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Nonlinear swarm intelligence of genetic algorithm and grey wolf optimization hybridized with ANFIS approximating energy performance in building

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Abstract

Traditional energy performance analysis methods have become obsolete because of the development of novel swarm-based optimization methods. The research examines the potential of two hybrid approaches, notably genetic algorithm (GA) and grey wolf optimization (GWO), for enhancing the neural evaluation of cooling load (CL) in green buildings. To accomplish such an objective, preparing the necessary dataset considers eight CL-influencing elements, such as relative compactness, surface area, glazing area distribution, wall area, overall height, roof area, and orientation. A population-based analysis is conducted using the best-fitting architectures of every approach. According to the findings, using both GA and GWO algorithms increased neural network accuracy. The analysis outcomes indicate that the GA model was the most incredible ANFIS model. Significantly, the GA-ANFIS model had a greater R^2 amount of 0.98 and the lowest RMSE amount of 0.09 among the two models examined. The GWO-ANFIS approach achieved R^2 amounts of 0.95 and RMSE amounts of 0.15, indicating that GA-ANFIS offers superior performance.

1. Introduction

Buildings currently utilize 32% of all final energy consumed globally, accounting for 33% of all greenhouse gas emissions, making them the world's most significant energy consumer [1]. Buildings seem to have far more considerable potential for energy savings than the transportation and industrial sectors and might approach 30–80 percent utilizing existing building technologies [2]. Compared to alternative service systems in buildings, the Heating, Ventilation, and Air-Conditioning (HVAC) system uses the most energy (approximately 50% in the US). It offers the most significant potential for energy savings (15–30% for commercial buildings) [3, 4]. Therefore, the HVAC system is the primary focus of current energy-saving strategies in building operations. For numerous building and energy management activities, like optimum control and fault detection and diagnosis (FDD) approaches [5-7], an accurate forecast of the short-term (less than one week) CL profile seems to be necessary.

Mahmoud and Ben-Nakhi employed ANN to forecast the CL of the next day to maximize the efficiency of the system of HVAC thermal energy [6]. It has been demonstrated that optimal control strategies may enhance operational flexibility while reducing operating expenses. Lu et al. [7] utilized artificial intelligence to optimize HVAC system operations by predicting the buildings' CL. Shan et al. [8] devised a viable approach for chiller control depending on predicting the CL. The method has been displayed to save 3% more energy than conventional procedures. Directly or indirectly, the cooling load has been utilized to indicate FDD. Earlier research utilized cooling load to diagnose and identify low delta-T syndrome in chilling systems [9], to lower air-handling unit energy use [10], and to recognize unusual building-level energy use [9]. Predicting

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building cooling loads seems to be essential for building demand-side management. Numerous investigations have examined the most economical demand response strategies (like load shifting), analyzing building-smart grid interactions [5]. Such analyses make the crucial premise that it is possible to employ accurate estimates of the profiles of the short-term cooling load of buildings.

The two primary short cooling load prediction approaches are based on physical models and data. Building thermal behaviors are defined by physical-model-based techniques using a wide range of information about the building, its systems, and physical principles. Typically, the resulting models are commonly known as white-box approaches. They could capture the real thermal answer of the structure to many influencing elements, including the indoor and outdoor environments. Nevertheless, it necessitates a substantial quantity of specific building information (such as data on the building envelope and the choice of building equipment). If certain physical principle assumptions are not achieved, the model's performance cannot be stable [10].

The alternative prediction techniques, or data-driven techniques, primarily rely on operational building data to determine the association between the structure's cooling load and pertinent variables (outdoor temperature, relative humidity, and indoor occupancy). Black-box and grey-box methods [11, 12] are used to describe these models. The modeling process seems more effective and adaptable when using data-driven methods, particularly black-box methods. Modern data analytics approaches, containing machine learning and artificial intelligence, allow data-driven methods to be very accurate and to find previously unknown but potentially essential connections. Two aspects primarily influence the data-driven models' performance: the prediction methods used in the model creation and the inputs to the model used. Earlier studies demonstrated prediction techniques from artificial intelligence and machine learning, including artificial neural networks [13, 14] and support vector regression [15, 16], which performed exceptionally well in estimating buildings' energy consumption. Diverse research has also displayed that nonlinear approaches, such as autoregressive moving averages and multiple linear regression [17, 18], may provide more precise findings than linear methods. Prior studies concentrated mainly on the knowledge of engineering or basic statistical models to establish model input characteristics or to detect the model's inputs. Engineering knowledge demonstrates that the cooling demand of a building is strongly connected to the exterior temperature and internal occupancy.

Consequently, the relative humidity, outdoor dry-bulb temperature, solar irradiance, and the indoor occupancy schedule were commonly used as the method's inputs [19, 20]. When assessing the building's thermal capacity, several researchers [17, 21] have employed historical data as model inputs. Employing original historical information as model inputs, including humidity and outdoor temperature at earlier time steps, is typically discouraged since it could significantly raise the input number of the model, making forecast methods more complex and costly. Feature derivation, which compresses crude data while maintaining information, may be utilized to create features as model inputs. Earlier research has identified three feature extraction approaches: statistical, engineering, and structural feature derivation [20-25]. Engineering attributes are built utilizing engineering expertise, such as data from the preceding hour as model inputs [21]. Summarizing statistics, such as the data's maximum, minimum, and mean amounts across a period, generate statistical features [20, 22-25].

Artificial intelligence (AI) methods are gaining popularity as a viable option to conventional methods, notably in the inverse simulating method. An artificial neural network (ANN) may be developed to adapt to a complex environment and could be employed to approximate any nonlinear system. ANNs obtain knowledge of the procedure of a complex system devoid of sophisticated rules and mathematical procedures [26]. Consequently, the ANNs unique characteristics, such as flexibility, nonlinearity, and the capacity to map arbitrary functions, make them appropriate for prediction functions among AI approaches such as expert systems, fuzzy logic, and genetic algorithms. Furthermore, ANN is an excellent candidate for occupancy data and equipment management in inherently noisy and incomplete buildings. In addition, ANN technology has been effectively used in various building services engineering domains [27-33]. In this article, the overall cooling load of residential buildings is simulated using two ANN models. The actual data from the air-conditioning system in the building and the hourly meteorological data acquired from Hong Kong Observatory are utilized as the input parameters of the models. In contrast, the entire cooling load of the building is chosen as the output.

