AI in Sustainable Energy and Environment

Journal homepage: aisesjournal.com

Online

Applicability of Grey Wolf Optimizer combined with Adaptive neuro-fuzzy inference system estimating energy performance in residential buildings

Mohamed Salem

School of Electrical and Electronic Engineering, Universiti Sains Malaysia (USM), Nibong Tebal 14300, Penang, Malaysia

Article Info

Received 24 May 2025

Received in Revised form 27 May 2025

Accepted 31 May 2025

Published online 07 June 2025

DOI:

Keywords

ANFIS

Residential buildings

Metaheuristic

Cooling-load

Abstract

Planning, management, and energy conservation all benefit from accurate predictions of building energy usage. The secret to ensuring energy systems' performance and sustainability is continuously improving and enhancing forecasting models' effectiveness. In this context, the current research presents, after studying and evaluating several kinds of HL forecasting models, a new enhanced hybrid approach of machine learning application for predicting residential buildings' heating load (HL). The suggested hybrid model, GWO-ANIFS, combines the support vector regression (GWO) and group technique of ANFIS models. The forecasting models used the building's technical characteristics as input factors, and the HL was chosen as the network's output variable. The findings showed that the suggested ANFIS approach with a 100-person population size was the best approach for forecasting building energy because it had the highest R^2 (0.97905 and 0.9789) and the lowest error amunts in the forms of MSE (0.012433), RMSE (0.1115), and MAE (0.088128) for predicting HL.

1. Introduction

Today, there is a far greater demand for energy than ever, and the commercial and residential sectors account for most of the world's enormous energy use. As a result, regulating sectors like construction and transportation and reducing energy use may be complex challenges [1, 2]. Due to the rising population, a recent study has shown that residential structures account for a significant portion of energy utilization [3, 4]. Comprehensive information about the facility's performance is essential to monitor and improve a building's energy usage. First, the building's energy sources and end usage must be determined [1]. The primary energy resources in a building are natural gas, electricity, and district heating. At the same time, the main end-use uses are heating, ventilation, air conditioning (HVAC), elevators, lighting, kitchen appliances, and domestic hot water. Among the energy sources mentioned above, sources and primary building applications, the HVAC operation schedule and interior and outside circumstances are two essential variables in determining how well a building performs [5, 6]. As a crucial component of a building's infrastructure, HVAC is critical in influencing the internal environment of residential structures by contributing to or subtracting from the heating load (HL) and cooling load (CL). These systems use around 40% of the total energy, especially in office buildings [7, 8], which is a severe cause for worry. However, relatively few basic approaches to enhancing the management and performance of HVAC systems have been created. The HVAC systems' performance cannot be adjusted to external climatic change because of the strong influence of meteorological elements on CL and HL; nonetheless, the poor efficiency of these systems may increase energy consumption and decrease comfort in cooling and heating [7, 8]. Accurate dynamic load forecasting and sustainable construction management in urban

Corresponding author: Email: salemm@usm.my (Mohamed Salem)

settings may be necessary to enhance HVAC system performance and reduce energy consumption in residential buildings [9, 10].

Buildings with poor design and construction use these technologies excessively, require a lot of energy, and emit more carbon dioxide, roughly 40% more. In light of the growing worries about energy loss and its detrimental impacts on the environment, a more recent study has been conducted globally on the buildings' energy performance (EPB) [11-13]. One of the most essential energy management methods to reduce energy demand and save energy is designing energy-efficient buildings with improved energy conservation features. Initial forecast of CL and HL in green structures may help with this. Construction designers need knowledge of the building specs and local weather conditions to anticipate the necessary cooling and heating capacity [14, 15]. Temperature is one of the most critical climatic parameters in predicting the buildings' HL and CL. Other important climatic aspects include wind speed, humidity, and pressure. The relative compactness of structures, the size of the roof, the glazing area, the wall surface, the height of the roof, the walls' number, and the area should all be considered when calculating a building's CL and HL. [16, 17].

Building energy modeling tools are being used extensively in different sectors to support effective design, energy-efficient structures' optimum performance, and comparison of buildings with similar sizes, where the influence of a single changing variable is evaluated throughout a range of amounts. The design and comparison simulation findings in various works have often accurately reflected the calculations [20, 21] precisely.

Generally speaking, utilizing building energy modeling software can be a good solution for evaluating the effects of building design indicators; however, this method is time-consuming and requires expert users to perform the simulations, and occasionally, there is inconsistent accuracy in the estimated results in different building simulation software packages [18]. Thus, to anticipate the CL and HL of buildings and examine the impact of different architectural factors, new approaches, including artificial neural networks, statistical analysis, and machine learning, are used in specific research [13, 14]. These approaches have the benefit that, after appropriately training the model, a precise and trustworthy answer may be achieved even while modifying a few building design factors. Additionally, techniques like statistical analysis help us better comprehend the effects of diverse numbers that architects or designers have concentrated on.

Principal component analysis (PCA) [19], extreme learning machines (ELM) [8, 20], applications of support vector machines (SVM) [21-27], and k-means are among the data mining approaches. In EPB and predicting the needed energy for residential buildings, deep learning techniques [26-34], decision trees (DT) [11], various regression methods, artificial neural networks [14, 18, 24, 35], and hybrid approaches based on regression methods [36-38] have all been utilized. The use of facade retrofitting techniques to reduce the need for cooling and heating in commercial and residential buildings is examined in proper research [39].

A mixed-integer linear program (MILP) has also been used to predict the optimum functioning of the HVAC system in significant buildings [40]. A residential building's HL and CL were forecasted utilizing multivariate adaptive regression splines (MARS), an ELM, and a hybrid approach [20], where the building's structural features were considered network inputs. In different research [41], the residential structures' HL and CL were forecasted using the ELM approach to construct an energy-efficient building. A deep neural network (DNN) was used in ref [34] to forecast CL and HL, together with the structural characteristics of the building as inputs. Reference [42] used ANN techniques like FFNN, radial basis function networks (RBFN), and adaptive neuro-fuzzy interference systems (ANFIS) to predict a building's HL for above-normal energy usage detection on a university campus. In this case, the heating usage from the previous day, temperature data, and week's day were chosen as network input parameters. In [10, 43], an ANN was used to predict the HL and CL of a building to control the HVAC system. As input variables for both studies, 11 air-handling units and meteorological data, respectively, were used. Reference [44] used the MLP approach and considered the climatic data as network input parameters to forecast the building's HL. In a different study [45], the MLP approach was used to anticipate a building's CL and HL to construct an energy-efficient architecture. The meteorological and date data were taken into consideration as input factors. [14] used machine learning techniques such as general linear regression, ANN, DT, support vector regression (SVR), and ensemble inference models to anticipate the CL and HL and analyze a building's energy efficiency. Reference [46] used six regression models of data mining methods, where the meteorological data, previous load usage, and date and time information were taken as the network's input parameters, to predict the HL and CL of a building in order to find the peak load of a water source heat pump (WSHP) in the building environment and supply the cooling and heating demand. The CL and HL of a building were predicted using the autoregressive with exogenous (ARX) approach in [47], where the meteorological data were regarded as network input variables. This was done to control the supply and demand of energy. [48] estimated the energy needed for the HVAC system from the CL and HL demand of the building by using several regression models. In [49], the building's HL was predicted using multiple regression techniques and considering certain environmental parameters as network inputs, including thermal resistance, sol-air temperature, and surface-to-volume ratio. In [50], neural networks were used to extract a black box method, which was the trained network, and use it to predict CL and HL. Climate data, such as temperature, wind speed, humidity, and sunshine, were utilized as input data in their methodology. Using multiple machine learning approaches such as SVM, FFNN, RF, Gradient Boosted Regression Trees, and XGBoost, the HL and CL's prediction linked with residential buildings has been carried out in [51]. In [52], a multi-layer hybrid approach (APNN) that takes into account the technical details of the building and meteorological data as its input has been presented to anticipate a residential building's HL and CL.

