ANFIS-BASED PREDICTION OF HEATING AND COOLING LOADS IN RESIDENTIAL BUILDINGS

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Abstract. Accurate forecasting of energy consumption during the early design phases of buildings is crucial for optimizing energy performance, minimizing consumption, and reducing emissions. This study presents the development of an Adaptive Neuro-Fuzzy Inference System (ANFIS) model for estimating the heating and cooling energy loads of typical Algerian multifamily residential buildings. Using dynamic simulations in EnergyPlus, calibrated with real climatic data from Biskra (2003-2017), a dataset of 1200 cases was generated based on six key building envelope variables identified via sensitivity analysis. Two separate ANFIS models were trained and validated using 80/20 data splits and Gaussian membership functions. Results demonstrate high accuracy with R^2 values of 0.9 for cooling and 0.88 for heating loads. The proposed ANFIS models enable fast, early-stage evaluation of design alternatives without the need for complex simulations. These findings support architects and decision-makers in creating more energy-efficient building designs under hot and dry climate conditions typical of Algeria.

Key words: adaptive neuro-fuzzy inference system (ANFIS), building energy prediction, heating and cooling loads, sensitivity analysis, algerian climate conditions.

1. Introduction

In the early phases of building design, architects and engineers typically face limited information about how specific design parameters influence energy performance. This uncertainty is exacerbated by the sensitivity of many variables to climatic conditions. Making optimal early-stage decisions tailored to the local climate can substantially enhance energy efficiency, reduce consumption, and lower emissions (Ekici and Aksoy, 2011; Yıldız and Arsan, 2011). Accurate energy demand forecasting at this stage is therefore vital for effective planning and sustainable architecture (Asadi *et al*., 2014; Tabrizchi *et al*., 2019, Semahi *et al*., 2020).

Approaches for predicting building energy consumption are generally grouped into three categories: engineering-based (white-box), statistical (grey-box), and artificial intelligence (black-box) models (Zhao and Magoulès, 2012; Ahmad *et al*., 2014).

Engineering models apply thermodynamic laws to estimate energy use at both the whole-building and subsystem levels. These models are detailed and data-intensive, requiring a wide range of input parameters to function effectively (Amasyali and El-Gohary, 2018; Seyedzadeh *et al*., 2018; Tabrizchi *et al*., 2019). When inputs are missing or inaccurate, their predictive capacity diminishes.

Statistical methods, such as regression models, use historical data to establish correlations between energy use and influencing factors. While less data-intensive, these models are often less flexible and may not capture complex interactions between variables (Zhao and Magoulès, 2012).

Artificial intelligence (*AI*) techniques, which include learning, reasoning, and adaptation, offer enhanced capabilities for handling complex and nonlinear relationships in energy forecasting tasks (Amin, 2021; Alioua *et al*., 2024; Habal and Benbouras, 2025). Among these, Artificial Neural Networks (*ANNs*) are widely used due to their ability to approximate nonlinear systems effectively (Zhao and Magoulès, 2012; Ahmad *et al*., 2014; Wei *et al*., 2018).

ANNs simulate biological neural structures through layered networks—comprising input, hidden, and output layers. When provided with sufficient training data, *ANNs* adjust connection weights through iterative learning to minimize error and improve accuracy (Ahmad *et al*., 2014; Mlakić *et al*., 2016; Ascione *et al*., 2017; Brahma *et al*., 2025; Benbouras *et al*., 2023).

Among advanced *AI* models, the Adaptive Neuro-Fuzzy Inference System (ANFIS), proposed by Jang in 1993, stands out for its ability to integrate fuzzy logic with neural networks (Jang, 1993). *ANFIS* combines the learning strengths of *ANNs* with the linguistic rule-based reasoning of fuzzy systems. This hybrid approach is particularly effective in managing uncertainty and modeling nonlinear systems (Al-Ghandoor *et al*., 2012; Shamshirband *et al*., 2015; Naji *et al*., 2016; Mardani *et al*., 2019).

The main aim of this paper is to facilitate the estimation of building energy performance during the early design phase by examining the influence of building construction and design characteristics on heating and cooling loads under Algeria's arid climate through sensitivity analysis and by developing a high-performance predictive model using the Adaptive Neuro-Fuzzy Inference System (ANFIS) approach to estimate the heating and cooling energy loads of typical Algerian multifamily residential buildings.