2. Established database

According to Tsanas and Xifara's [34] work, we employed the database from https://cml.ics.uci.edu/ in our experiment. The dataset contains eight input factors (overall height, relative compactness, surface area, roof area, wall area, glazing area, orientation, and glazing area distribution of a green building) and one response parameter (cooling load (CL) of the proposed structure). The input parameters are X1, X2, ..., and X8 (Table 1). A graphical illustration of the data preparation process is presented in Figure 1. The Ecotect software simulated and analyzed 768 structures while considering 12 different building types, five distribution scenarios, four orientations, and four glazing zones [35]. Reference [34] discusses the major assumptions and aspects of the analyzed construction in depth.

Table 1. Input variables

	Input variables
X1	Relative Compactness (-)
X2	Surface Area (m^2)
X3	Wall Area (m^2)
X4	Roof Area (m^2)
X5	Overall height (m)
X6	Orientation (-)
X7	Glazing Area (m^2)
X8	Glazing Area Distribution

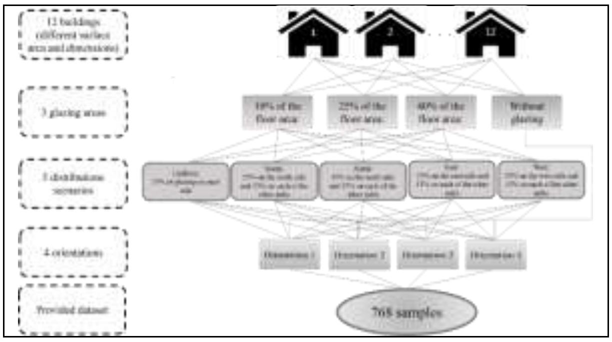


Figure 1: Graphical view of data preparation

3. Methodology

Due to two variables, this study used the GA and GWO models to develop the ANFIS model for calculating building cooling loads during the early design phase. First, they are the most effective and widely utilized strategies [36]. Second, they are possible models for solving nonlinear issues influenced by several factors. General building information is in detail in section 2 as inputs for the models used in this investigation. In this research, building cooling loads are the outputs of such models. The connection between the inputs and the output will be established using the GA-ANFIS and GWO-ANFIS models.

3.1. Adaptive Network Based Fuzzy Inference System (ANFIS):

ANFIS is a technique of artificial intelligence that handles very complicated and nonlinear problems. ANFIS efficiently resoles complicated and nonlinear issues in a single framework because it integrates with FIS and ANN. Accordingly, the ANFIS architecture employed in the investigation contains five layers and two inputs. The Takagi-Sugeno fuzzy system was used as FIS in this structure, it was determined that the FIS has two inputs (x1 and x2) and one output (F) to describe the ANFIS procedure. Generally, the fuzzy rules are expressed as follows [36]:

Rule 1:

$$\text{If } x_1 \text{ is } I_1 \text{ and } x_2 \text{ is } J_1 \text{ and etc.; then } F_1 = a_1x_1 + b_1x_2 + \cdots + r_1 \quad (1)$$

Rule 2:

$$\text{If } x_2 \text{ is } I_2 \text{ and } x_2 \text{ is } J_2 \text{ and etc.; then } F_2 = a_2x_1 + b_2x_2 + \cdots + r_2 \quad (2)$$

Where x_2 and x_1 are input variables. a_2; b_2; r_2; a_1; b_1; r_1 are the output parameters. I_2, I_1, J_2, J· are the inputs' MFs (x_2 and x_1). The ANFIS setup is based on a feedforward network including five levels and multiple functions. The function of every layer is described using equations (8)-(13). The membership connection between this layer's output and input functions of and input nodes in layer one is defined as:

$$F_{1.i} = \mu_{Ai}(I), \quad i = 1,2 \quad (3)$$

$$F_{1.i} = \mu_{Bi}(J), \quad i = 1,2 \quad (4)$$

The rule nodes or second layer's output is the outcome of the input signal, also referred to as:

$$F_{2.i} = W_i = \mu_i(I)\mu_i(J), \quad i = 1,2 \quad (5)$$

Where $\mu_i(J)$ and $\mu_i(I)$ represents the MFs. In 3rd layer, or the normalized layer, the function of weight is normalized as follows:

$$F_{3.i} = w = \frac{w_i}{w_1 + w_2}, \quad i = 1,2 \tag{6}$$

Sugeno fuzzy rule's function is multiplied with the preceding layer's output in 4th layer or subsequent nodes that is the defuzzy layer:

$$F_{4.i} = \overline{w}_i f_i = w_i(a_1 x + b_i x_2 + \cdots + r_i), \; i = 1,2 \tag{7}$$

All the outputs from the rules in the prior layer is calculated in a single-node output node (layer 5).

$$F_{5.i} = \sum_{i=1}^{n} \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{8}$$

3.2. Genetic Algorithm (GA)

A standard stochastic method for optimization, genetic algorithms (GA), is based on genetics and natural selection concepts. Since it applies probabilistic transition rules instead of deterministic ones, the GA seems capable of exploring expansive solution spaces. GA consists of three fundamental steps: (I) initialization of the population, (II) GA operators, and (III) evaluation [37].

I. Initialization of the population: The primary or initial population, including solutions from the initial candidate, is randomly generated. In GA, a set of variables presents each solution, referred to as a series. Such variables could be actual or binary in nature. The initial population of solutions should meet every limitation or criterion of the optimization issue.

II. GA operators

1. Selection: Comparable to Darwin's theory of natural selection, the selection operator selects persons or solutions, also known as parents, with a greater probability of survival. These are the solutions that exhibit excellent performance and high fitness levels. There are several selection methods, such as "Tournament," "Roulette Wheel," and "Elitist." The investigation combines Tournament and Elitist approaches. Following ranking all solutions based on their fitness values, a few solutions are passed immediately as elite solutions to the subsequent generation. At the same time, other people (randomly formed) will compete together.
2. Crossover: The operator switches two selected individuals to construct new ones for the next generation. The method of GA employs the distributed technique, in which a randomized string of double values is generated initially. Then, the genes filled out by one are picked out from the first parent, and the other genes are picked out from the other.
3. Mutation: The operator randomizes the information included in chromosomes or series. Genes often undergo mutations with a reasonable possibility of becoming new genes. Through mutation, it is feasible to alter the population's diversity and increase the capacity of the search plan to exclude the algorithm from converging to local optima.