Although several models have been put out for predicting heat load, the models still have drawbacks in terms of accuracy and time-consuming calculations. ANN may be an alternative to analytical approaches since they have benefits, including fact calculation and no internal system parameter knowledge requirements [53-57]. This study aims to design and evaluate heat load prediction models using the Adaptive Neuro-Fuzzy Inference System (ANFIS) [49] approach, a subset of the ANN family.

ANFIS has excellent prediction and learning skills, which make it a valuable tool for addressing system-level uncertainty. Deploying a fuzzy inference system does not need prior knowledge of the physical procedure [50]. The fuzzy inference system and a neural network learning model are combined to form ANFIS.

The main aim of this investigation is to develop an ANFIS for predicting the heat load of residential structures. The basic idea underlying the soft computing approach is gathering input/output information and using them to infer the proposed system. Using this technique, fuzzy logic may change the participation capacity settings to support the best. The results of an inquiry are used to focus on gathering training and data for the ANFIS system. Head load data from a heating substation attached to the heating plant "Krivi vir," an autonomous component of Serbia's Nis district heating system, was measured and obtained as case studies, or ANFIS training data, for the currently built neural network. The primary aim of this research is to assess the ANFIS's capabilities for predicting heat load and exploring the potential for use in a brand-new distributed intelligent control scheme for DH systems.

The rest of this essay is structured as follows: The case study and the dataset are introduced in Section 2. Section 3 of the proposal details its suggested techniques. The results of the HL forecasting utilizing the provided approaches are shown in Section 4. The article is concluded in Section 6.

2. Established database

Using Ecotect software, Tsanas and Xifara (2012) simulate a dataset with 12 alternative building forms [58]. The simulations' buildings were considered to be situated in Greece, namely Athens. Building forms were developed considering the original cubes (3.5 x 3.5 x 3.5), each with 18 parts. Each building had a 771.75 m3 volume and was made of the same materials. The simulated structures varied in orientation, glazing area, interior size, glazing area distribution, and a few other factors.

The dataset included 768 simulated buildings, each with eight distinguishing characteristics (treated as input parameters and denoted in the data by the letter X) and two valuable replies (HL intended as an output variable and marked with Y). Table 5 illustrates the number of potential amounts for this data [58], the output and input parameters, and each variable's mathematical definition.

Three kinds of glazing are considered for the glazing regions depending on the floor area: 10%, 25%, and 40%. Additionally, five distinct distribution scenarios were simulated for each glazing area: (1) uniform: each side has 25%

glazing; (2) north: each side has 55% glazing; (3) east: each side has 55% glazing; (4) south: each side has 55% glazing; and (5) west: each side has 55% glazing; all other sides have 15% glazing. Additionally, we got examples without glazing. The four cardinal points were finally turned to face all forms (Figure 1).

Table 1. The output and input parameters are mathematical symbols

Mathematical Symbols	Variable Names	Number of Values
X1	Relative Compactness	12
X2	Surface Area	12
X3	Wall Area	7
X4	Roof Area	4
X5	Overall Height	2
X6	Orientation	4
X7	Glazing Area	4
X8	Glazing Area Distribution	6
Y1	Heating Load	568

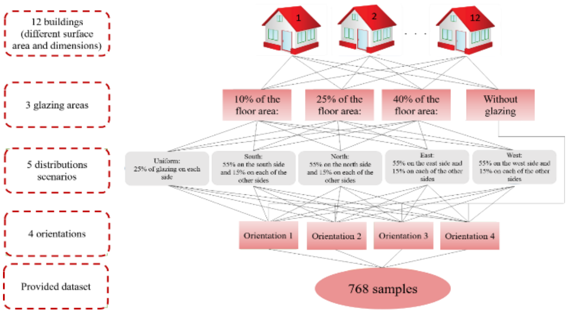


Figure 1: Data preparation's graphical view

3. Methodology

To examine the data for estimating the buildings' HL and to assess the outcomes, this section briefly explains artificial neural network methods and regression approaches.

3.1. Adaptive neuro-fuzzy interface system (ANFIS)

Jang developed the ANFIS. It performed duties similar to those of the first-order fuzzy inference system. ANFIS can approximate any linear or nonlinear system because it combines the neural networks' self-learning capability with the benefit of fuzzy inference. In ANFIS, the fuzzy rule and the membership function are derived through learning with the data sets instead of experience or intuitions. This is crucial for complicated systems or systems with underutilized characteristics [59].

Figure 4 [60] shows how the usual structure of ANFIS is laid up. The output of the layer i's membership functions was set to O (l, i), and the system's input and output were x, y, and f, respectively.

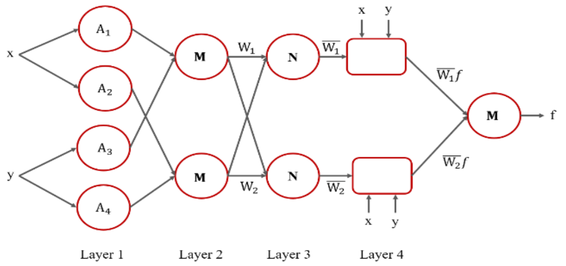


Figure 2: A typical ANFIS model's structure.

The first layer: In this layer, the input signals are converted into fuzzy values by the corresponding nodes.

$$O_{1,i} = \mu_{Ai}(x), \quad i = 1,2$$
$$O_{1,i} = \mu_{Bj-2}(y), \quad i = 3,4 \tag{1}$$

Here, A and B represent fuzzy sets, and $O_{l,i}$ denotes their membership function, which by default follows a bell-shaped form.

The second layer: the output of this layer is the product of calculating the fitness of each rule:

$$O_{2,i} = \omega = \mu_{Ai}(x)\mu_{Bj}(y), i = 1,2 \tag{2}$$

The third layer: is normalizes the fitness of each rule:

$$O_{3,i} = \overline{\omega} = \omega/(\omega_1 + \omega_2), \qquad i = 1,2 \tag{3}$$

The fourth layer: estimate the output of each rule:

$$O_{4,i} = \overline{\omega} f_i = \overline{\omega}(p_i x + q_i y + r_i), i = 1,2 \tag{4}$$

The fifth layer: This layer contains a single node responsible for computing the final output of the system.

$$O_{5,i} = y = \sum_i \overline{\omega} f_i = \frac{\sum_i \overline{\omega} f_i}{\sum_i \overline{\omega}}, i = 1,2 \tag{5}$$

ANFIS was trained using a hybrid approach that included the test squares technique with black propagation, which may aid the system in modeling the data sets.

3.2. Grey Wolf Optimization Algorithm (GWO):

Initially, S. Mirjalilli presented the Grey Wolf Optimizer (GWO) in 2014 [61]. This program simulates the distinct hunting and prey-finding behaviors of grey wolves. The GWO has adopted the four-level social hierarchy of grey wolves, which includes wolves at the first, second, third, and final levels. Wolves are in charge of leading, directing, and controlling the whole pack of grey wolves. Additionally, it oversees the whole hunting procedure and makes all decisions related to hunting, upholding order, and the resting and waking hours for the entire pack. The wolf who is the best contender to head the pack will solicit input from the other wolves and pass it along to the leader. The wolves of the fourth and final level, known as the wolves, are subordinate to the third level of grey wolves, or the wolves, who are in charge of upholding the integrity and safety of the wolf pack [61].

