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Artificial Neural Network for Predicting Heating Load in Energy-Efficient Buildings

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ABSTRACT Precise forecasting of building energy requirements is crucial for enhancing energy efficiency and facilitating sustainable architectural design. This paper develops a machine learning strategy to forecast the heating load (kWh/m²) of residential buildings using the well-known Energy Efficiency dataset, comprising 768 samples and eight input variables describing building geometry and design parameters. The dataset was randomly partitioned into training (80%) and testing (20%) subsets, including 614 and 156 samples, respectively. A feedforward Artificial Neural Network (ANN) with a single hidden layer was used to model the nonlinear relationship between input variables and heating demand. A parametric study was conducted to determine the optimal model structure by varying the number of hidden-layer neurons (HLNN = 5, 15, 25, and 35). The model's performance was assessed by the coefficient of determination (R^2), mean squared error (MSE), and mean error percentage (MEP). The findings demonstrate that the ANN model attained elevated prediction accuracy across all configurations. Optimal performance was achieved with HLNN set to 35, yielding R^2 values of 0.99795 for the training dataset and 0.99609 for the test dataset. The associated MSE values were 0.21457 and 0.36658, but the MEP values were 0.04618 and 0.32088. The close correlation between training and test outcomes indicates robust generalization without significant overfitting. These results validate that a basic ANN design may proficiently represent intricate nonlinear interactions in building energy systems. The proposed machine learning framework offers a precise, computationally efficient solution for predicting heating loads, aiding the design and optimization of energy-efficient buildings.

KEYWORDS
Heating load
ANN
Energy-efficient buildings
Feedforward neural network
Supervised learning

INTRODUCTION

Accurate prediction of heating and cooling demands in residential structures is essential for enhancing energy efficiency, minimizing carbon emissions, and promoting sustainable architecture practices. Buildings account for over 40% of global energy consumption, making precise forecasting of their thermal energy needs crucial for optimizing design parameters and reducing operational expenses (Bourdeau 2019). Conventional physics-based simulation tools, such as EnergyPlus, yield high-fidelity results but can entail significant computational effort and expense, limiting their applicability in preliminary design or real-time applications. In recent years, data-driven machine learning (ML) methodologies have emerged as effective alternatives, demonstrating significant proficiency in elucidating intricate nonlinear correlations among building geometry, envelope attributes, and energy demands (Zhang 2021).

Among numerous machine learning techniques, ANNs are widely used for their adaptability and superior predictive accuracy. Feedforward neural networks, especially multilayer perceptrons (MLPs) with a solitary hidden layer, have demonstrated exceptional efficacy in predicting heating load (HL) and cooling load (CL) utilizing building design variables (Chou and Bui 2014; Moayedi *et al.* 2019). The Energy Efficiency dataset, introduced by Tsanas and Xifara (2012), is a seminal addition to this domain. This benchmark dataset comprises 768 simulated residential building configurations characterized by eight input features, relative compactness, surface area, wall area, roof area, overall height, orientation, glazing area, and glazing area distribution, and two target outputs: heating load and cooling load (measured in kWh/m²). Researchers have extensively utilized the dataset to assess and compare machine learning models for predicting building energy performance. Subsequent research has investigated and improved ANN-based modeling on this dataset.

Chou and Bui (2014) conducted a comparison of ensemble inference models, support vector regression (SVR), and ANN versions, concluding that hybrid and intelligent methodologies substantially surpass conventional techniques in estimating heating and cooling loads. Moayedi *et al.* (2019) combined evolutionary optimization algorithms, including the genetic algorithm (GA) and imperialist competition algorithm (ICA), with artificial neural networks (ANN) to optimize network weights and biases, resulting in enhanced accuracy in high-level (HL) and classification (CL) predictions. Recent studies have concentrated on hybrid and optimal neural network topologies. Khastar (2025) introduced a multi-output radial basis function neural network (RBFNN) enhanced by the mountain gazelle optimizer (MGO), exhibiting enhanced efficacy in forecasting heating and cooling demands of energy-efficient structures.