III. Evaluation: The operator is concerned with individualization. Typically, an optimization issue's objective function is the fitness function.

3.3. Grey Wolf Optimization (GWO):

The GWO [38] seems to be another meta-heuristic algorithm built on grey wolf hunting treatment and natural social hierarchy [39]. Grey wolves live in packs that follow an exacting social dominating structure and mimic the headship hierarchy [40].

Grey wolves engage in different behaviors, notably hunting their prey. Figure 2 depicts the social dominating hierarchy of grey wolves, which consists of four forms: omega (ω) delta (δ), beta (β), and alpha (α). The α-wolves are the top-ranking decision-makers in the social order, and the other wolves obey them [41]. The β -wolves assist and organize the leaders. The δ-Wolves' position at the next level while obeying the α- and β-wolves. The ω-wolves must eventually submit to them all [40]. The GWO approach was created as a mathematical model for grey wolves. It uses an optimization procedure, which is comparable to other algorithms via the collecting of random solutions [42]. Particularlyα,β, δ, and ω represent the ideal, second optimal, and third optimal solutions, accordingly [43].

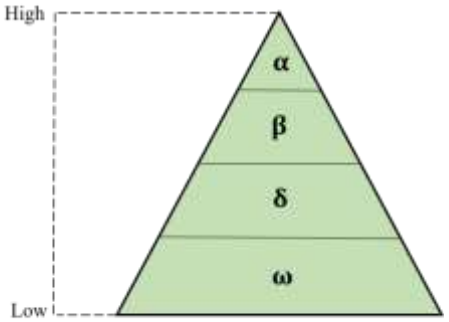


Figure 2: Grey wolves' social hierarchy

(1) Prey encircling

The initial hunting stage involves the grey wolves harassing and encircling their prey. The value of the *D* parameter, which quantifies the space between the grey wolf and the prey, appears as bellows:

$$D = \left|\vec{C} \cdot \vec{X}_P(t) - \vec{X}(t)\right| \tag{9}$$

When *t* denotes the current repetition, $\vec{X}$ and $\vec{X}_P$ signify the grey wolf and prey location vectors, correspondingly, and the coefficient's vector is determined by $\vec{C}$ is expressed as bellow:

$$\vec{C} = 2 \cdot \vec{r}_1 \tag{10}$$

r_1 stand as an accidental vector with amounts between 0 and 1. The location of prey could be expressed as bellow:

$$\vec{X}(t+1) = \vec{X}_P(t) - \vec{A} \cdot \vec{D} \tag{11}$$

The following formula is employed to calculate the coefficient $\vec{A}$'s value:

$$\vec{A} = 2a \cdot r_2 - a \tag{12}$$

Where *a* is a variable which is reducing linearly, and r_2 is a vector randomly chosen between [0, 1] as r_1.

(1) Hunting

Since α β and δ each contain compressive knowledge regarding the prey's position; they serve as the respective guides for the hunting behavior following the phase of encircling the prey.

$$\vec{D}_\alpha = \left|\vec{C}_1 \cdot \vec{X}_\alpha - \vec{X}\right|, \vec{D}_\beta = \left|\vec{C}_2 \cdot \vec{X}_\beta - \vec{X}\right|, \vec{D}_\delta = \left|\vec{C}_3 \cdot \vec{X}_\delta - \vec{X}\right| \tag{13}$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1 \cdot \vec{D}, \vec{X}_2 = \vec{X}_\beta - \vec{A}_2 \cdot \vec{D}, \vec{X}_3 = \vec{X}_\delta - \vec{A}_3 \cdot \vec{D} \tag{14}$$

Where $\vec{X}_1$, $\vec{X}_2$, and $\vec{X}_3$ signify the position vectors of α, β andδ. Coefficients$\vec{A}_1$, $\vec{A}_2$, $\vec{A}_3$ and $\vec{C}_1$, $\vec{C}_2$, and $\vec{C}_3$ could be calculated utilizing (11) and (12). The following could be used to update a grey wolf's position in the search area:

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{15}$$

Other wolves' positions are updated randomly based on the prey's position.

(1) Attacking prey (exploitation)

Once the prey has stopped moving, the hunt is ended. $\vec{A}$ is reduced linearly from 2 to 0 in mathematics. When $\left|\vec{A}\right| < 1$ and $\left|\vec{C}\right| < 1$, the exploration trend occurs. Meanwhile, the wolves are attacking the prey.

(2) Prey searching (exploration)

Grey wolves pursue and track their prey. In the GWO algorithm, the phase of pursuing prey is called exploration [44]. In such a process, the parametersα, β, and δ have the duty of assisting. If $\left|\vec{A}\right| > 1$, it indicates that grey wolves scatter and seek prey in various directions. They converge to assault [41] after discovering it. The coefficient $\vec{C}$ offers an accidental weight for the prey, whereas $\left|\vec{C}\right| > 1$ promotes exploration during discovery. The natural obstacles to grey wolf hunting are also modeled by $\vec{C}$ [45].

4. Results and Discussion:

Tables 2 and 3 highlight the forecasts performance of the two ANFIS models, comprising the GA-ANFIS and GWO-ANFIS methods, while applying the test data of building cooling loads. The fact that each model computes in less than 0.5 seconds demonstrates how effectively they predict building cooling loads. These tables' performance findings show that the GA-ANFIS model consistently outperforms the GWO-ANFIS model regarding prediction accuracy. In particular, the GA-ANFIS model's accuracy was 0.98 in R^2 and 0.09 in RMSE, compared to 0.95 and 0.15 for the GWO-ANFIS model.

4.1. Accuracy Indicators

Statistical measurements such as the linear correlation coefficient (R^2) and root-mean-square error (RMSE) are employed to assess the prediction effectiveness of ANFIS models. The range for RMSE and R^2 values is between 0 and 1. Conversely, an ANFIS model indicates improved performance with a higher R^2 and a lower RMSE. In this investigation, the performance of ANFIS models was evaluated utilizing the open-source WEKA data mining tool. Throughout the training and assessment processes, its parameters have defaulted to allow a proper comparison of prediction performance across ANFIS models. The correlation coefficient and root means squared error (RMSE) are two metrics (as described in Eqs. (16) and (17)) that are used to assess prediction performance (R^2).