Using equation (6), the distances between the three wolves, α, β and δ, and D_α, D_β and D_δ, are computed. From these distances, the impact of the three wolves on the prey, $\vec{X}_1, \vec{X}_2$ and $\vec{X}_3$, may be estimated as shown in equation (7).

$$\begin{aligned} \vec{D}_\alpha &= |\vec{C}_1 \cdot \vec{X}_\alpha - \vec{X}|, \\ \vec{D}_\beta &= |\vec{C}_2 \cdot \vec{X}_\beta - \vec{X}|, \\ \vec{D}_\delta &= |\vec{C}_3 \cdot \vec{X}_\delta - \vec{X}| \end{aligned} \tag{6}$$

$$\begin{aligned} \vec{X}_1 &= \vec{X}_\alpha - \vec{A}_1 \cdot \vec{D}_\alpha, \\ \vec{X}_2 &= \vec{X}_\beta - \vec{A}_2 \cdot \vec{D}_\beta, \\ \vec{X}_3 &= \vec{X}_\delta - \vec{A}_3 \cdot \vec{D}_\delta \end{aligned} \tag{7}$$

$$\begin{aligned} \vec{A} &= 2\vec{a} \cdot \vec{r}_1 - \vec{a}, \\ \vec{C} &= 2 \cdot \vec{r}_2 \end{aligned} \tag{8}$$

$$\vec{X}(t+1) = (\vec{X}_1 + \vec{X}_2 + \vec{X}_3)/3 \tag{9}$$

Equation 9 determines the values of the algorithm's governing parameters, a, A, and C. (8). Here, accidental vectors [0; 1] are denoted by r2 and r1. Thanks to these vectors, wolves may now approach their prey at any point between them. The GWO algorithm's activity is controlled by the vector a, which is also used to calculate A. Throughout repetitions, the component amounts of a vector decline linearly from 2 to 0 [61]. C makes it more difficult for the wolves to locate the prey by adding additional weight. Finally, using equation (9), all other wolves upgrade their locations X (t+1).

Despite its youth, GWO is already being employed in a wide variety of practical contexts. For example, a improved version of the GWO method was presented and successfully used for training q-gaussian radial basis functional link networks [62]; the binary version of the GWO algorithm was suggested to be utilized for feature selection, which was one of the significant and crucial modifications of the GWO algorithm [63]. A modified GWO algorithm called the multiverse optimizer (MVO) was also proposed for solving various optimization problems [64]. To reduce the amount of CO_2 emissions from the capacitor, a 30-bus system was employed in a multi-objective GWO model, and the GWO algorithm was then used to optimize the DC motor's control parameters [65, 66]. The GWO technique resolved the stage 2 flow shop scheduling issue, and its release time was optimized [67].

4. Results and Discussion

Figures 3 to 9 displays the outcomes for the ANFIS heat load prediction algorithm. These figures show scatter plots that compare expected and observed heat load levels. The RMSE and R^2 are well-known statistical measures used to evaluate the ANFIS method's capacities for heat load forecasts in specified district heating systems (R^2). Figures 3 to 9 and Table 2 describe the performance findings of the suggested approaches.

4.1. Accuracy Indicators

Many techniques may be utilized to guarantee the correctness of findings and their assessment. The performance of the suggested approaches is evaluated in this work using the R^2, mean absolute error (MAE), mean squared error (MSE), and RMSE [68, 69]. The emphasis of each sign varies. The calculated model's R^2 between the predicted and actual values is shown. MAE displays the mean distance between the anticipated value and the actual value. The mean squared difference between the predicted values and the exact value of the proposed model is known as MSE, or mean squared error. The RMSE identifies big mistakes and evaluates the variation in method responsiveness concerning variance. The approach's performance will be modified by increasing the amount of the R^2 indicator and decreasing the amounts of MAE, MSE, and RMSE. The following formulae [68] were used to construct the statistical performance indicators for the N number of inputs that were previously mentioned:

$$R^2 = \frac{[\sum_{i=1}^{N}(X_i - \bar{X}_i) \cdot (Y_i - \bar{Y}_i)]^2}{\sum_{i=1}^{n}(X_i - \bar{X}_i) \cdot (Y_i - \bar{Y}_i)} \tag{10}$$

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}|X_i - Y_i| \tag{11}$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(X_i - Y_i)^2 \quad (12)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(X_i - Y_i)^2}{N}} \quad (13)$$

Where the real amount, the mean of actual value, the estimated amount, and the mean of actual value are represented by X_i, $\vec{X}$, Y_i, and $\vec{Y}$, respectively.

The ANFIS network is first trained using the data retrieved from the experimental calculation process. Data were utilized for ANFIS testing by 20% and training by 80%. During the training method, input fuzzification uses three bell-shaped membership functions. There are 24 nonlinear and 80 linear parameters in the ANFIS network. The ANFIS network uses 16 fuzzy rules. Three experimental datasets were constructed in accordance with the time steps to examine the effect of the time step range on the ANFIS prediction. For each dataset, a prediction of the following four stages was made, and the outcomes were compared. To contrast variations, several prediction processes were explored.

4.2. Incorporated FIS with Optimizers

The amounts of each index are shown in this diagram as the accuracy attained relative to their ideal values. For instance, RMSE and R^2 should be zero and one, respectively. For the GWO-ANFIS approach in the training stage of the current study, these indices are determined to have values of 0.0.1115 and 0.97905, respectively. Regarding RMSE and R^2 values, it can be deduced that the above model obtained 88.85% (10.1115=0.8885) and 97.90% (0.97905/1=0.97905) accuracy. The same conclusions about the accuracy of the other indexes are made. Keep in mind that percentage-based performance indexes should be translated to decimal figures. In the current investigation, the MSE value for ten swarm sizes (50, 100, 150, 200, 250, 300, 350, 400, 450, and 500) for HL is shown in Fig. 3 as a function of iterations (1000 iterations). The lowest RMSE value produces the best results. The swarm size of 100 (RMSE=0.1115 and 0.1093) produced the lowest MSE value for GWO-ANFIS, as shown in Figure 3 and Table 2. The 400 population size also had the highest MSE value (RMSE=0.16468 and 0.1557), demonstrating the lowest performance in forecasting HL in residential structures.

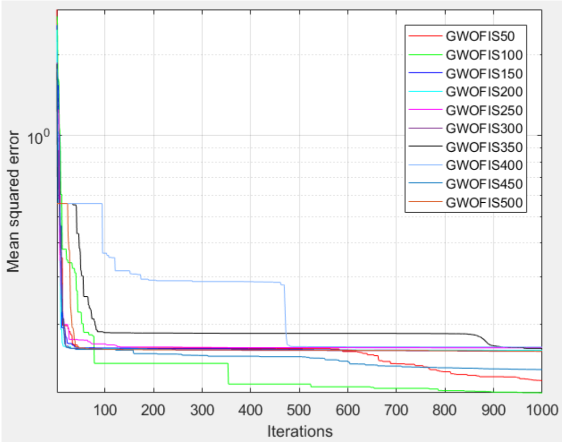


Figure 13: Mean squared error variation versus repetitions for the GWOANFIS

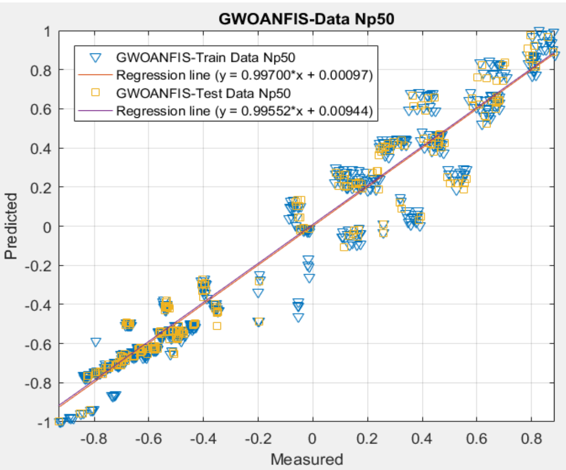
The work of Zhang et al. [48] was when rank analysis was first introduced. This method, used separately for the training and testing outcomes, awarded the approach with the best value for each index, a maximum rank (equivalent to the number of approaches being compared). In contrast, the approach with the lowest value was ranked 1. Then, the sum of their rankings was used to compute the final score. The rankings from the testing and training phases are added together to get the final score for each approach.