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Chaganti (2022) examined extreme learning machines (ELM) in conjunction with ensemble approaches, revealing minimal mean absolute mistakes and substantial generalization capacity. Further breakthroughs encompass the use of deep learning and explainable AI methodologies. Mirindi (2026) compared traditional artificial neural networks (ANN) with convolutional neural networks (CNN), concluding that CNN models may attain R^2 values beyond 0.99 for both HL and CL, while demonstrating superior robustness to outliers. Abdel-Jaber (2024) conducted an extensive analysis of machine learning methodologies, emphasizing the advantages of artificial neural networks, support vector regression, and ensemble learners in predicting energy efficiency in residential buildings.

Additional significant contributions include multi-output modeling and feature optimization. Sajjad (2020) created multi-output neural network frameworks for concurrent prediction of HL and CL, whereas Ghasemkhani (2022) integrated feature selection metho, such as MRMR, with tri-layered neural networks to improve accuracy in IoT-enabled smart buildings. Gao (2024) investigated hybrid ANN-SVR methodologies for short-term load forecasting, whereas Aruta (2025) utilized ANN to predict thermal energy demand under prospective climate scenarios, employing envelope parameters and climatic stress indices. Review articles have consolidated these advancements and discerned patterns. Zhang (2021) performed a comprehensive survey on machine learning applications in building load prediction, highlighting the significance of data engineering, feature selection, and hybrid modeling. Ghasemkhani (2022) conducted a bibliometric analysis of works on ANN-based building energy, whereas Li (2025) examined data-driven methodologies for projecting HVAC energy use, encompassing statistical, machine learning, and deep learning techniques from 2019 to 2024. These works collectively demonstrate that even basic ANN architectures with a single hidden layer can proficiently describe the complex nonlinear relationships that govern building thermal loads when appropriately calibrated (e.g., by adjusting the number of hidden neurons). Elevated coefficients of determination (R^2 frequently exceeding 0.99) reduced MSE, and negligible mean error percentages (MEP) in both training and testing datasets signify robust generalization without considerable overfitting (Tien Bui *et al.* 2019; Moayedi *et al.* 2019; Khastar 2025).

This study advances the existing literature by developing a single-hidden-layer feedforward ANN to predict heating load using the Energy Efficiency dataset. A parametric study is performed by evaluating various numbers of hidden-layer neurons (5, 15, 25, and 35). Model performance is evaluated using R^2, MSE, and MEP metrics on randomly split training (80%) and testing (20%) subsets. The findings aim to demonstrate that a simple ANN configuration can achieve high predictive accuracy and computational efficiency, thereby providing a viable tool for the design and optimization of energy-efficient buildings.

DESCRIPTION OF INPUT VARIABLES AND HEATING LOAD

In building energy analysis, heating load is a vital performance metric that measures the energy required to maintain indoor thermal comfort amid fluctuating environmental and structural factors. The forecast of heating load is fundamentally reliant on a combination of geometric, physical, and operational elements that collectively characterize a building's energy dynamics. This study examines eight input variables to reflect these characteristics thoroughly: relative compactness, surface area, wall area, roof area, overall height, orientation, glazing area, and glazing area distribution.

Figure 1 demonstrates that these metrics signify the essential physical characteristics of the building envelope and its interaction with environmental variables. Relative compactness, the ratio of building volume to surface area, is crucial for assessing heat transfer efficiency. The surface, wall, and roof areas directly affect the extent of heat losses or gains through the building envelope. In contrast, the overall height correlates with interior air volume and stratification effects. Orientation, despite being dimensionless, dictates the exposure of building facades to solar radiation, thereby influencing passive heat gains. The glazing area and its distribution are crucial in controlling solar heat transmission and daylight infiltration, hence affecting thermal performance and occupant comfort.