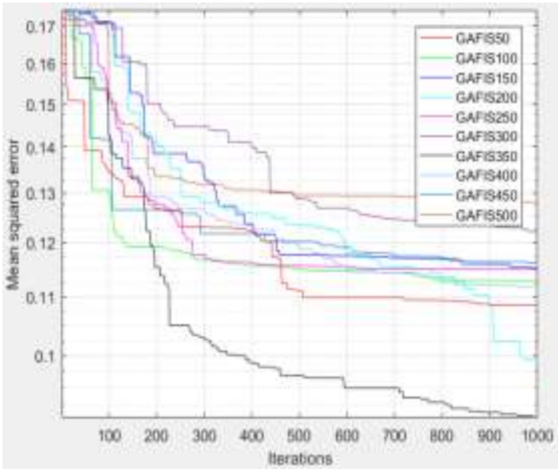
$$\text{RMSE} = \sqrt{\frac{1}{U}\sum_{i=1}^{U}[(S_{i_{observed}} - S_{i_{predicted}})]^2} \tag{16}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{U}(S_{i_{predicted}} - S_{i_{observed}})^2}{\sum_{i=1}^{U}(S_{i_{observed}} - \overline{S}_{observed})^2} \tag{17}$$

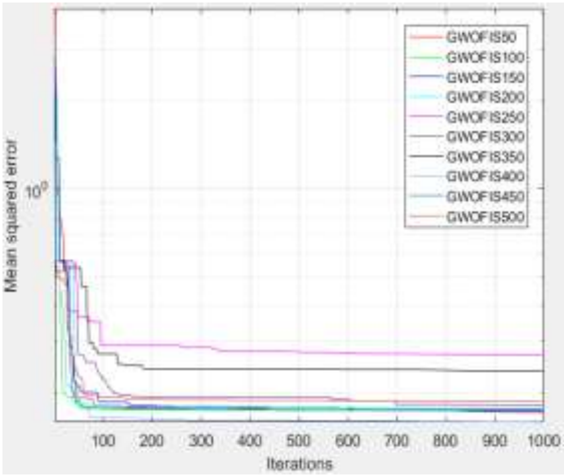
Where $S_{i\ observed}$, and $S_{i\ anticipated}$ representing the green residential building's actual and projected CL values, respectively. The variables U and $\overline{s}_{Observed}$ represent the total data and the mean of the actual CL amounts. Machine-learning approaches were developed in the Weka software environment using the enhanced data set. The outcomes of this process are offered in the following subsection.

4.2. Incorporated Optimizers and FIS

The GA and GWO were presented with the calculated ANFIS's mathematical equation as the primary problem. In this part, we will evaluate how the size of the train and test datasets was selected for the cross-validation process. The cross-validation process involves selecting random samples from the initial training and validation sets (80%) to generate a new training and validation set (20%) while leaving the testing set (20%) intact for utilization in analyzing the prediction performance of the various models. Population sizes 50, 100, 150, 200, 250, 300, 350, 400, 450, and 500 are selected for the new training and validation sets. Every network was created between 1000 repeats to provide sufficient possibility for minimizing the error. The described technique yields ten convergence curves, represented in Figure 3. The process of choosing the predictor variables and building the model remains the same; however, the new train and test sets are utilized separately to substitute the initial train and test set. Figure 3 displays the prediction effectiveness of models depending on MSE amount employing training set with different sample sizes. The figure indicates that the GA-ANFIS technique results the most precise outcomes due to its low MSE value.



(a)



(b)

Figure 3: Variation of mean squared error versus repetitions for (a) GAANFIS, (b) GWOANFIS

Tables 2 and 3 demonstrate the essential metrics of the GA-ANFIS and GWO-ANFIS models in forecasting CLs in buildings utilizing train and test stages using ten population sizes. Such models yielded consistent results, with R^2 amounts varying from 0.95 ~0.98 and RMSE amounts from 0.09 ~0.15. With R^2 of (0.98422 and 0.98339) and RMSE of (0.09056 and 0.09312) in the train and test phases, the optimal swarm size for GA-ANFIS is 350. With a population size of 400, the GWO-ANFIS approach seems to have the greatest R^2 (0.95148, 0.95191) and the smallest RMSE (0.15745, 0.15718) in the train and test stages. The findings indicate that the GA-ANFIS approach performs more effectively and makes more precise predictions when the R^2 and RMSE amounts are greater.

Table 2. The outcomes of the GAANFIS algorithm with various population sizes

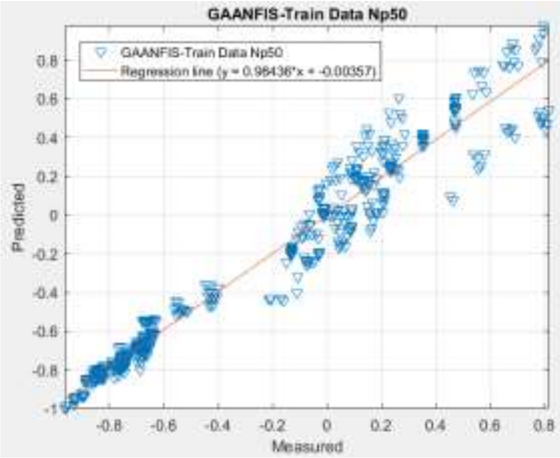
Swam size	Training dataset		Testing dataset		Scoring				Total Score	Rank
	RMSE	R^2	RMSE	R^2	Training		Testing			
50	0.10826	0.97736	0.10987	0.9768	8	8	8	8	32	3
100	0.11283	0.97538	0.11422	0.9749	6	6	6	6	24	4
150	0.11449	0.97465	0.12023	0.97215	5	5	4	4	18	7
200	0.09728	0.98176	0.09832	0.98147	9	9	9	9	36	2
250	0.11486	0.97448	0.11353	0.97521	4	4	7	7	22	6
300	0.12214	0.97109	0.12777	0.96849	2	2	2	2	8	9
350	0.09056	0.98422	0.09312	0.98339	10	10	10	10	40	1
400	0.11112	0.97613	0.11565	0.97426	7	7	5	5	24	4
450	0.11618	0.97388	0.12077	0.9719	3	3	3	3	12	8
500	0.12778	0.96832	0.13472	0.96491	1	1	1	1	4	10