The values of the performance variables estimated for the suggested approach and their corresponding rankings for heating load are shown in Table 2. These statistics show that GWO-ANFIS, with a swarm size of 100, is the most precise model for HL prediction. R^2 has the most outstanding amount during the testing and training sets when the population size is 100, respectively, at 0.97905 and 0.9789. Additionally, the swarm size of 100 has a lower RMSE value than the others when considering the RMSE value (0.1115 and 0.1093). The greatest RMSE, with values of 0.16468 and 0.1557 in the training and testing phases, respectively, and the lowest R^2 associated with a population size of 400.

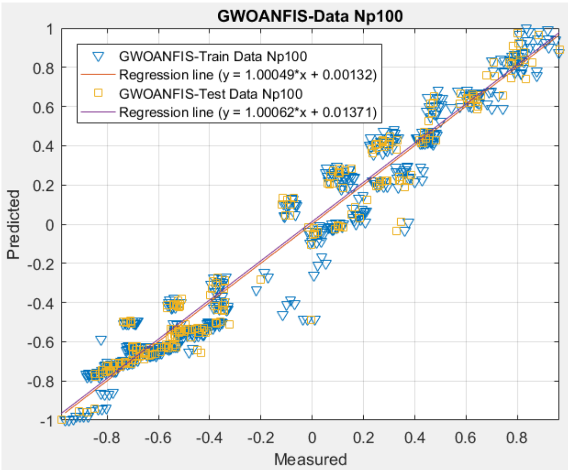
A sophisticated computer technique has been created to forecast the heating demands of residential structures. The approach is initially trained utilizing the training dataset. Figure 4 clarifies that varied time steps and prediction stages result in somewhat different predictions for the model's findings. The overall pattern is still there, and changing the time steps and prediction stages will affect the prediction outcome. The findings are more responsive to modifying time steps than prediction steps. It is simple to verify this finding using Table 2. In terms of the prediction outcomes, a population size of 100 has the lowest RMSE (0.1115 and 0.1093) and highest R2 (0.97905 and 0.9789, respectively) in training and testing. According to the analysis, most of the projected values strongly correlated with the observed data in the testing set.

Table 2. The network results for the GWOANFIS having different swarm size

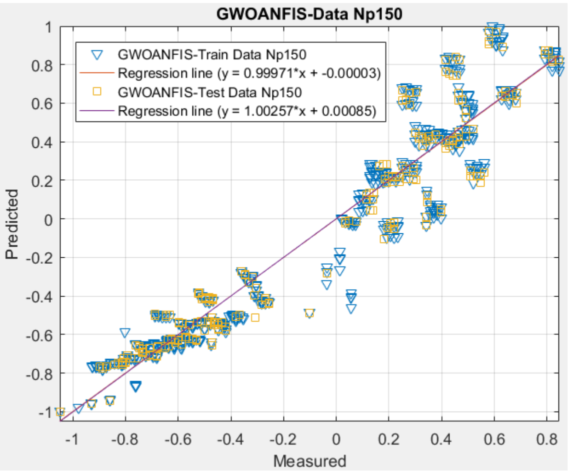
Swam size	Training dataset		Testing dataset		Scoring				Total Score	Rank
	RMSE	R^2	RMSE	R^2	Training		Testing			
50	0.12372	0.97413	0.11938	0.97477	9	9	9	9	36	2
100	0.1115	0.97905	0.1093	0.9789	10	10	10	10	40	1
150	0.16031	0.95617	0.15267	0.95839	4	4	5	5	18	6
200	0.1603	0.95618	0.15269	0.95838	5	5	4	4	18	6
250	0.16373	0.95424	0.15655	0.9562	2	2	1	1	6	9
300	0.15884	0.95699	0.15097	0.95933	7	7	7	7	28	4
350	0.16293	0.9547	0.15406	0.95761	3	3	3	3	12	8
400	0.16468	0.95369	0.1557	0.95669	1	1	2	2	6	9
450	0.13596	0.96868	0.13035	0.96984	8	8	8	8	32	3
500	0.15897	0.95692	0.15152	0.95903	6	6	6	6	24	5