The proposed ANFIS model exhibits high predictive accuracy, achieving coefficient of determination (R^2) values of 0.90 for cooling load and 0.88 for heating load, which demonstrate a strong agreement between predicted and actual building energy demands. By utilizing only passive design variables, the model enables rapid and accurate heating and cooling load estimations without the need for complex and time-consuming simulation procedures. Consequently, this tool offers practical utility for architects, energy consultants, and policymakers focused on energy-efficient residential building design in hot and arid climates. Its precise energy load forecasts facilitate optimal HVAC system sizing and operation, leading to improved occupant comfort and significant reductions in energy costs for households and communities. Moreover, by enhancing prediction accuracy, the model contributes to sustainability goals by potentially lowering total building energy consumption by 10% to 30% (Ma *et al*., 2025), thereby reducing associated carbon emissions.

The model developed in this study offers significant value to design teams by enabling evaluation of trade-offs related to building envelope characteristics during the early design stage, while also advancing academic research by introducing an approach that integrates the learning capabilities of neural networks with the interpretability of fuzzy logic. The methodology is further distinguished by its rigorous sensitivity analysis, which identifies the most influential envelope design variables and ensures the model's efficiency and physical interpretability.

To the best of our knowledge, this research is the first to develop and validate an Adaptive Neuro-Fuzzy Inference System (ANFIS) model for predicting the heating and cooling energy loads of residential buildings in Algeria, based on a calibrated dynamic simulation dataset. This study makes an important contribution to the existing literature by addressing a critical gap in energy efficiency research for the MENA region. To date, few studies have utilized machine learning techniques to predict residential heating and cooling loads for energy-efficient building design in this context (Al-Shargabi *et al*., 2022).

2. Related works

AI-based techniques, especially machine learning (ML) approaches, have attracted considerable interest in both research and professional communities for predicting building energy consumption (Sundaram *et al*., 2024; Khastar *et al*., 2025; Ji *et al*., 2025). Unlike physical models, which require detailed, building-specific data for simulations, ML methods can generate accurate predictions by leveraging historical data (Khalil *et al*., 2022; Afzal *et al*., 2024). ML techniques are particularly effective at capturing complex and nonlinear relationships between building design parameters and energy performance, as they can identify hidden patterns within the data (Villano *et al*., 2024; Chen *et al*., 2025). In recent years, a variety of ML algorithms have been widely applied to predict building energy efficiency with high accuracy, including Artificial Neural Networks (ANN) (Fouladfar *et al*., 2023), Support Vector Machines (SVM) (El Mghouchi and Udristioiu, 2025), Random Forest (RF) (Chaganti *et al*., 2022; Hussien *et al*., 2023), and Extreme Gradient Boosting (XGBoost) (Riyadh Baqer and Rashidi-Khazaee, 2025).

Conversely, while fuzzy logic has proven highly effective in control systems and decision-making applications, its adoption for building energy performance estimation has been relatively limited (Nebot and Mugica, 2020). This disparity highlights a critical research gap that may be addressed by hybrid approaches combining the strengths of both paradigms. Adaptive Neuro-Fuzzy Inference Systems (ANFIS) have emerged as a particularly promising solution, as evidenced by several applications in the field of energy forecasting. For example, Ekici and Aksoy (2011) developed an ANFIS model to predict energy demand in cold-climate regions of Turkey. Aramesh *et al*. (2014) proposed a fuzzy-neural approach for estimating natural gas transmission in city gate stations. Other studies applied ANFIS to optimize air conditioning systems and reduce energy use (Costa and La Neve, 2015), or addressed energy consumption modeling based on temperature variations and thermal building parameters (Mlakić *et al*., 2016; Naji *et al*., 2016). Chen and Lee (2019) utilized weather-based ANFIS models for electricity use forecasting in public buildings, while Jallal *et al*. (2020) applied a hybrid neuro-fuzzy system for hourly energy demand forecasting in educational facilities.

Several studies have compared the predictive accuracy of ANFIS with other machine learning models. For instance, Deb *et al*. (2015), Aldin and Sözer (2022), and Khaligh Fard *et al*. (2023) conducted comparative analyses of ANN and ANFIS in forecasting energy usage in institutional buildings in Singapore, assessing short-term heating performance, and modeling residential energy consumption, respectively. Similarly, Panagiotou and Dounis (2022) evaluated the predictive performance of ANN, ANFIS, and LSTM models in the context of hospital building energy consumption.