Table 3. The outcomes of the GWOANFIS algorithm with various population sizes

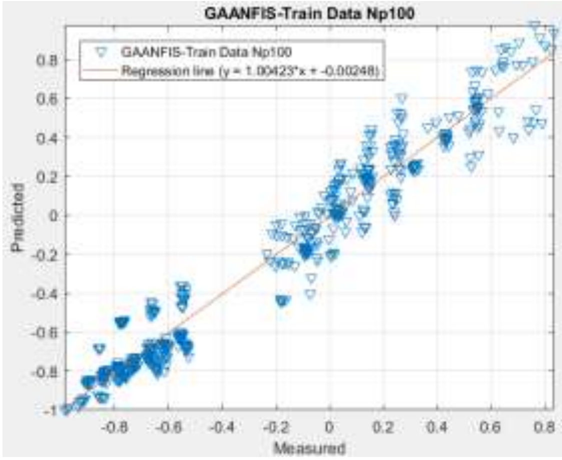
Swam size	Training dataset		Testing dataset		Scoring				Total Score	Rank
	RMSE	R^2	RMSE	R^2	Training		Testing			
50	0.1721	0.94174	0.16386	0.94762	9	9	9	9	36	2
100	0.17457	0.94	0.16469	0.94708	7	7	8	8	30	3
150	0.17395	0.94044	0.17312	0.94135	8	8	5	5	26	4
200	0.17739	0.93798	0.16682	0.94566	5	5	6	6	22	6
250	0.22984	0.89344	0.21392	0.90893	1	1	1	1	4	10
300	0.18165	0.93487	0.19128	0.9279	4	4	3	3	14	7
350	0.22094	0.90198	0.21032	0.91211	2	2	2	2	8	9
400	0.15745	0.95148	0.15718	0.95191	10	10	10	10	40	1
450	0.17568	0.93921	0.16567	0.94642	6	6	7	7	26	4
500	0.18771	0.93028	0.18336	0.93395	3	3	4	4	14	7

The actual and expected building CLs scatter plot generated from two ANFIS methods are displayed in Figures 4 and 5. Such figures suggest that the GA-ANFIS model had the most excellent correlation between projected and actual cooling load values. This is consistent with the model performance outcomes in Tables 2 and 3.

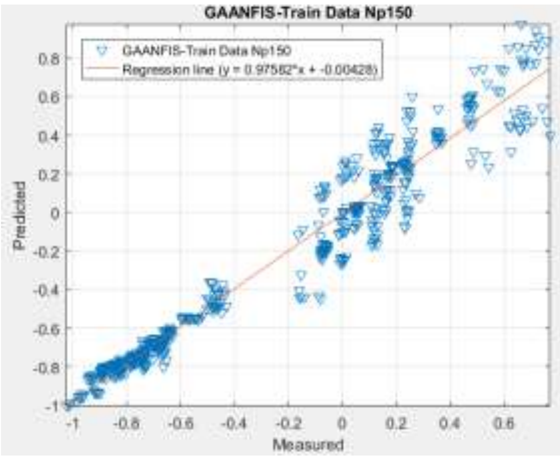
In this regard, as shown by the training R^2 values of 0.98422 and 0.95148the, GA-ANFIS achieved more precise prediction for unseen situations. The GA-mean ANFIS's absolute error was lowest at RMSE of 0.09056 and 0.15745. Additionally, the testing R^2 values (0.98339 and 0.95191) indicated greater consistency for the GA-ANFIS products.