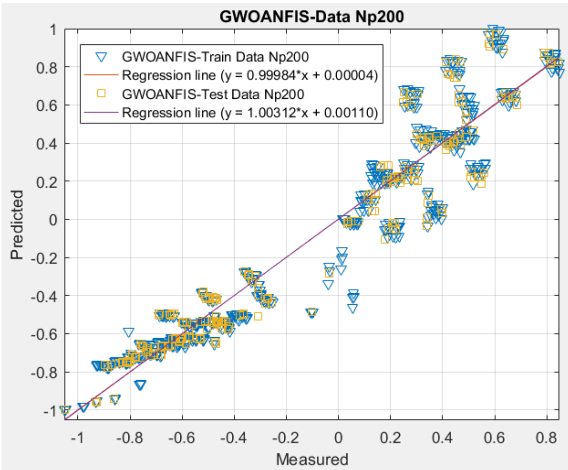
(a) GWOANFIS Np=50



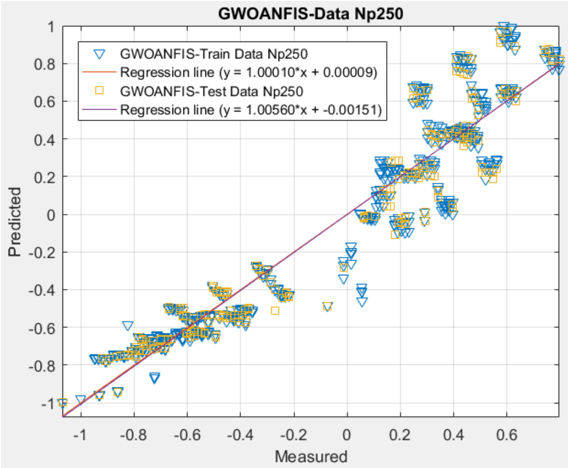
(b) GWOANFIS Np=100



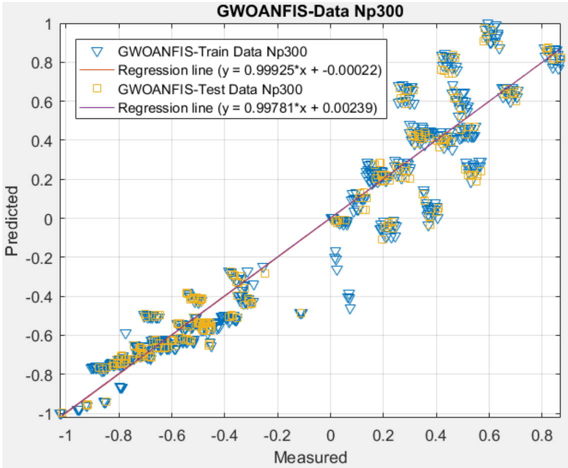
(c) GWOANFIS Np=150



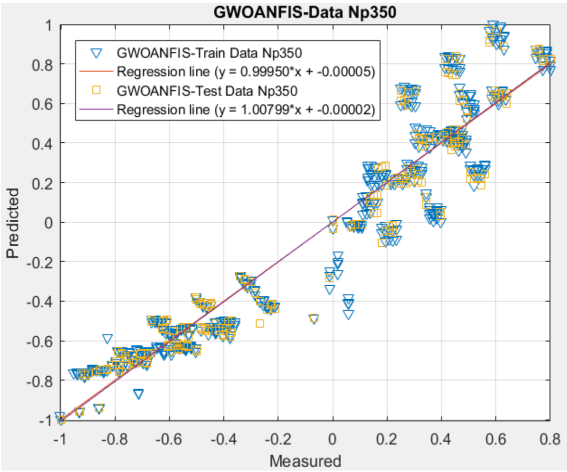
(d) GWOANFIS Np=200



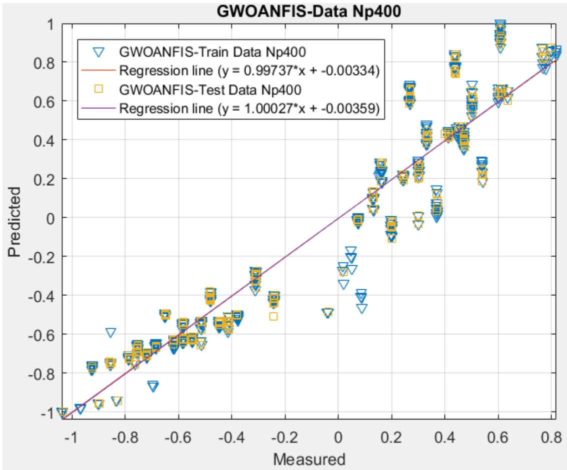
(e) GWOANFIS Np=250



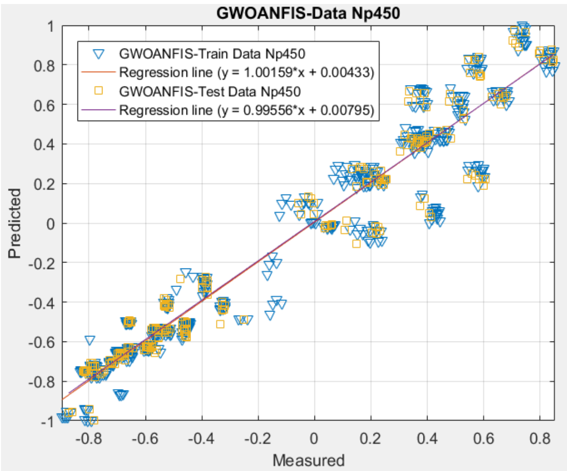
(f) GWOANFIS Np=300



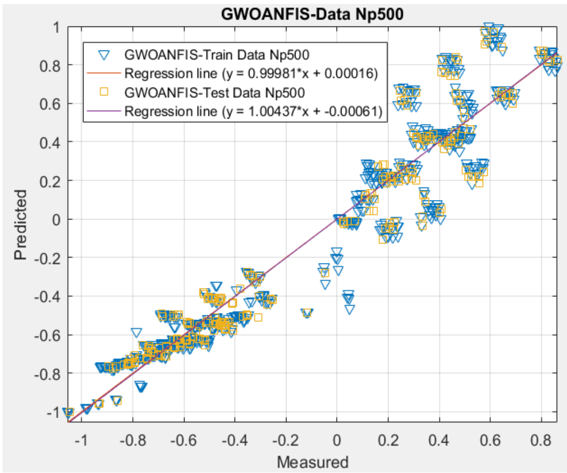
(g) GWOANFIS Np=350



(h) GWOANFIS Np=400



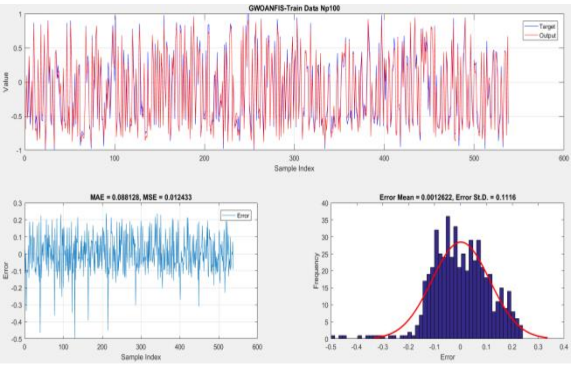
(i) GWOANFIS Np=450



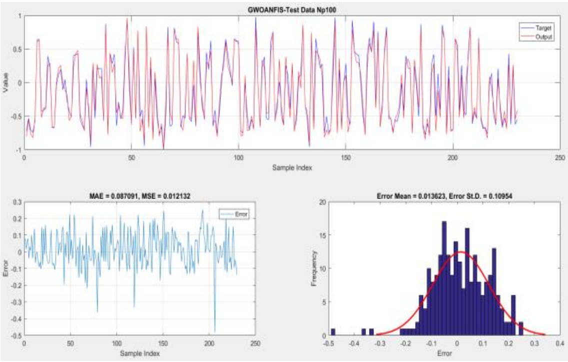
(j) GWOANFIS Np=500

Figure 4: The precision of testing and training sets performance of GWOANFIS in the best-fit optimization structure

The GWO-ANFIS training and testing errors for HL prediction are shown in Figs. 5-9 as MAE and MSE. These graphs show the accuracy coefficients and testing and training errors for each population size (100, 200, 300, 400, and 500). The results demonstrated that the suggested approach could, upon training, predict the test data. Data mining applications' studies revealed that, for a range of machine learning algorithms and neural networks, the kind of data significantly impacted the training and prediction processes.

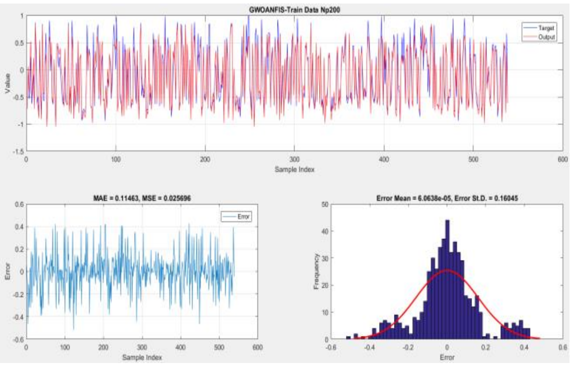


(a) Training dataset

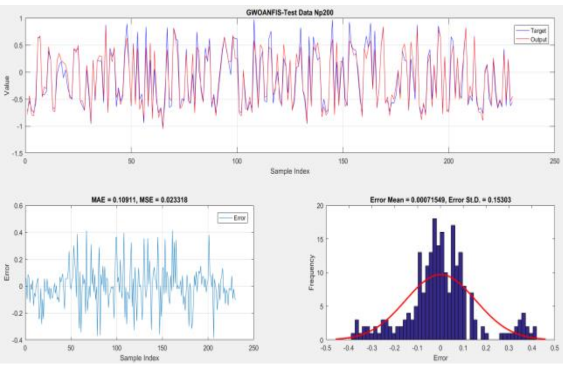


(b) Testing dataset

Figure 5: Frequency and minimum value of errors in GWOANFIS-100 best-fit structure

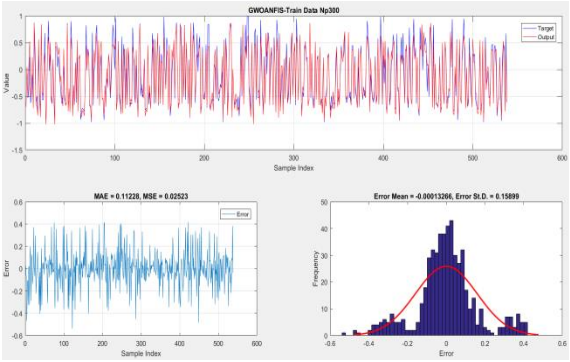


(a) Training dataset

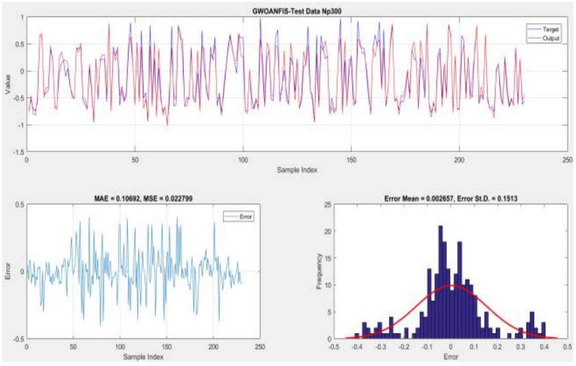


(b) Testing dataset

Figure 6: Frequency and minimum value of errors in GWOANFIS-200 best-fit structure

