277	0.0048	146
CFBP and EBP	0.1052	0.0244	0.0076	0.0663	0.0102	0.0032	196

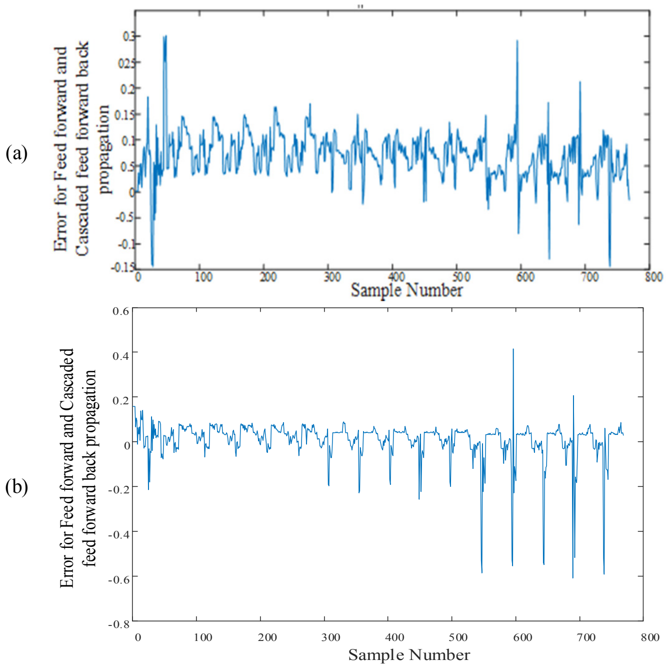

Fig. 6. Error plots for: (a) heating load, (b) cooling load.

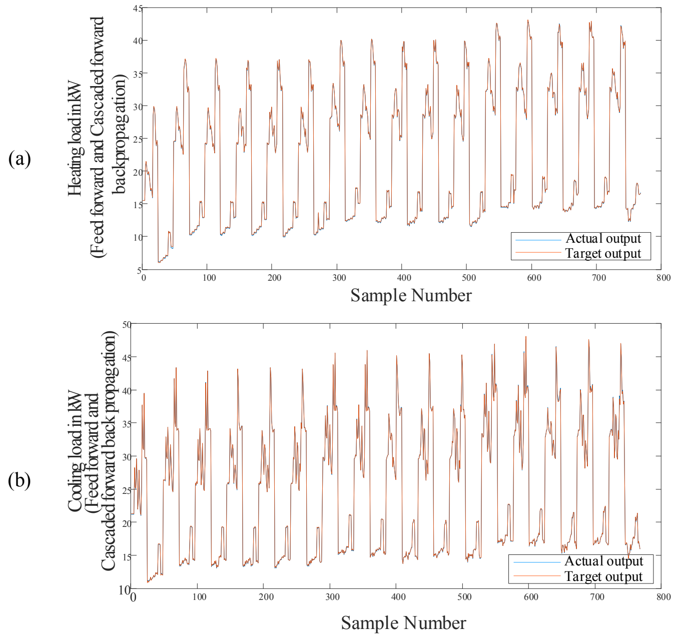

Fig. 7. Target vs actual outputs: (a) heating load, (b) cooling load.

VII. Comparison with Other Methods

The proposed method was also compared with other methods. Different performance evaluators like MAE, MSE, and MRE were considered for error analysis. In [6], Iteratively Reweighted Least Squares (IRLS) and Random Forests (RF) were used for the prediction of heating and cooling loads. It was found that MAE, MSE, and MRE for the HL using IRLS were 2.14, 9.87, 10.09, and using RF were 0.51, 1.03, and 9.41 respectively, while the MAE, MSE, and MRE for CL using IRLS were 2.21, 11.46, 2.18, and using RF were 1.42, 6.59, 4.62. SVR and MLP were implemented with the same data in [14] to predict the heating and cooling loads, using MAE and MSE as performance evaluators. The results were found to be 0.778, 0.7838 in SVR and 0.4118, 0.2335 in MLP for HL, and 1.4762, 3.024 in SVR and 2.0973, 6.896 in MLP for CL. In [15], the backpropagation method achieved MAE, MSE, and MRE of 0.1000, 0.0335, and 0.0053 for HL, and 0.1254, 0.763, and 0.0062 for CL. The error analysis is shown in Table III. It can be observed that the proposed hybrid FF and CFBP method improved MAE, MSE, and MRE for both heating and cooling loads, compared to the above-mentioned methods.