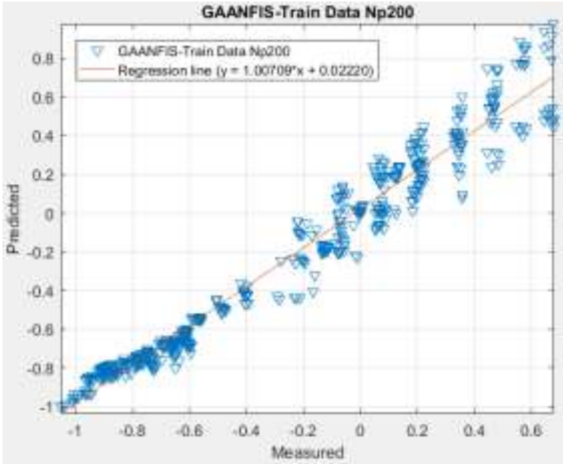
(a) GAANFIS train Np=50



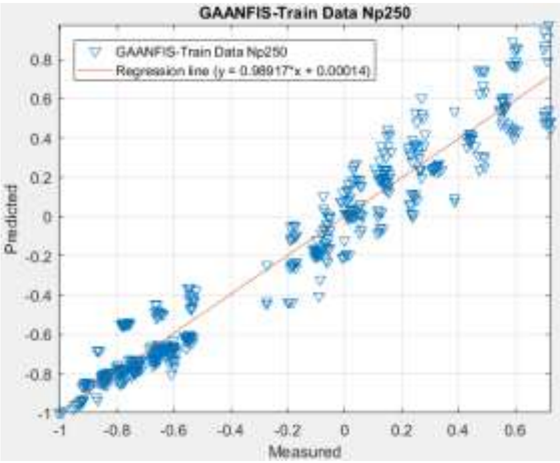
(b) GAANFIS train Np=100



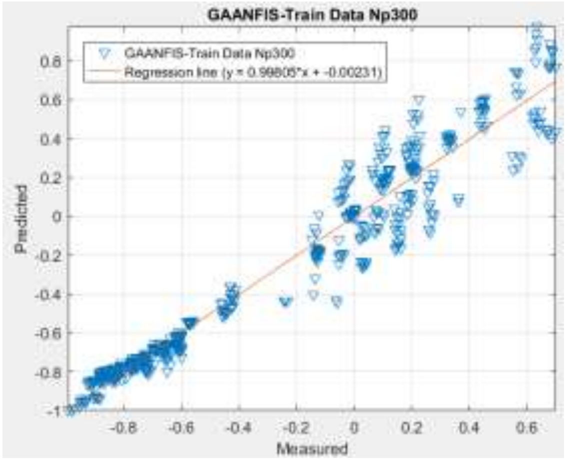
(c) GAANFIS train Np=150



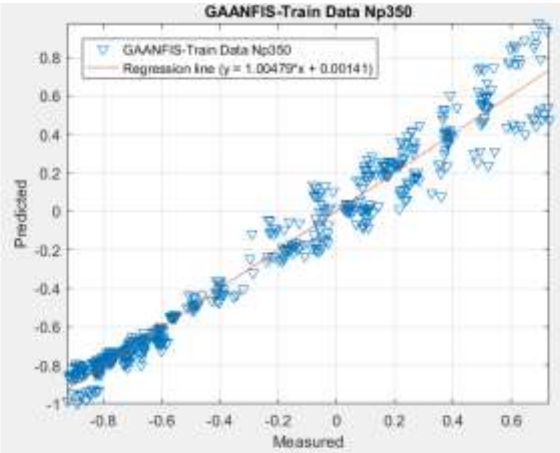
(d) GAANFIS train Np=200



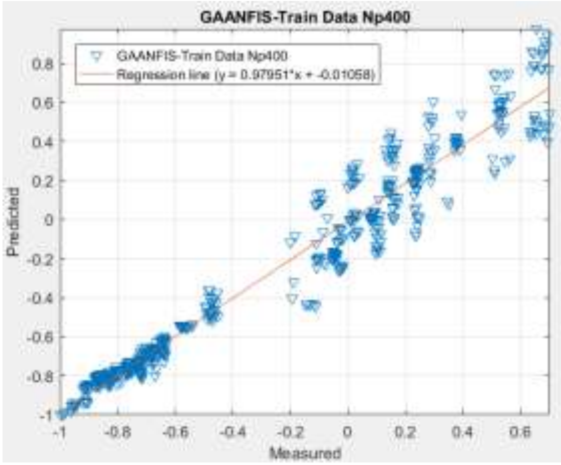
(e) GAANFIS train Np=250



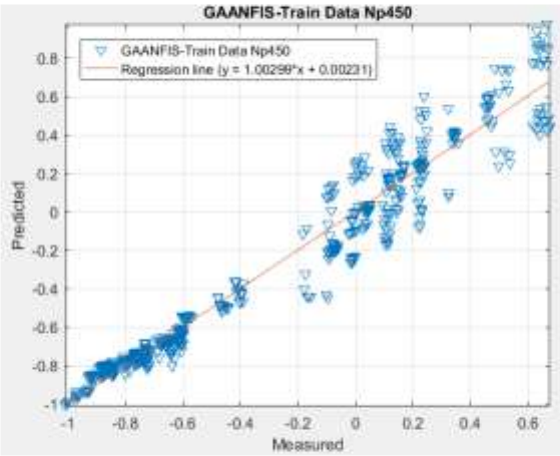
(f) GAANFIS train Np=300



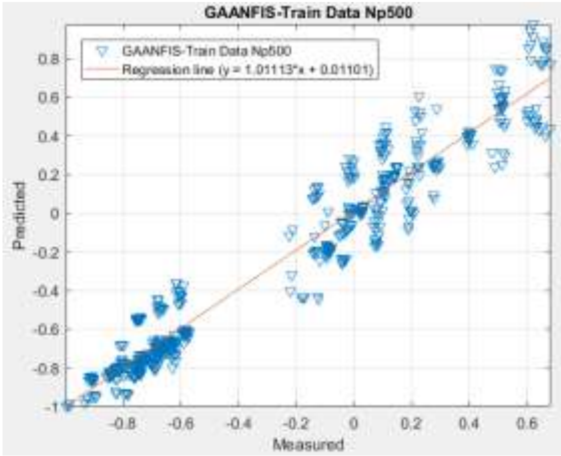
(g) GAANFIS train Np=350



(h) GAANFIS train Np=400

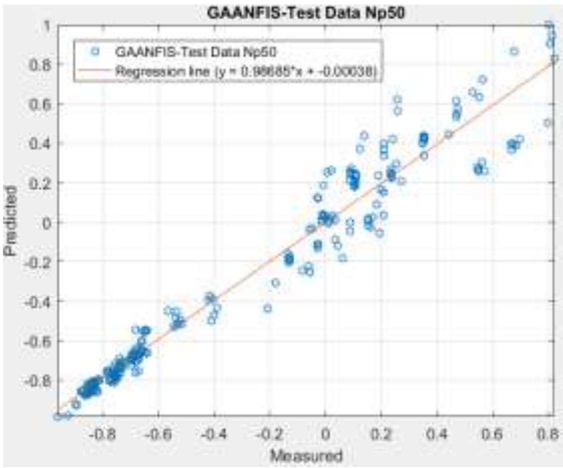


(i) GAANFIS train Np=450

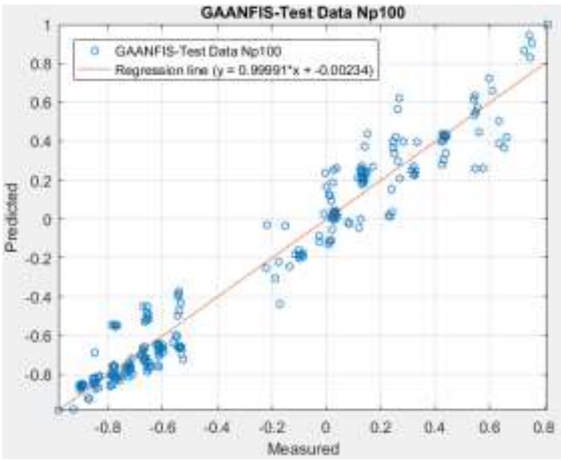


(j) GAANFIS train Np=500

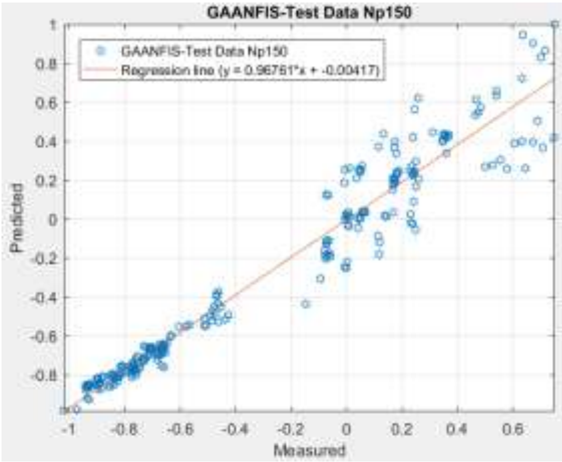
Figure 4: The training dataset accuracy of GAANFIS in the best fit structure of optimization