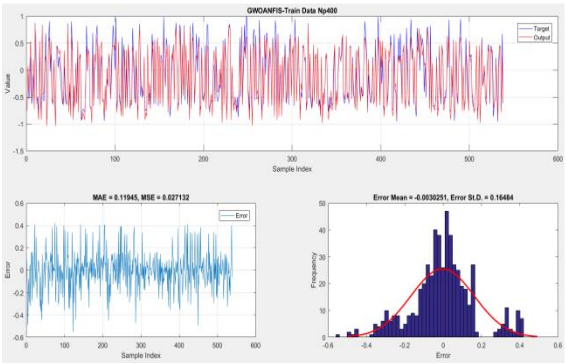


(a) Training dataset

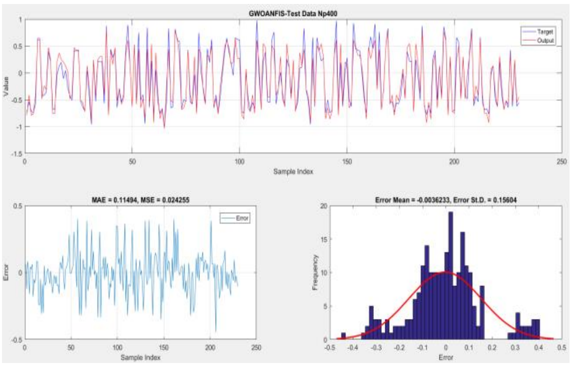


(b) Testing dataset

Figure 7: Frequency and minimum value of errors in GWOANFIS-300 best-fit structure

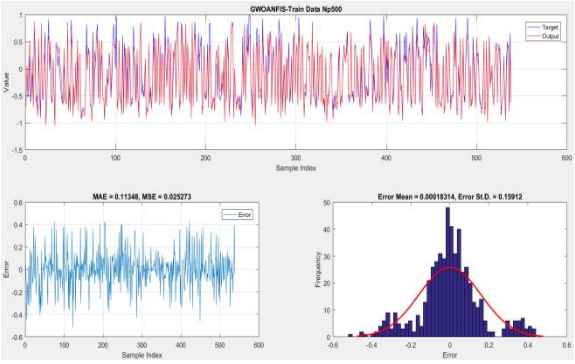


(a) Training dataset

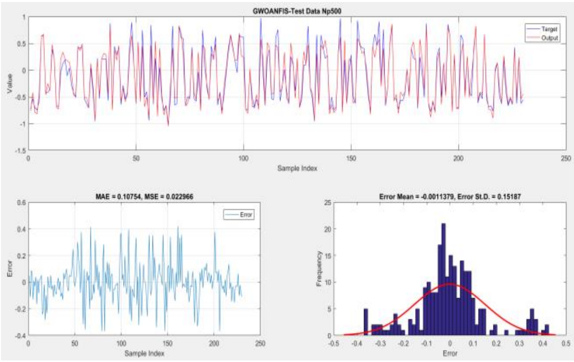


(b) Testing dataset

Figure 8: Frequency and minimum value of errors in GWOANFIS-400 best-fit structure



(a) Training dataset



(b) Testing dataset

Figure 9: Frequency and minimum value of errors in GWOANFIS-500 best-fit structure

5. Discussion

The buildings' HL and CL were primarily forecasted using a variety of algorithms and various pieces of data based on the literature mentioned above. The CL and HL of buildings may be indicated using these approaches, which are divided into categories based on the datasets they use. In the end, the strategies' efficacy was evaluated using comparable data. The datasets were separated into four groups for this classification: actual calculations, simulated (Energy plus), simulated (DeST), and simulated (Ecotect). Each study's real-world calculation data was unique.

The buildings' HL and CL have been forecasted by much research using different machine learning, ANNs, deep learning, hybrid techniques, and ELM, as indicated in the literature mentioned above. To enhance the forecasts of HL and CL, researchers are increasingly considering the possibility of mixing approaches, according to an analysis of recent publications. The accuracy coefficient and error are specific to the methodologies used to forecast CL and HL. Various statistical performance measures have been used in multiple studies to assess each algorithm's performance.

The majority of research conducted to forecast the buildings' HL and CL based on various parameters was evaluated in this study. The article share is often listed as follows:

- A thorough analysis of works predicting and simulating the HL and CL of residential structures.
- It outlines a new ANFIS method called GWO-ANFIS that combines it with Grey Wolf Optimization (GWO) to model and predict HL following the technological requirements.

A determination was made on the technique indicated (GWO-ANFIS). The R^2, MSE, RMSE, and MAE variables derived from the findings of the suggested approaches were contrasted with the findings from previous articles. The database was split into three sections: testing, validation, and training operations. The training and testing datasets received 80%–20% of the database. As can be seen, the best forecasting model was the GWO-ANFIS model, which had a population size of 100 and the most incredible R^2 value for HL on fresh test data (0.97905 and 0.9789). GWO-training ANFIA's errors for HL prediction were at their lowest in terms of MSE (0.012433), MAE (0.088128), and RMSE (0.1115). The 400-person population had the highest MSE (0.027132), MAE (0.11945), and RMSE values, as well as the lowest R^2 values (0.95369 and 0.95669). (0.16468). The population size of 50, which had R2 values of 0.97413 and 0.97477, was the next-best size for predicting the HL after that of 100. By looking at the data, comparing the energy forecast outcomes for buildings connected with the suggested technique with other models used in previous research for comparable data is possible. The proposed approach may use all accessible energy and real-world data, including water and gas.

6. Conclusions

Several difficulties are associated with estimating, managing, and reducing the buildings' energy usage, notably HL and CL. Most scientists nowadays are searching for an enhanced model with excellent prediction performance. This study evaluated the effectiveness of an energy forecasting model for residential structures. This research developed a novel ANFIS model to anticipate the HL of a residential structure using hybrid models. The ANFIS and GWO models were mainly combined in the suggested model. Eight building technical factors (X1, X2,..., X8) were used as input parameters, and HL was chosen as the model's output parameter. The HL was anticipated using the dataset after training and preserving the learned network. The findings showed that the suggested ANFIS approach with a 100-person population size was the best approach for forecasting building energy because it had the highest R^2 (0.97905 and 0.9789) and the lowest error in the forms of MSE (0.012433), RMSE (0.1115), and MAE (0.088128) for predicting HL. Notably, the suggested strategy works with all accessible energies, including water and gas, as well as real-world data.

7. References

[1] Leitao, Joaquim, Paulo Gil, Bernardete Ribeiro, Alberto Cardoso, A survey on home energy management, IEEE Access, 8 (2020) 5699-5722,

[2] Baldi, Simone, Iakovos Michailidis, Vasiliki Ntampasi, Elias B Kosmatopoulos, Ioannis Papamichail, Markos Papageorgiou, Simulation-based synthesis for approximately optimal urban traffic light management, 2015 American Control Conference (ACC), IEEE, 2015, pp. 868-873.

[3] Dugan, Joanne Bechta, Salvatore J Bavuso, Mark A Boyd, Fault trees and sequence dependencies, Annual Proceedings on Reliability and Maintainability Symposium, IEEE, 1990, pp. 286-293.