To enhance predictive accuracy, some studies have integrated ANFIS models with metaheuristic optimization algorithms, such as Genetic Algorithms (GA) (K. Li *et al*., 2011; Oladipo and Sun, 2023), Particle Swarm Optimization (PSO) (Oladipo *et al*., 2023; 2024), the Reptile Search Algorithm (RSA), and the Flow Direction Algorithm (FDA) (Seyed Hatami and Seifi Majdar, 2025). Beyond metaheuristics, researchers have also applied supplementary techniques to boost ANFIS performance; Nilashi *et al*. (2017), for example, combined Principal Component Analysis (PCA) for dimensionality reduction and Expectation-Maximization (EM) for data imputation within the ANFIS framework, thereby improving the accuracy of heating and cooling load predictions.

Given its demonstrated potential, this study investigates the application of ANFIS for predicting building heating and cooling loads. Previous research has established that ANFIS significantly enhances energy efficiency assessments by combining the neural network's learning capacity with the interpretability of fuzzy logic. This hybrid methodology enables precise modeling of the nonlinear relationships inherent in building energy consumption data, which is critically important for energy performance analysis during building design (Tan et al., 2017; Shahsavari-Pour *et al*., 2025). Furthermore, ANFIS demonstrates robust capability in managing the uncertainties present in real-world building energy data—including variable occupancy, weather, and equipment performance (Khaligh Fard *et al*., 2023; Oladipo *et al*., 2024). By automatically extracting optimal "if-then" fuzzy rules and membership functions from data, ANFIS reduces reliance on expert knowledge while emulating human reasoning processes in building design, resulting in more adaptive, nuanced, and reliable energy predictions (Cao *et al*., 2021).

Within the Algerian context, building energy forecasting research has primarily focused on macro-level analyses. For instance, Ouahab (2015) and Ghedamsi *et al*. (2016) used bottom-up statistical models to project national residential energy consumption and related emissions through 2040–2050, but did not employ simulation-based, building-level modeling. Some initiatives have explored AI techniques for Algerian buildings, such as Bouabaz *et al*. (2015), who applied ANN to predict energy use in rehabilitated residential buildings, and Mordjaoui *et al*. (2017), who implemented dynamic neural networks to forecast daily household electricity loads. Bouziane and Khadir (2020) used agent-based modeling coupled with ANN to estimate CO_2 emissions in Annaba, while Boukarta (2021) and Soufiane and Nia (2023) predicted energy demand in residential buildings using linear regression and ANN, respectively.

Despite these efforts, Algerian literature lacks studies that directly relate building envelope characteristics to energy loads using AI, and particularly the ANFIS approach. Notably, none have reported using simulation data from calibrated building models. The present study addresses this gap by applying ANFIS modeling to predict space conditioning loads based on passive design factors, utilizing a calibrated building energy simulation dataset generated with EnergyPlus and local weather data to ensure regional accuracy. The dataset in this study comprises the six most influential building design variables, identified through sensitivity analysis from an initial set of twenty variables. Unlike most prior studies, which utilize the dataset by Tsanas and Xifara (2012), this refined variable selection improves the robustness of load prediction. This paper thus makes a significant contribution to energy efficiency research in the Middle East and North Africa (MENA) region, where the application of ML for building energy prediction—particularly in forecasting residential heating and cooling loads—remains limited (Al-Shargabi *et al*., 2022; Qavidel Fard *et al*., 2022). Given the region's extreme climatic conditions and increasing energy demands, advancing ML applications in this domain is essential for optimizing sustainable building performance.

3. Data and methodology

This research is centred on developing a predictive model to estimate heating and cooling energy loads in residential buildings at the early design stage under Algerian climatic conditions. The methodology integrates artificial intelligence—specifically the Adaptive Neuro-Fuzzy Inference System (*ANFIS*)—to model the relationship between building design inputs and energy demand outputs. The methodology consists of two main stages, as illustrated in Fig. 1. Each stage is comprised of several sequential steps, which are explained in detail in the following subsections to provide a comprehensive understanding of the overall research process.

3.1. Dataset creation

The datasets used in this study were generated through dynamic simulations of heating and cooling energy demands using a calibrated building model in EnergyPlus. Before dataset creation, a sensitivity analysis was performed to identify the most influential building design parameters among the twenty (20) initially selected variables. The analysis revealed that only six (6) variables had a significant impact on energy consumption. Using these key parameters, 1200 Latin Hypercube Sampling (LHS) samples were generated by varying the selected variables within their defined ranges. The simulations were executed automatically via jEPlus software, which enables automated parametric runs. A detailed description of the dataset creation steps is provided in the following.