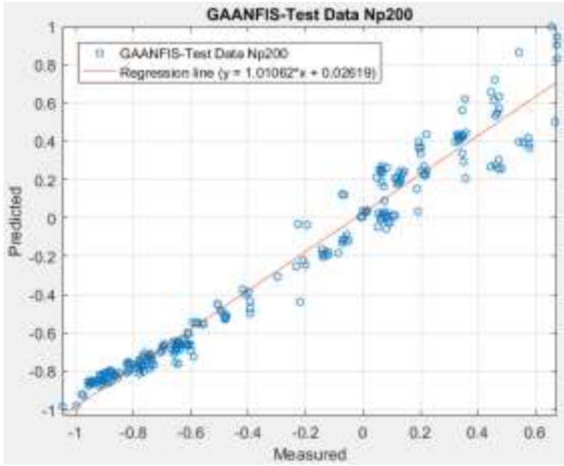
(a) GAANFIS test Np=50



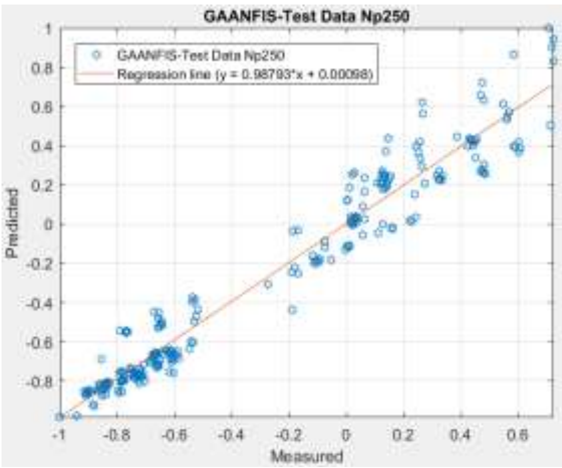
(b) GAANFIS test Np=100



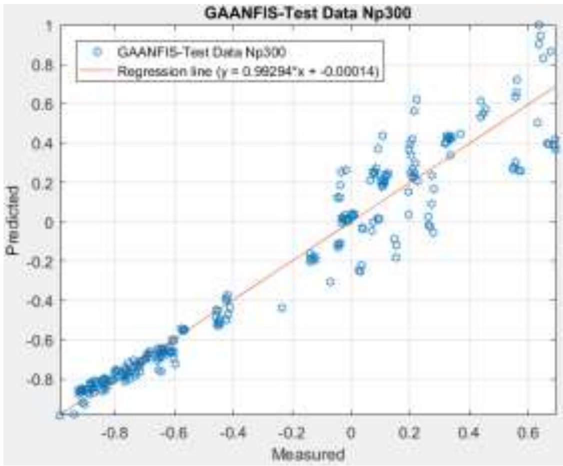
(c) GAANFIS test Np=150



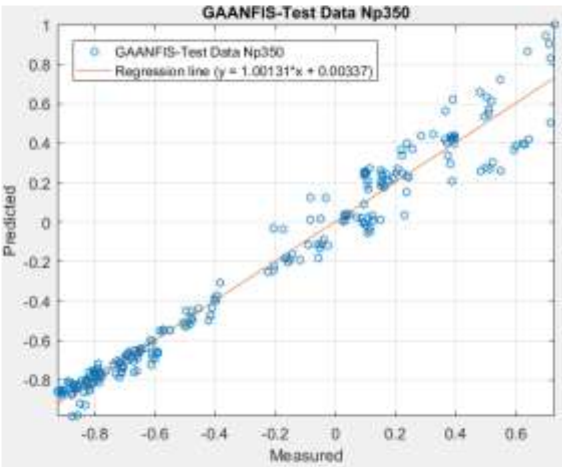
(d) GAANFIS test Np=200



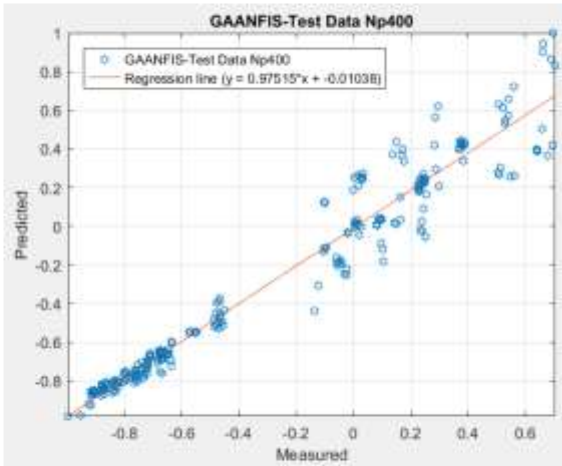
(e) GAANFIS test Np=250



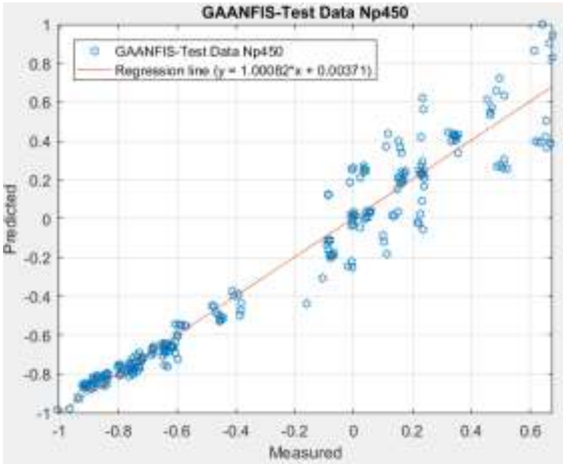
(f) GAANFIS test Np=300



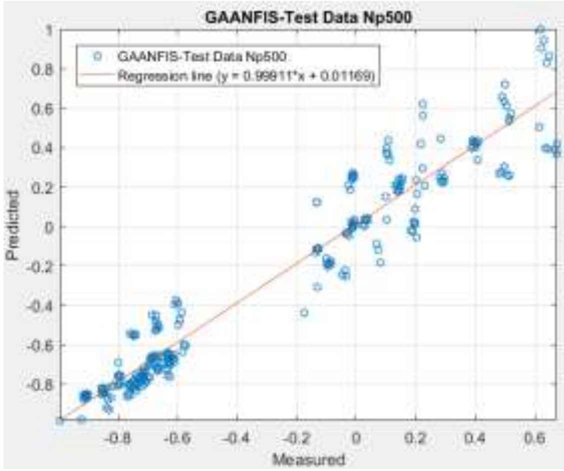
(g) GAANFIS test Np=350



(h) GAANFIS test Np=400



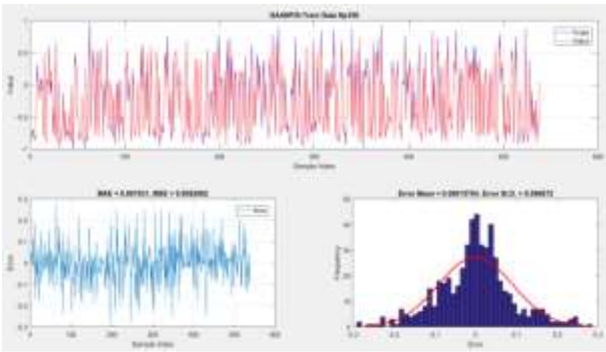
(i) GAANFIS test Np=450



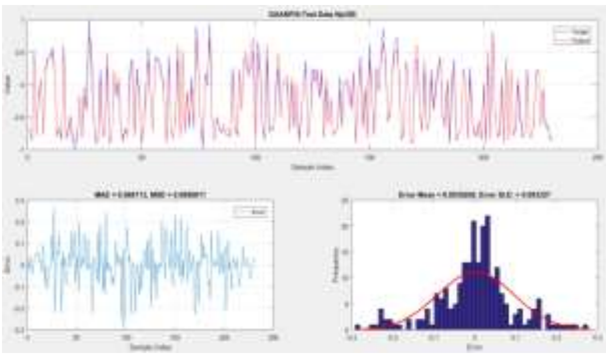
(j) GAANFIS test Np=500

Figure 5: The testing dataset accuracy of GAANFIS in the best-fit structure of optimization

The section evaluates the accuracy of the created methods by comparing the expected and absolute CL values. Two error criteria (MAE and MSE) were determined to quantify the performance error for the testing and training specimens. Figures 6 and 7 depict a graphical comparison of the CL's initial and expected patterns (for the training dataset). As can be noticed, the CL pattern was accurately approximated by both models. The MAEs (0.067031 and 0.11596) and computed training MSEs (0.0082062 and 0.025336 for the GA-ANFIS and GWO-ANFIS, correspondingly) demonstrate that the GA-ANFIS algorithm developed a more accurate understanding of the link between the CL and effective variables. The acquired R^2 values (0.98422 and 0.95148), which demonstrate a stronger correlation between the GA-ANFIS training outputs and real CLs, could be used to support the conclusion.

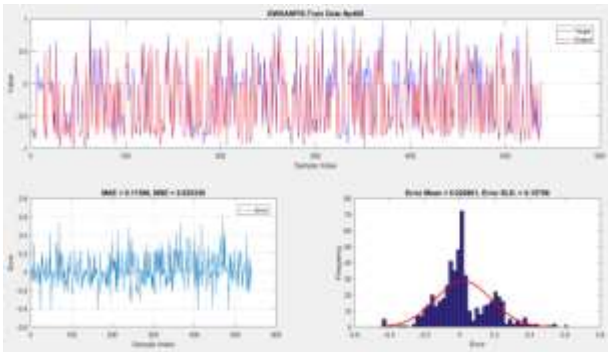


(a) Train database

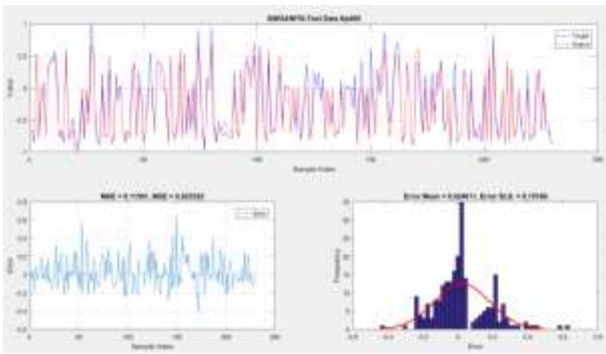


(b) Test database

Figure 6: Minimum values of errors and frequency in GAANFIS best fit structure



(a) Train database



(b) Test database

Figure 6: Minimum values of errors and frequency in GWOANFIS best-fit structure

5. Discussion

The ANFIS models have the benefit of being able to learn and model effectively nonlinear and complicated relationships, including the prediction of a building's cooling load. The ANFIS models possess a high potential for generalization (e.g., CLs in buildings) after learning the link between the inputs and the outputs. Two ANFIS models may have been trained and extensively assessed to estimate building cooling loads at the beginning