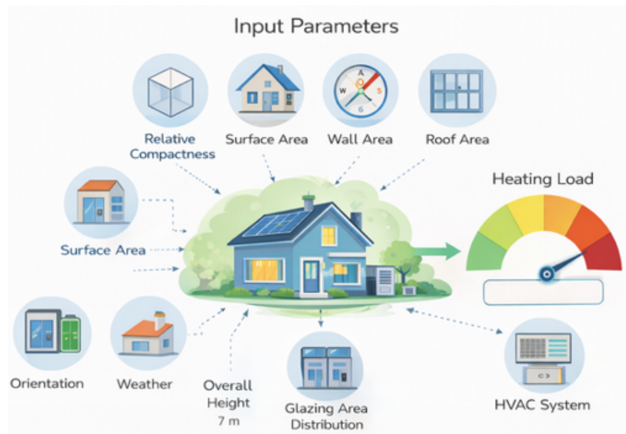

Figure 1 Input variables used for heating and cooling load prediction in energy-efficient buildings

From an energy-efficiency standpoint, these characteristics collectively determine the balance between heat losses and gains, making them crucial inputs for data-driven modeling techniques such as artificial neural networks (ANNs). Figure 1 illustrates the correlation between the input parameters and the heating load output, providing a physical depiction of the building's energy dynamics. By modeling the nonlinear interactions among these variables, ANN models can accurately predict heating load as the target output. In this setting, heating load functions as both a quantitative measure of energy consumption and a critical indication for assessing building design efficiency and sustainability. Precise modeling of this parameter facilitates the optimization of building layouts, diminishes energy use, and improves overall energy performance, which are fundamental goals in contemporary energy-efficient building design.

ANN MODEL USED IN THE STUDY

An ANN comprises numerous interconnected processing units functioning concurrently. Each unit comprises five primary components: input signals, corresponding weights, an aggregation process, an activation function, and the resultant output. Figure 2 depicts the structural representation of a standard processing unit.

In an ANN architecture, inputs denote the information provided to a processing unit, sourced from external entities or other associated units within the network. The impact of each input on the processing unit is determined by its corresponding weight, which reflects its relative importance. An aggregation technique is used to compute the unit's total input from these inputs. Various aggregation algorithms may be utilized, including summation, multiplication, maximum selection, or majority-based methods.

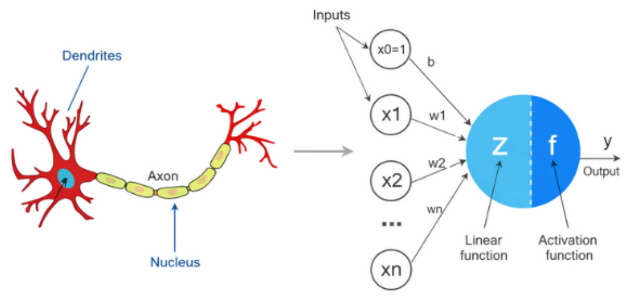

Figure 2 Structural representation of a standard processing unit

This study used a weighted aggregation approach, in which the net input is calculated by combining the magnitudes of the inputs and their associated weights, as shown in the Equation (Zadeh 1965):

$$\mathrm{NET} = \sum_{i=1}^{N} I_{p,i}\, w_i \tag{1}$$

Eq. (1), (Ip) denotes the input signals, whereas (w) signifies the corresponding weights. The symbol (N) represents the aggregate quantity of inputs received by a processing unit. The aggregated input, known as the net (NET) value, is subsequently transmitted to the activation function. This function converts the net input into the processing unit's output signal. Activation functions, akin to aggregation functions, can be characterized by several mathematical formulations. This study used a sigmoid activation function to construct the multilayer neural network model. The sigmoid function is both continuous and differentiable, and it may be articulated as follows:

$$F_o(\mathrm{NET}) = \frac{1}{1 + e^{-\mathrm{NET}}} \tag{2}$$

Figure 3 illustrates the architecture of the ANN model formulated in this study, comprising three principal layers: input, hidden, and output layers. The input layer comprises eight neurons that correspond to the building-related metrics included in the Energy Efficiency dataset: relative compactness (m^2), surface area (m^2), wall area (m^2), roof area(m^2), overall height(m), orientation, glazing area (m^2), and glazing area distribution. All input variables and the target heating load were normalized to the range of [0,1] using min–max normalization before training, and the predicted outputs were transformed back to their original scale using the inverse min–max transformation during testing.As the output parameter, heating load (kWh/m^2) was selected. The input variables are directly transmitted to the hidden layer without any manipulation or preparation. The hidden layer performs the network's fundamental computational function, in which nonlinear associations between input variables and the target output are learned via weighted connections and activation functions. This study examined a single hidden layer with varying numbers of neurons to identify the optimal arrangement. The output layer comprises a single neuron that signifies the anticipated heating demand. This multilayer ANN architecture enables the model to capture intricate nonlinear relationships within the dataset proficiently. The training procedure aims to reduce prediction errors via iterative optimization, thereby ensuring high accuracy, robustness, and dependable generalization performance of the generated model.