3.1.1. Reference building model creation

The selected prototype for this study is a representative multifamily social residential building, a typology commonly found across Algeria. The thermophysical properties of the building elements, construction details, and geometric design of the representative dwelling are presented in (Semahi *et al*., 2019). The energy performance modeling was carried out using EnergyPlus version 9.1, with calibration based on actual operational data. This calibration utilized both hourly and monthly datasets, including indoor temperatures during summer and winter, as well as gas and electricity consumption records, to ensure the model's accuracy.

Simulations were performed for the climatic conditions of Biskra, a city located in southeastern Algeria. According to the Köppen-Geiger classification system (Beck *et al*., 2018), Biskra is characterized by a hot desert climate (*BWh*), typified by large temperature fluctuations between day and night and across seasons. In national terms, the city falls under climate zone *D* as defined by Algerian Standart, denoting arid conditions.

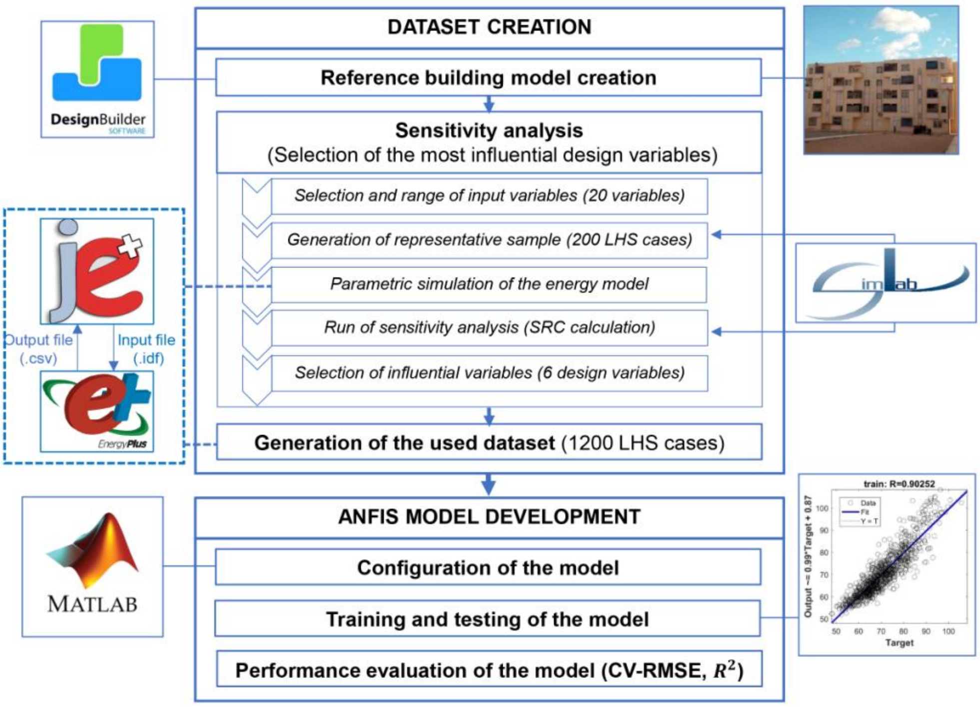


Fig. 1. Research methodology framework

To capture realistic weather conditions, this research utilized the latest version of the Typical Meteorological Year (*TMY*) weather file for Biskra. This dataset spans from 2004 to 2018 and was sourced from the U.S. Department of Energy's open-access climate database. The *TMY* dataset ensures that the simulated energy loads accurately reflect long-term climatic trends in the region.

3.1.2. Sensitivity analysis

A sensitivity analysis was carried out to determine the design variables that most significantly impact the annual energy demands for heating, cooling, and their combined totals. The main goal of this analysis was to streamline the input variables for the ANFIS model, improving both accuracy and computational efficiency. The methodology was structured into five main steps: (1) selection of input variables and corresponding output metrics, (2) creation of a representative sample from the input distributions, (3) simulation of the energy model for each scenario in the sample, (4) execution of the sensitivity analysis, and (5) identification of the most influential design variables. This approach aligns with widely accepted practices in the building performance simulation field, as outlined by (Tian, 2013) The same steps were followed by (Breesch and Janssens, 2010; Yıldız and Arsan, 2011; Rodríguez *et al*., 2013; Song Yanga *et al*., 2016; Gou *et al*., 2018; Mahar *et al*., 2020).