of the design phase. It was verified that the GA-ANFIS approach is the most proposed precise ANFIS model. Between such two models, the GA-ANFIS model had the best correlation between actual and modeled values of CLs. The suggested ANFIS models show excellent agreement with the entire building energy simulation that is physics-based. Additionally, the computing time for ANFIS models is only a few seconds, whereas physics-based energy simulations for entire buildings can take hours or even a whole day to run. Consequently, the model bagging ANFIS method could be regarded as an alternate tool in the initial stages of design to increase the buildings' energy efficiency via a more excellent knowledge of the links between building energy performance and building features.

6. Conclusions

Scientists and professionals are embracing green building practices due to the popularity of energy-efficient building designs. Predicting building energy usage early in the design phase is crucial to providing architects with different design options. The research suggests a different strategy relying on ANFIS methods to predict building cooling loads. The forecast performance of ensemble and single ANFIS methods was generated and evaluated in this study using a dataset of 243 buildings. The analysis outcomes demonstrate that the GA model was the optimum ANFIS model. Significantly, the GA-ANFIS model had the greatest R^2 amount of 0.98 and the lowest RMSE amount of 0.09 among the two models examined in this research. The GWO-ANFIS approach achieved R^2 amounts of 0.95 and RMSE amounts of 0.15, suggesting that GA-ANFIS provides superior performance. The research explored using ML models for estimating building cooling loads as one of its contributions. The outcomes of this research offer designers a different approach to gaining accessibility to links between building cooling loads and building attributes to improve building energy efficiency. Future research might broaden the application of ANFIS models to include calibrating a building energy model to retrofit existing structures. Their parameter values determine the performance of ANFIS models. Determining the ideal values for these variables is a demanding and potential area of future researches that might modify the predictive accuracy of the ANFIS model.

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