This study systematically varied the number of neurons in the hidden layer (HLNN) to 5, 15, 25, and 35 to determine the optimal

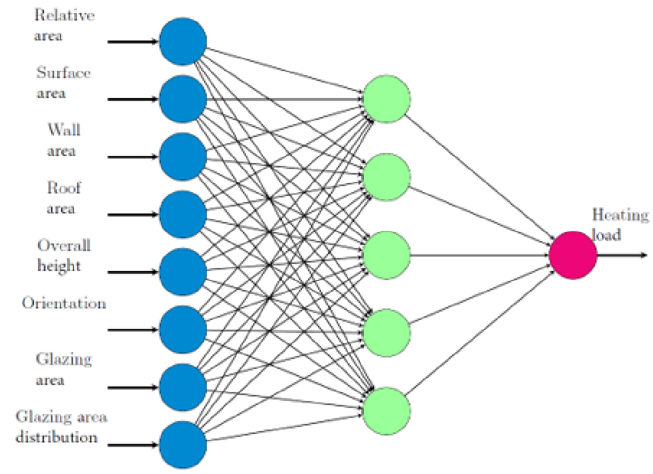

Figure 3 The architecture of the proposed artificial neural network (ANN) model. The network consists of eight input parameters (relative compactness, surface area, wall area, roof area, overall height, orientation, glazing area, and glazing area distribution), a hidden layer, and a single output neuron representing the heating load

network architecture. The hidden layer is essential for digesting input signals and relaying the discovered nonlinear properties to the output layer. The ANN model's performance was assessed by examining the impact of various HLNN settings, as depicted in Figure 2. The constructed neural network features a single output neuron representing the heating load, enabling the model to forecast the target variable directly from the input parameters. The network employs a supervised learning methodology to ascertain the correlation between input factors and heating demand from the dataset. The learning process relies on the Generalized Delta Rule (GDR), which encompasses two primary phases: forward propagation and backward propagation. During forward propagation, input values are passed to the hidden layer, as no computations occur at the input layer. The hidden layer subsequently analyzes the inputs using weighted connections and activation functions to produce the output. During backward propagation, the prediction error is propagated backward through the network to update the weights, thereby minimizing the overall error iteratively. The net input to the k-th neuron in the hidden layer is calculated as follows (Zhou *et al.* 2021):

$$NET_j^a = \sum_{k=1}^{N} G_{kj}\, O_k^i \tag{3}$$

$$G = \begin{bmatrix} g_{11} & g_{12} & g_{13} & \cdots & g_{1j} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ g_{k1} & g_{k2} & g_{k3} & \cdots & g_{kj} \end{bmatrix}, \qquad (k = 8,\ j = \mathrm{HLNN}) \tag{4}$$

In Equation (3), the connection weight between the kth neuron in the input layer and the jth neuron in the hidden layer is denoted as (Gkj), as elaborated in Equation (4). The jth neuron in the hidden layer processes the cumulative input using a sigmoid activation function. The output of this neuron is derived as a nonlinear transformation of its net input and can be articulated as follows:

$$I_j^a = \frac{1}{1+e^{-NET_j^a}} \tag{5}$$

The processing units in the hidden layer possess identical structural attributes to those in the output layer. In the output layer, each neuron computes its response by aggregating incoming signals to derive the net input, subsequently using the sigmoid activation function to produce the final output.

$$I_m = \frac{1}{1+e^{-NET_m}}, \tag{6a}$$

$$NET_m = \sum_{j=1}^{N} H_{jm} O_j. \tag{6b}$$

The connection weight linking the hidden layer to the output layer is represented by Hjm in Equation (6), with its formulation given in Equation (7).

$$H = \begin{bmatrix} h_{11} & h_{21} & h_{31} & \cdots & h_{j1} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ h_{k1} & h_{k2} & h_{k3} & \cdots & h_{kj} \end{bmatrix}, \qquad (k = 1,\ j = \text{HLNN}) \tag{7}$$