[4] Sadeghian, Omid, Arash Moradzadeh, Behnam Mohammadi-Ivatloo, Mehdi Abapour, Amjad Anvari-Moghaddam, Jeng Shiun Lim, Fausto Pedro Garcia Marquez, A comprehensive review on energy saving options and saving potential in low voltage electricity distribution networks: Building and public lighting, Sustainable Cities and Society, 72 (2021) 103064,

[5] Shareef, Hussain, Maytham S Ahmed, Azah Mohamed, Eslam Al Hassan, Review on home energy management system considering demand responses, smart technologies, and intelligent controllers, Ieee Access, 6 (2018) 24498-24509,

[6] Al-Ghaili, Abbas M, Hairoladenan Kasim, Naif M Al-Hada, Bo Nørregaard Jørgensen, Marini Othman, Jihua Wang, Energy management systems and strategies in buildings sector: A scoping review, IEEE Access, 9 (2021) 63790-63813,

[7] Lin, Tao, Yu Pan, Guixiang Xue, Jiancai Song, Chengying Qi, A novel hybrid spatial-temporal attention-LSTM model for heat load prediction, IEEE Access, 8 (2020) 159182-159195,

[8] Zhao, Jing, Xiaojuan Liu, A hybrid method of dynamic cooling and heating load forecasting for office buildings based on artificial intelligence and regression analysis, Energy and Buildings, 174 (2018) 293-308,

[9] Chen, Qifang, Mingchao Xia, Teng Lu, Xichen Jiang, Wenxia Liu, Qinfei Sun, Short-term load forecasting based on deep learning for end-user transformer subject to volatile electric heating loads, IEEE Access, 7 (2019) 162697-162707,

[10] Hong, Taehoon, Choongwan Koo, Jimin Kim, Minhyun Lee, Kwangbok Jeong, A review on sustainable construction management strategies for monitoring, diagnosing, and retrofitting the building's dynamic energy performance: Focused on the operation and maintenance phase, Applied Energy, 155 (2015) 671-707,

[11] Yu, Zhun, Fariborz Haghighat, Benjamin CM Fung, Hiroshi Yoshino, A decision tree method for building energy demand modeling, Energy and Buildings, 42 (2010) 1637-1646,

[12] Platt, Glenn, Jiaming Li, Ronxin Li, Geoff Poulton, Geoff James, Josh Wall, Adaptive HVAC zone modeling for sustainable buildings, Energy and Buildings, 42 (2010) 412-421,

[13] Yao, Runming, Baizhan Li, Koen Steemers, Energy policy and standard for built environment in China, Renewable Energy, 30 (2005) 1973-1988,

[14] Chou, Jui-Sheng, Dac-Khuong Bui, Modeling heating and cooling loads by artificial intelligence for energy-efficient building design, Energy and Buildings, 82 (2014) 437-446,

[15] Moradzadeh, Arash, Hamed Moayyed, Sahar Zakeri, Behnam Mohammadi-Ivatloo, A Pedro Aguiar, Deep learning-assisted short-term load forecasting for sustainable management of energy in microgrid, Inventions, 6 (2021) 15,

[16] Kumar, Sachin, Saibal K Pal, Ram Pal Singh, A novel method based on extreme learning machine to predict heating and cooling load through design and structural attributes, Energy and Buildings, 176 (2018) 275-286,

[17] Chen, Shuqin, Xiyong Zhang, Shen Wei, Tong Yang, Jun Guan, Wenxiao Yang, Lijuan Qu, Yunqing Xu, An energy planning oriented method for analyzing spatial-temporal characteristics of electric loads for heating/cooling in district buildings with a case study of one university campus, Sustainable Cities and Society, 51 (2019) 101629,

[18] Yezioro, Abraham, Bing Dong, Fernanda Leite, An applied artificial intelligence approach towards assessing building performance simulation tools, Energy and Buildings, 40 (2008) 612-620,

[19] Moradzadeh, Arash, Omid Sadeghian, Kazem Pourhossein, Behnam Mohammadi-Ivatloo, Amjad Anvari-Moghaddam, Improving residential load disaggregation for sustainable development of energy via principal component analysis, Sustainability, 12 (2020) 3158,

[20] Roy, Sanjiban Sekhar, Reetika Roy, Valentina E Balas, Estimating heating load in buildings using multivariate adaptive regression splines, extreme

learning machine, a hybrid model of MARS and ELM, Renewable and Sustainable Energy Reviews, 82 (2018) 4256-4268,

[21] Dong, Bing, Cheng Cao, Siew Eang Lee, Applying support vector machines to predict building energy consumption in tropical region, Energy and Buildings, 37 (2005) 545-553,

[22] Ding, Yan, Qiang Zhang, Tianhao Yuan, Fan Yang, Effect of input variables on cooling load prediction accuracy of an office building, Applied Thermal Engineering, 128 (2018) 225-234,

[23] Xuemei, Li, Lu Jin-hu, Ding Lixing, Xu Gang, Li Jibin, Building cooling load forecasting model based on LS-SVM, 2009 Asia-Pacific Conference on Information Processing, IEEE, 2009, pp. 55-58.

[24] Moradzadeh, Arash, Amin Mansour-Saatloo, Behnam Mohammadi-Ivatloo, Amjad Anvari-Moghaddam, Performance evaluation of two machine learning techniques in heating and cooling loads forecasting of residential buildings, Applied Sciences, 10 (2020) 3829, https://doi.org/10.3390/app10113829.

[25] Moradzadeh, Arash, Sevda Zeinal-Kheiri, Behnam Mohammadi-Ivatloo, Mehdi Abapour, Amjad Anvari-Moghaddam, Support vector machine-assisted improvement residential load disaggregation, 2020 28th Iranian conference on electrical engineering (ICEE), IEEE, 2020, pp. 1-6.

[26] Luo, XJ, Lukumon O Oyedele, Anuoluwapo O Ajayi, Olugbenga O Akinade, Comparative study of machine learning-based multi-objective prediction framework for multiple building energy loads, Sustainable Cities and Society, 61 (2020) 102283,

[27] Moradzadeh, Arash, Sahar Zakeri, Maryam Shoaran, Behnam Mohammadi-Ivatloo, Fazel Mohammadi, Short-term load forecasting of microgrid via hybrid support vector regression and long short-term memory algorithms, Sustainability, 12 (2020) 7076,

[28] Fan, Cheng, Fu Xiao, Yang Zhao, A short-term building cooling load prediction method using deep learning algorithms, Applied energy, 195 (2017) 222-233,

[29] Fan, Cheng, Jiayuan Wang, Wenjie Gang, Shenghan Li, Assessment of deep recurrent neural network-based strategies for short-term building energy predictions, Applied energy, 236 (2019) 700-710,

[30] Wang, Zhe, Tianzhen Hong, Mary Ann Piette, Data fusion in predicting internal heat gains for office buildings through a deep learning approach, Applied energy, 240 (2019) 386-398,

[31] Roy, Sanjiban Sekhar, Pijush Samui, Ishan Nagtode, Hemant Jain, Vishal Shivaramakrishnan, Behnam Mohammadi-Ivatloo, Forecasting heating and cooling loads of buildings: A comparative performance analysis, Journal of Ambient Intelligence and Humanized Computing, 11 (2020) 1253-1264, https://doi.org/10.1007/s12652-019-01317-y.