TABLE III. COMPARISON WITH OTHER METHODS

Proposed methods	MAE		MSE		MRE	
	HL	CL	HL	CL	HL	CL
IRLS [6]	2.14	2.21	9.87	11.46	10.09	2.18
RF [6]	0.51	1.42	1.03	6.59	9.41	4.62
SVR [14]	0.778	1.4762	0.7838	3.024	-	-
MLP [14]	0.4118	2.0973	0.2335	6.896	-	-
Back-propagation [15]	0.1000	0.1254	0.0335	0.763	0.0053	0.0062
FF and CFBP	0.0466	0.0797	0.0071	0.0166	0.0031	0.0039

VIII. CONCLUSION

In this study, a hybrid ANN was proposed to estimate the consumption of HVAC loads in a residential building for an eight-input dataset with 768 building samples. The hybrid model of Feed-Forward and Cascaded Forward Back Propagation (FF and CFBP) gave mean absolute errors of 0.0466 and 0.0797, mean square errors of 0.0071 and 0.0166, mean relative errors of 0.0031 and 0.0039 for heating and cooling loads respectively. The results showed that the suggested hybrid neural network had the lowest statistical errors and the best prediction performance. The difficulty of collecting actual building energy datasets is a drawback in this field of building efficiency enhancement. The use of real-world data by considering weather parameters like temperature, global solar radiation, etc, can give better results in future studies.

REFERENCES

[1] "IEA – International Energy Agency," *IEA*. https://www.iea.org.

[2] A. Yezioro, B. Dong, and F. Leite, "An applied artificial intelligence approach towards assessing building performance simulation tools," *Energy and Buildings*, vol. 40, no. 4, pp. 612–620, Jan. 2008, https://doi.org/10.1016/j.enbuild.2007.04.014.

[3] T. Catalina, J. Virgone, and E. Blanco, "Development and validation of regression models to predict monthly heating demand for residential buildings," *Energy and Buildings*, vol. 40, no. 10, pp. 1825–1832, Jan. 2008, https://doi.org/10.1016/j.enbuild.2008.04.001.

[4] B. Dong, C. Cao, and S. E. Lee, "Applying support vector machines to predict building energy consumption in tropical region," *Energy and Buildings*, vol. 37, no. 5, pp. 545–553, May 2005, https://doi.org/10.1016/j.enbuild.2004.09.009.

[5] Q. Li, Q. Meng, J. Cai, H. Yoshino, and A. Mochida, "Applying support vector machine to predict hourly cooling load in the building," *Applied Energy*, vol. 86, no. 10, pp. 2249–2256, Oct. 2009, https://doi.org/10.1016/j.apenergy.2008.11.035.

[6] A. Tsanas and A. Xifara, "Accurate quantitative estimation of energy performance of residential buildings using statistical machine learning tools," *Energy and Buildings*, vol. 49, pp. 560–567, Jun. 2012, https://doi.org/10.1016/j.enbuild.2012.03.003.

[7] E. A. Al-Ammar, N. H. Malik, and M. Usman, "Application of using Hybrid Renewable Energy in Saudi Arabia," *Engineering, Technology & Applied Science Research*, vol. 1, no. 4, pp. 84–89, Aug. 2011, https://doi.org/10.48084/etasr.33.

[8] B. Zahran, "Using Neural Networks to Predict the Hardness of Aluminum Alloys," *Engineering, Technology & Applied Science Research*, vol. 5, no. 1, pp. 757–759, Feb. 2015, https://doi.org/10.48084/etasr.529.

[9] S. N. Truong, "A Low-cost Artificial Neural Network Model for Raspberry Pi," *Engineering, Technology & Applied Science Research*, vol. 10, no. 2, pp. 5466–5469, Apr. 2020, https://doi.org/10.48084/etasr.3357.

[10] R. Yao, B. Li, and K. Steemers, "Energy policy and standard for built environment in China," *Renewable Energy*, vol. 30, no. 13, pp. 1973–1988, Oct. 2005, https://doi.org/10.1016/j.renene.2005.01.013.

[11] J.-S. Chou and D.-K. Bui, "Modeling heating and cooling loads by artificial intelligence for energy-efficient building design," *Energy and Buildings*, vol. 82, pp. 437–446, Oct. 2014, https://doi.org/10.1016/j.enbuild.2014.07.036.

[12] Y. Sonmez, U. Guvenc, H. T. Kahraman, and C. Yilmaz, "A comperative study on novel machine learning algorithms for estimation of energy performance of residential buildings," in *2015 3rd International Istanbul Smart Grid Congress and Fair (ICSG)*, Istanbul, Turkey, Apr. 2015, pp. 1–7, https://doi.org/10.1109/SGCF.2015.7354915.

[13] W. Qiao and Z. Yang, "Modified Dolphin Swarm Algorithm Based on Chaotic Maps for Solving High-Dimensional Function Optimization Problems," *IEEE Access*, vol. 7, pp. 110472–110486, 2019, https://doi.org/10.1109/ACCESS.2019.2931910.

[14] A. Moradzadeh, A. Mansour-Saatloo, B. Mohammadi-Ivatloo, and A. Anvari-Moghaddam, "Performance Evaluation of Two Machine Learning Techniques in Heating and Cooling Loads Forecasting of Residential Buildings," *Applied Sciences*, vol. 10, no. 11, Jan. 2020, Art. no. 3829, https://doi.org/10.3390/app10113829.

[15] S. Das, A. Swetapadma, C. Panigrahi, and A. Y. Abdelaziz, "Improved Method for Approximation of Heating and Cooling Load in Urban Buildings for Energy Performance Enhancement," *Electric Power Components and Systems*, vol. 48, no. 4–5, pp. 436–446, Mar. 2020, https://doi.org/10.1080/15325008.2020.1793838.