After an input pattern from the training dataset is presented to the network, the network generates an output and subsequently compares it with the expected output. The difference between these two values is defined as the error. The training of an ANN consists of repeatedly reducing this error for each training pattern. The error associated with the mth processing unit in the output layer is calculated using the following expression.

$$E_m = B_m - O_m, \qquad m = 1. \tag{8}$$

In Equation (8), B_m represents the target output corresponding to the m_{th} processing unit, whereas O_m denotes the output produced by the neural network for that unit. The difference between these two values defines the processing element's error. Error minimization is achieved by updating the connection weights between the input and hidden layers and between the hidden and output layers. The overall network error is evaluated using the mean squared error (MSE), while the coefficient of determination (R^2) and the mean error percentage (MEP) are computed as follows (Çelik *et al.* 2023; Koç 2022a,b; Koç and Şener 2021):

$$\text{MSE} = \frac{1}{N_p} \sum_{i=1}^{N_p} (y_i - y_k)^2, \tag{9a}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N_p} (y_i - y_k)^2}{\sum_{i=1}^{N_p} y_i^2}, \tag{9b}$$

$$\text{MEP} = \frac{100}{N_p} \sum_{i=1}^{N_p} \left(\frac{y_k - y_i}{y_k} \right), \tag{9c}$$

Equation (9) defines the variables used in the neural network training process. N_p represents the total number of patterns in the training set, y_i represents the output value produced by the neural network for the i_{th} instance in the training set, and y_k represents the actual value.

Training an ANN must be halted once the weights accurately represent the problem domain. This occurs because, if training persists after the weights have acquired the ability to accurately describe the issue space, subsequent modifications to the network weights may lead to decreased performance. Two algorithms are employed to determine the stopping point for training. Initially, the training process halts when the computed error values for all patterns in the training set drop below a predetermined threshold. In the second scenario, training is halted after a specific number of iterations. This necessitates conducting several trials to ascertain the optimal number of iterations. This study employs the second algorithm. While establishing the optimal number of repeats may be time-consuming, the outcome justified the exertion.

SIMULATION RESULTS

This section presents simulation results that comprehensively evaluate the learning behavior, convergence features, and predictive ability of the built ANN models for heating load estimation. The study systematically varies the number of hidden-layer neurons (HLNN) to examine the effects of model complexity on training efficiency and generalization. The findings are evaluated using various performance indicators, including the coefficient of determination (R^2), MSE, and MEP, thereby facilitating a comprehensive, multifaceted assessment of model accuracy. Special attention is given to understanding how increased network capacity affects convergence rate, error reduction, and stability throughout training.

The alignment between training and test results is rigorously analyzed to assess potential overfitting and ensure reliable performance on novel data. This analysis seeks to determine the ideal ANN configuration that balances predictive accuracy, computational efficiency, and model robustness, offering valuable insights for applying machine learning techniques to building energy prediction challenges. The DNN model was implemented using a custom code developed in the MATLAB environment. The network was trained for 5000 epochs with a learning rate of 0.5, and the initial weights were randomly assigned within the range of 0 to 1.

Figures 4 and 5 jointly depict the learning dynamics and predictive efficacy of ANN models with varying hidden-layer neuron counts (HLNN = 5, 15, 25, and 35). Figure 4 shows that all models exhibit a rapid increase in the coefficient of determination (R^2) during the initial training cycles, followed by gradual stabilization. This behavior implies proficient comprehension of the fundamental nonlinear correlations between input parameters and heating demand. Significantly, increasing the number of hidden neurons enhances both the convergence rate and the ultimate R^2 value, with the HLNN = 35 model achieving the best performance, approaching unity, indicative of exceptional model accuracy. Figure 5 corroborates these findings by illustrating fluctuations in MSE throughout training cycles.