3.1.2.1. Selection of input and output variables

For this analysis, a total of 20 design variables were selected. These variables represent critical decisions made during the early stages of design and fall into three major categories: building orientation, characteristics of the opaque envelope, and elements associated with transparent surfaces and shading. Collectively denoted by the vector X, these inputs are summarized in Table 1, which provides their respective distribution types and permissible ranges. The upper and lower bounds for these variables are defined according to the Algerian thermal building code named D.T.R C3-2, to reflect actual construction practices in Algeria.

The sensitivity analysis considered annual heating, cooling, and total energy demands as output metrics, aiming to identify the variables with the most significant impact on these outputs.

3.1.2.2. Generation of representative sample

To represent the diverse design possibilities, Latin Hypercube Sampling (LHS) was applied to the 20 selected variables. This approach enabled the reduction of the massive potential combination space (1.19×10^{18}) to a manageable set of 200 representative scenarios, adhering to best-practice guidelines for regression-based global sensitivity analysis (Loeppky *et al*., 2009; Helton and Davis, 2003; Tian, 2013).

To conduct the sensitivity analysis, a sample of 200 cases was generated using the Latin Hypercube Sampling (LHS) method. This sample size follows the guidance of Loeppky *et al*. (2009), who recommend using a number of samples equivalent to ten times the number of design variables. Previous research has demonstrated that even smaller sample sizes, such as 100 LHS samples, can yield stable estimations and substantially reduce deviation from reference solutions (Helton and Davis, 2003; Helton *et al*., 2005; Janssen, 2013). Moreover, Rodríguez *et al*. (2013) found that a sample size of 200 is sufficient to produce robust and consistent results for annual energy consumption. Accordingly, selecting 200 samples in this study ensures a reliable and accurate sensitivity analysis.

Table 1. Input variables and their ranges for sensitivity analysis.

Design variables	Options Unit	Variables number	Variables type	Lower and upper bounds of variables
Building orientation	(°)	X_1	Continuous uniform	[0,345]
Block thickness for the external walls	(m)	X_2	Continuous uniform	[0.075, 0.25]
Block thickness for the floor	(m)	X_3	Continuous uniform	[0.12, 0.25]
Block thickness for the roof	(m)	X_4	Continuous uniform	[0.12, 0.25]
Block thermal conductivity / density of the external wall	(W/m-K) (Kg/m³)	X_5	Discrete	[0.33, 1.75] (750, 2500)
Block thermal conductivity / density of the floor	(W/m-K) (Kg/m³)	X_6	Discrete	[0.23, 1.75] (830, 2500)
Block thermal conductivity / density of the roof	(W/m-K) (Kg/m³)	X_7	Discrete	[0.23, 1.75] (830, 2500)
Insulation thickness of external wall	(m)	X_8	Continuous uniform	[0, 0.09]
Insulation thickness of the floor	(m)	X_9	Continuous uniform	[0, 0.09]
Insulation thickness of the roof	(m)	X_{10}	Continuous uniform	[0, 0.09]
Insulation type of external wall (thermal conductivity)	(W/m-K)	X_{11}	Discrete	[0.031, 0.047]
Insulation type of the floor (thermal conductivity)	(W/m-K)	X_{12}	Discrete	[0.031, 0.047]
Insulation type of the roof (thermal conductivity)	(W/m-K)	X_{13}	Discrete	[0.031, 0.047]
Solar absorptance of the external walls	(-)	X_{14}	Continuous uniform	[0.1,0.9]
Solar absorptance of the roof	(-)	X_{15}	Continuous uniform	[0.1,0.9]
Living room window to wall ratio	(%)	X_{16}	Continuous uniform	[10,60]
Bedroom window to wall ratio	(%)	X_{17}	Continuous uniform	[10,60]
Window type (Window U value)	(W/m²K)	X_{18}	Discrete	[0.78, 5.89]
Living room overhang depth to window height ratio	(-)	X_{19}	Continuous uniform	[0,1]
Bedroom overhang depth to window height ratio	(-)	X_{20}	Continuous uniform	[0,1]

3.1.2.3. Simulation of the energy model

The generated sample of 200 cases obtained via Latin Hypercube Sampling (LHS) was simulated using EnergyPlus version 9.1.0, integrated with the jEPlus v2.0 platform (Zhang, 2009), a parametric analysis tool that automates the systematic variation of input parameters in building simulation models. jEPlus facilitates the execution of multiple EnergyPlus simulations by efficiently modifying design variables across cases (H. Li et al., 2018). For each sampled case, annual heating, cooling, and total energy loads were computed. The resulting simulation outputs were then compiled to conduct the subsequent sensitivity analysis.