[32] Moradzadeh, Arash, Behnam Mohammadi-Ivatloo, Mehdi Abapour, Amjad Anvari-Moghaddam, Saeid Gholami Farkoush, Sang-Bong Rhee, A practical solution based on convolutional neural network for non-intrusive load monitoring, Journal of Ambient Intelligence and Humanized Computing, 12 (2021) 9775-9789,

[33] Song, Jiancai, Guixiang Xue, Xuhua Pan, Yunpeng Ma, Han Li, Hourly heat load prediction model based on temporal convolutional neural network, IEEE Access, 8 (2020) 16726-16741,

[34] Liu, Junyu, Xiao Wang, Yan Zhao, Bin Dong, Kuan Lu, Ranran Wang, Heating load forecasting for combined heat and power plants via strand-based LSTM, IEEE Access, 8 (2020) 33360-33369,

[35] Kwok, Simon SK, Richard KK Yuen, Eric WM Lee, An intelligent approach to assessing the effect of building occupancy on building cooling load prediction, Building and Environment, 46 (2011) 1681-1690,

[36] Geysen, Davy, Oscar De Somer, Christian Johansson, Jens Brage, Dirk Vanhoudt, Operational thermal load forecasting in district heating networks using machine learning and expert advice, Energy and Buildings, 162 (2018) 144-153,

[37] Cui, Borui, Cheng Fan, Jeffrey Munk, Ning Mao, Fu Xiao, Jin Dong, Teja Kuruganti, A hybrid building thermal modeling approach for predicting temperatures in typical, detached, two-story houses, Applied energy, 236 (2019) 101-116,

[38] Wang, Ran, Shilei Lu, Wei Feng, A novel improved model for building energy consumption prediction based on model integration, Applied Energy, 262 (2020) 114561,

[39] Sarihi, Soad, Fatemeh Mehdizadeh Saradj, Mohsen Faizi, A critical review of façade retrofit measures for minimizing heating and cooling demand in existing buildings, Sustainable Cities and Society, 64 (2021) 102525,

[40] Bianchini, Gianni, Marco Casini, Daniele Pepe, Antonio Vicino, Giovanni Gino Zanvettor, An integrated model predictive control approach for optimal HVAC and energy storage operation in large-scale buildings, Applied energy, 240 (2019) 327-340,

[41] Naji, Sareh, Afram Keivani, Shahaboddin Shamshirband, U Johnson Alengaram, Mohd Zamin Jumaat, Zulkefli Mansor, Malrey Lee, Estimating building energy consumption using extreme learning machine method, Energy, 97 (2016) 506-516,

[42] Jovanović, Radiša Ž, Aleksandra A Sretenović, Branislav D Živković, Ensemble of various neural networks for prediction of heating energy consumption, Energy and Buildings, 94 (2015) 189-199,

[43] Jinhu, Lv, Li Xuemei, Ding Lixing, Jiang Liangzhong, Applying principal component analysis and weighted support vector machine in building cooling load forecasting, 2010 international conference on computer and communication technologies in agriculture engineering, IEEE, 2010, pp. 434-437.

[44] Paudel, Subodh, Mohamed Elmtiri, Wil L Kling, Olivier Le Corre, Bruno Lacarrière, Pseudo dynamic transitional modeling of building heating energy demand using artificial neural network, Energy and Buildings, 70 (2014) 81-93,

[45] Wong, Sai Li, Kevin KW Wan, Tony NT Lam, Artificial neural networks for energy analysis of office buildings with daylighting, Applied Energy, 87 (2010) 551-557,

[46] Ahmad, Tanveer, Huanxin Chen, Short and medium-term forecasting of cooling and heating load demand in building environment with data-mining based approaches, Energy and Buildings, 166 (2018) 460-476,

[47] Yun, Kyungtae, Rogelio Luck, Pedro J Mago, Heejin Cho, Building hourly thermal load prediction using an indexed ARX model, Energy and Buildings, 54 (2012) 225-233,

[48] Korolija, Ivan, Yi Zhang, Ljiljana Marjanovic-Halburd, Victor I Hanby, Regression models for predicting UK office building energy consumption from heating and cooling demands, Energy and Buildings, 59 (2013) 214-227,

[49] Catalina, Tiberiu, Vlad Iordache, Bogdan Caracaleanu, Multiple regression model for fast prediction of the heating energy demand, Energy and buildings, 57 (2013) 302-312,

[50] Gunay, Burak, Weiming Shen, Guy Newsham, Inverse blackbox modeling of the heating and cooling load in office buildings, Energy and Buildings, 142 (2017) 200-210,

[51] Seyedzadeh, Saleh, Farzad Pour Rahimian, Parag Rastogi, Ivan Glesk, Tuning machine learning models for prediction of building energy loads, Sustainable Cities and Society, 47 (2019) 101484,

[52] Liu, Kai, Ting-Zhang Liu, Pan Jian, Yue Lin, The re-optimization strategy of multi-layer hybrid building's cooling and heating load soft sensing technology research based on temperature interval and hierarchical modeling techniques, Sustainable cities and society, 38 (2018) 42-54,

[53] Ding, Yan, Qiang Zhang, Tianhao Yuan, Research on short-term and ultra-short-term cooling load prediction models for office buildings, Energy and Buildings, 154 (2017) 254-267,

[54] Chen, Yibo, Hongwei Tan, Short-term prediction of electric demand in building sector via hybrid support vector regression, Applied energy, 204 (2017) 1363-1374,

[55] Zhong, Hai, Jiajun Wang, Hongjie Jia, Yunfei Mu, Shilei Lv, Vector field-based support vector regression for building energy consumption prediction, Applied Energy, 242 (2019) 403-414,

[56] Fan, Chengliang, Yunfei Ding, Cooling load prediction and optimal operation of HVAC systems using a multiple nonlinear regression model, Energy and Buildings, 197 (2019) 7-17,

[57] Kwok, Simon SK, Eric WM Lee, A study of the importance of occupancy to building cooling load in prediction by intelligent approach, Energy Conversion and Management, 52 (2011) 2555-2564,

[58] Tsanas, Athanasios, Angeliki Xifara, Accurate quantitative estimation of energy performance of residential buildings using statistical machine learning tools, Energy and buildings, 49 (2012) 560-567, https://doi.org/10.1016/j.enbuild.2012.03.003.

[59] Jang, J-SR, ANFIS: adaptive-network-based fuzzy inference system, IEEE transactions on systems, man, and cybernetics, 23 (1993) 665-685,

[60] Güler, Inan, Elif Derya Übeyli, Adaptive neuro-fuzzy inference system for classification of EEG signals using wavelet coefficients, Journal of neuroscience methods, 148 (2005) 113-121,

[61] Mirjalili, Seyedali, Seyed Mohammad Mirjalili, Andrew Lewis, Grey wolf optimizer, Advances in engineering software, 69 (2014) 46-61,

[62] Muangkote, Nipotepat, Khamron Sunat, Sirapat Chiewchanwattana, An improved grey wolf optimizer for training q-Gaussian Radial Basis Functional-link nets, 2014 international computer science and engineering conference (ICSEC), IEEE, 2014, pp. 209-214.

[63] Emary, Eid, Hossam M Zawbaa, Aboul Ella Hassanien, Binary grey wolf optimization approaches for feature selection, Neurocomputing, 172 (2016) 371-381,

[64] Mirjalili, Seyedali, Seyed Mohammad Mirjalili, Abdolreza Hatamlou, Multi-verse optimizer: a nature-inspired algorithm for global optimization, Neural Computing and Applications, 27 (2016) 495-513,

[65] Mohamed, Al-Attar A, AA El-Gaafary, Yahia S Mohamed, Ashraf M Hemeida, Energy management with capacitor placement for economics low carbon emissions using modified multi-objective grey wolf optimizer, 3rd International Conference on Energy Systems and Technologies, 2015, pp. 261-270.

[66] Madadi, Ali, Mahmood Mohseni Motlagh, Optimal control of DC motor using grey wolf optimizer algorithm, Technical Journal of Engineering and Applied Science, 4 (2014) 373-379,

[67] Komaki, GM, Vahid Kayvanfar, Grey Wolf Optimizer algorithm for the two-stage assembly flow shop scheduling problem with release time, Journal of Computational Science, 8 (2015) 109-120,

[68] Choubin, Bahram, Shahram Khalighi-Sigaroodi, Arash Malekian, Özgür Kişi, Multiple linear regression, multi-layer perceptron network and adaptive neuro-fuzzy inference system for forecasting precipitation based on large-scale climate signals, Hydrological sciences journal, 61 (2016) 1001-1009,

[69] Moradzadeh, Arash, Hamid Teimourzadeh, Behnam Mohammadi-Ivatloo, Kazem Pourhossein, Hybrid CNN-LSTM approaches for identification of type and locations of transmission line faults, International Journal of Electrical Power & Energy Systems, 135 (2022) 107563,