All models exhibit a substantial reduction in MSE during the initial phases of training, indicating effective error minimization. Models with increased neuron counts converge more rapidly and have lower final error rates. The HLNN = 35 model achieves the lowest MSE, validating its enhanced predictive performance. The inset plot highlights the region of ultimate convergence, where discrepancies between models become increasingly evident, underscoring the superiority of higher-capacity networks in identifying intricate patterns. The correlation between the rising R^2 (Figure

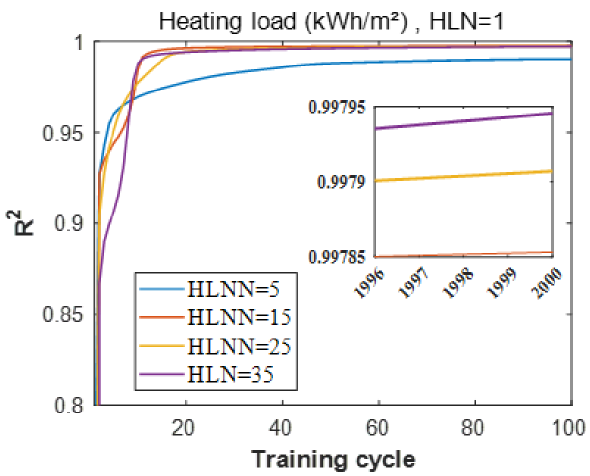

Figure 4 Performance curves of the ANN models during training, featuring varying quantities of hidden layer neurons (HLNN = 5, 15, 25, and 35). The figure illustrates the convergence characteristics of each model, as measured by the coefficient of determination (R^2), during training. As the number of hidden layer neurons increases, the models converge faster and achieve higher final accuracy

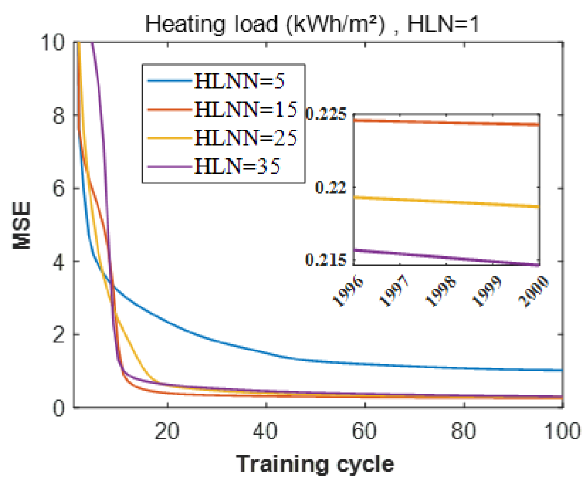

Figure 5 Variation of the mean squared error (MSE) during the training process for ANN models with different hidden layer neuron numbers (HLNN = 5, 15, 25, and 35). The results indicate that increasing the number of hidden layer neurons accelerates convergence and reduces the final training error, with the HLNN = 35 model achieving the best overall performance

3) and the declining MSE (Figure 4) validates the resilience and stability of the ANN models. The findings demonstrate that an optimal number of hidden neurons markedly improves model performance without causing instability, with HLNN = 35 offering the best balance between accuracy and learning efficiency.

Table 1 shows the training and test performance of ANN models with different numbers of hidden-layer neurons (HLNN). The findings demonstrate a distinct improvement in model performance with increasing HLNN, as evidenced by higher R^2 and lower MSE. The model with HLNN = 35 exhibits optimal performance across both datasets, with R^2 values of 0.99795 (training) and 0.99609 (testing), hence indicating robust predictive efficacy. The strong correlation between training and testing outcomes indicates effective generalization without overfitting. The declining trend in MSE corroborates the improved model accuracy with increased network capacity.

Figure 6 depicts the fluctuations in training error (E) for specific patterns in the training dataset as a function of training cycles. In the preliminary phases, error levels are comparatively high and widely dispersed, indicating inadequate understanding of the fundamental relationships. With an increase in training cycles, the error markedly diminishes, and the patterns become more uniform. This behavior illustrates that the ANN model incrementally learns and adjusts to the data architecture. The reduced error magnitude in subsequent phases indicates effective convergence and improved model performance on the training dataset.