3.1.2.4. Selection of sensitivity analysis approach

In the domain of building energy performance analysis, sensitivity analysis techniques are generally categorized into local and global methods (Tian, 2013; Osterg *et al*., 2016; Delgarm *et al*., 2018). Local methods, such as the One-At-a-Time (OAT) approach, isolate the effect of a single input variable by varying it while keeping all other variables constant. This approach assumes a linear relationship between inputs and outputs and does not account for correlations among variables (Heiselberg *et al*., 2009). In contrast, global sensitivity analysis techniques assess the influence of each input by simultaneously varying all parameters across the design space (Tian, 2013;

Menberg *et al*., 2016; Delgarm *et al*., 2018). These methods are better suited to capturing complex, nonlinear interactions and yield more comprehensive and reliable insights into variable influence (Delgarm *et al*., 2018).

To carry out the sensitivity analysis, a regression-based approach was adopted, which is classified under global sensitivity analysis methods. This technique is among the most commonly applied in building energy performance studies due to its computational efficiency and ease of interpretation (Pudleiner and Colton, 2015; Mao *et al*., 2017). Following the recommendation by Tian (2013), the SimLab 2.2 software was employed for this task. SimLab is a freely available statistical tool designed for conducting both uncertainty and sensitivity analyses, offering a variety of analytical methods including Standardized Regression Coefficients (SRC), Partial Correlation Coefficients (PCC), Standardized Rank Regression Coefficients (SRRC), and Partial Rank Correlation Coefficients (PRCC).

While *SRC* and *PCC* are best suited for linear models, their rank-based counterparts—*SRRC* and *PRCC*—are more appropriate for non-linear but monotonic relationships. Additionally, SRC is most effective when input variables are uncorrelated, whereas *PCC* can handle interdependent inputs (Yıldız and Arsan, 2011; Tian, 2013; Gou *et al*., 2018). In this study, *SRCs* were chosen to assess the influence of each input design variable, a method that has been widely applied in energy modeling research (Tian, 2013).

The 200-case dataset generated from the Latin Hypercube Sampling (*LHS*) was used to calculate *SRC* values, where the 20 selected input variables served as the independent predictors, and the outputs—annual heating, cooling, and combined energy loads—acted as the dependent responses. To assess the adequacy of the regression models, the coefficient of determination (R^2) was employed. In accordance with established guidelines, a regression model was considered valid only if its R^2 value exceeded 0.6 (Hoare *et al*., 2008).

3.1.2.5. Selection of influential variables

The Standardized Regression Coefficients (*SRCs*) were computed for all 20 input variables across the three key objectives: annual heating energy loads, annual cooling energy loads, and the combined total of both. These coefficients enabled the prioritization of variables based on their level of influence on each objective. A higher absolute *SRC* value signifies a greater impact of the corresponding variable on the model's output. Additionally, the sign of the SRC reveals the direction of influence—positive values indicate that an increase in the input leads to an increase in the output, while negative values suggest the opposite. For each objective, the *SRC* values were organized in descending order to highlight both positively and negatively influential variables.

This sensitivity analysis was conducted to streamline the input space for the *ANFIS* model by identifying and retaining only the most impactful variables. Specifically, input parameters exhibiting an absolute Standardized Regression Coefficient (*SRC*) greater than 0.1 were classified as influential and thus selected for further use in the model development.

3.1.3. Generation of the used dataset

Using the influential input variables identified through the sensitivity analysis, a dataset comprising 1,200 cases was constructed for training and validating the ANFIS model. This dataset was generated using SimLab software and the Latin Hypercube Sampling (*LHS*) technique. EnergyPlus simulations were conducted for each combination of the six influential variables: living room window-to-wall ratio (X16), window type (X18), external wall solar absorptance (X14), external wall insulation thickness (X8), bedroom window-to-wall ratio (X17), and building orientation (X1). EnergyPlus simulations were executed for each of these 1,200 input combinations via the jEPlus platform to automate the process. The resulting outputs—cooling and heating energy loads for each configuration—were compiled to serve as the training and validation data for the subsequent *ANFIS* model development phase.