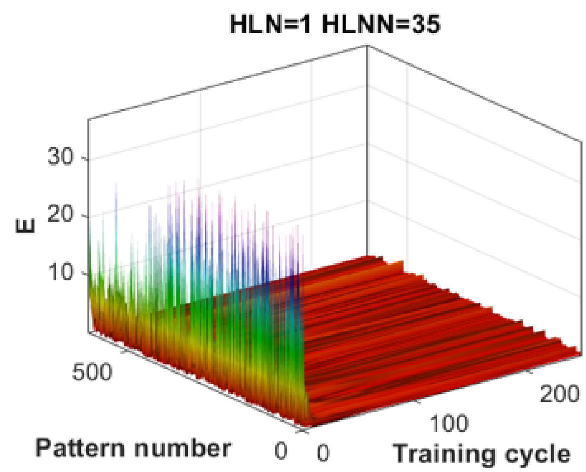

Figure 6 Evolution of the training error (*E*) for individual training patterns over successive training cycles using the ANN model with HLNN = 35. The error values are initially large and widely distributed across the training patterns but progressively decrease as training advances, demonstrating the network's learning capability and convergence toward the target outputs

Figures 7 and 8 depict the predictive performance of the ANN model at the optimal configuration (HLNN = 35) for the training and test datasets, respectively. Figure 7 shows that the projected values for the training set closely align with the experimental data, as evidenced by the strong coefficient of determination (R^2 = 0.99795) reported in Table 1. The error distribution is predominantly centered around zero, with the majority of percentage errors confined to a narrow range, indicating high precision and low variance.

Figure 8 illustrates the model's efficacy on the test dataset, with the ANN predictions showing strong agreement with the experimental results. The R^2 score of 0.99609 and the MSE of 0.36658 indicate that the model achieves high accuracy when evaluated on unseen data. The percentage error distribution is centered around zero, albeit with slightly greater dispersion than in the training set, as anticipated due to data unpredictability. The strong resemblance between training (R^2 = 0.99795, MSE = 0.21457) and testing (R^2 = 0.99609, MSE = 0.36658) outcomes demonstrates exceptional generalization without significant overfitting. The ANN model has strong, consistent, and exceptionally accurate prediction capabilities.

Table 1 Evaluating the training and testing efficacy of artificial neural network models with varying quantities of hidden layer neurons (HLNN = 5, 15, 25, and 35). The findings indicate that augmenting HLNN improves model performance, with HLNN = 35 achieving the highest R^2 and the lowest MSE in both the training and test datasets

Training performance				Testing performance			
HLNN	R^2	MSE	MEP	HLNN	R^2	MSE	MEP
5	0.99106	0.93385	0.13293	5	0.98960	0.97619	1.60522
15	0.99785	0.22425	-0.12260	15	0.99316	0.64167	1.07661
25	0.99791	0.21861	-0.12078	25	0.99403	0.56004	2.27797
35	**0.99795**	**0.21457**	**-0.04618**	**35**	**0.99609**	**0.36658**	**0.32088**

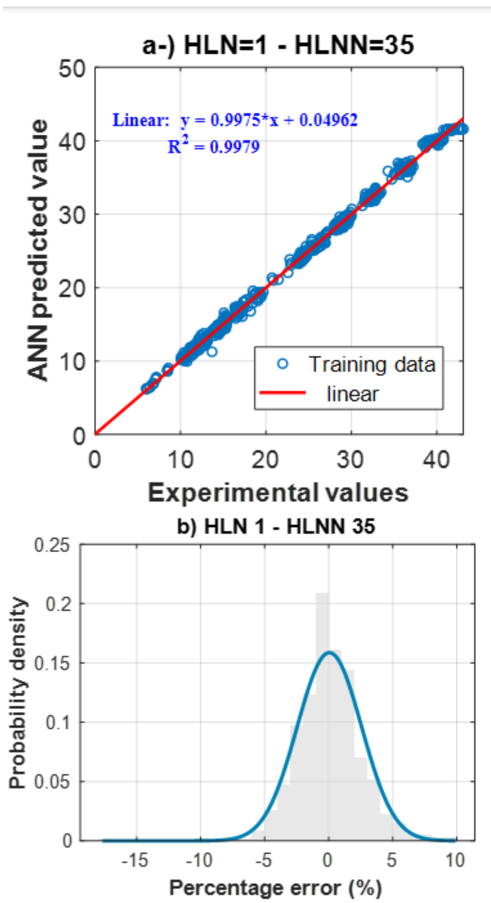

Figure 7 Comparison between the experimental and ANN-predicted heating load values for the training dataset using the optimal ANN model (HLNN = 35). The regression analysis ($R^2 = 0.9979$) and the probability density distribution of the percentage errors demonstrate excellent agreement between the predicted and measured values. The error distribution is centered near zero, indicating high prediction accuracy and reliability

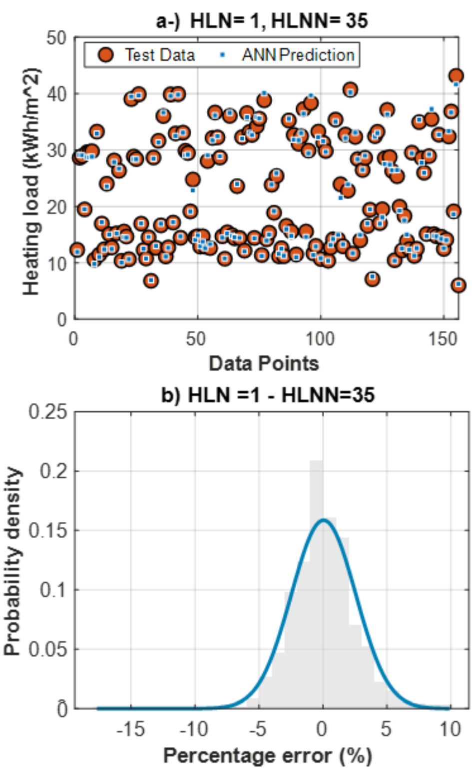

Figure 8 Performance evaluation of the optimal ANN model (HLNN = 35) using the testing dataset. (a) Comparison between the experimental and ANN-predicted heating load values, demonstrating excellent agreement. (b) Probability density distribution of the percentage errors, showing that the prediction errors are concentrated around zero, which confirms the model's strong generalization capability and predictive accuracy for unseen data

CONCLUSION

This study examined the predictive performance of a machine-learning-based ANN model for estimating the heating demand of residential structures. The study aims to develop an ideal network architecture by carefully examining various hidden-layer neuron numbers (HLNNs) to achieve high accuracy, stability, and generalization. The dataset consisted of 768 samples, which were divided into 614 samples (80%) for training and 156 samples (20%) for testing, thereby providing a robust framework for model evaluation. A parametric analysis was conducted using HLNN values of 5, 15, 25, and 35 to investigate the influence of network size on predictive performance. The results revealed a clear positive relationship between the number of hidden layer neurons and model efficacy, with the optimal configuration (HLNN = 35) achieving the highest predictive accuracy, as evidenced by R^2 values of 0.99795 for the training set and 0.99609 for the testing set.

Furthermore, the mean squared error (MSE) decreased substantially from 0.93385 to 0.21457 during training and from 0.97619 to 0.36658 during testing as the HLNN value increased. The close agreement between the training and testing results indicates that the developed ANN model generalized effectively without exhibiting signs of overfitting. Moreover, larger HLNN values accelerated the convergence process and reduced the final training error. The prediction error distributions were concentrated around zero, demonstrating high consistency and reliability of the model outputs. Despite its relatively simple architecture, the ANN model successfully captured the complex nonlinear relationships between building characteristics and heating demand. Overall, the findings indicate that a properly optimized shallow ANN architecture can achieve excellent predictive performance while maintaining a lower computational cost than more sophisticated deep learning models.

In summary, the suggested ANN-based architecture provides a reliable and effective approach for predicting heating loads. The results underscore the importance of model optimization and illustrate the practical utility of machine learning methods in the design of energy-efficient buildings. Subsequent research may enhance this methodology by integrating cooling load forecasting, hybrid modeling techniques, and empirical datasets. Despite the promising predictive performance achieved in this study, several limitations should be acknowledged. The proposed ANN model was developed and validated using a simulation-based dataset and did not explicitly incorporate climatic conditions or material-property variations. In addition, the model provides static heating-load predictions; therefore, future studies should investigate dynamic building behavior using experimental datasets and additional influencing parameters.

Availability of data and material

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of interest

The author declares that there is no conflict of interest regarding the publication of this paper.

Ethical standard

The author has no relevant financial or non-financial interests to disclose.

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