3.2. ANFIS model development

To estimate the cooling and heating energy demands of the selected multifamily social residential building, an Adaptive Neuro-Fuzzy Inference System (*ANFIS*) model was developed. Following the standard structure of AI-based prediction approaches, the modeling process was organized into four key phases: data collection, data preprocessing, model training, and model evaluation (Wang and Srinivasan, 2017).

3.2.1. ANFIS model configuration

Using the simulated dataset, two *ANFIS* networks were developed—each employing a Sugeno-style inference system. These networks map six independent input variables to the respective outputs: one for predicting cooling energy loads and the other for heating energy loads. For each input, three membership functions were assigned, specifically Gaussian functions, selected for their smooth characteristics and proven effectiveness within grid partitioning approaches (Talpur *et al.*, 2017). Each Gaussian membership function ranged from a minimum of 0 to a maximum of 1. The entire process of training and evaluating the fuzzy inference systems was carried out using the *ANFIS* Toolbox in MATLAB.

As illustrated in Fig. 2, the *ANFIS* architecture is composed of five distinct layers, each responsible for a specific stage in the fuzzy inference process:

Layer 1 represents the membership functions (*MFs*) corresponding to the input variables. This layer processes and transmits the input values to the next layer in the *ANFIS* architecture. The six inputs in this case include: living room window-to-wall ratio, window type, solar absorptance of the external wall, insulation thickness of the external wall, bedroom window-to-wall ratio, and building orientation. Each node in this layer is adaptive and applies a membership function to transform the crisp input values into fuzzy degrees of membership. The operation of each node is defined by the following function:

$$o_i^1 = \mu_{A_i}(x) \tag{1}$$

$$\mu_{A_i}(x) = e^{-\frac{1}{2}\left(\frac{x-c_i}{\sigma_i}\right)^2} \tag{2}$$

Where x is the crisp input to node, $\mu_{Ai}(x)$ is the membership function, and and σ_i, c_i are the parameter of the *MF* governing the Gaussian function (Talpur *et al.*, 2017).

Layer 2 is known as the rule layer or the fuzzy set layer. It receives the membership grades from Layer 1 and applies fuzzy logic operations to compute the firing strength of each rule. Each node in this layer is fixed (non-adaptive) and represents a single fuzzy rule. The firing strength of a rule is obtained by taking the product of the membership values from all corresponding input variables, assuming the use of the *AND* operator. Mathematically, this is expressed as:

$$o_i^2 = w_i = \mu_{Ai}(x) * \mu_{Bi}(y), \quad i = 1, 2 \qquad (3)$$

Layer 3 is the normalization layer, responsible for computing the normalized firing strength of each rule. Like Layer 2, this layer is non-adaptive—its structure remains fixed during the training process. Each node corresponds to one fuzzy rule and calculates the relative contribution of that rule by dividing its firing strength by the sum of all firing strengths. This ensures that the total contribution of all rules sums to one. The mathematical expression for the output of the i_{th} node in this layer is:

$$o_i^3 = \bar{w}_i = \frac{w_i}{w_1+w_2}, \qquad i = 1, 2 \qquad (4)$$

Layer 4, known as the defuzzification layer, consists of adaptive nodes that generate the output of each fuzzy rule. Each node takes the normalized firing strength w_i from Layer 3 and multiplies it by a first-order Sugeno-style output function, which is typically a linear combination of the input variables plus a bias term. The output of each node in this layer is calculated as:

$$o_i^4 = \bar{w}_i f_i = \bar{w}_i(p_i x + q_i y + r_i) \qquad (5)$$

where w_i is the output of Layer 3 and (p_i, q_i, r_i) is the consequent parameter set. And *f*1 and *f*2 are the fuzzy if-then rules as follows:

• *Rule 1:*
if x is A_1 and y is B_1 then $f_1 = p_1x + q_1y + r_1$
• *Rule 2:*
if x is A_2 and y is B_2 then $f_2 = p_2x + q_2y + r_2$

Layer 5, known as the output layer, contains a single fixed node responsible for computing the final output of the *ANFIS* model. This layer aggregates all the outputs from Layer 4 by summing them to produce a single scalar value, which represents the system's crisp prediction. The overall output is calculated as:

$$o_i^5 = f_{out} = \sum_i^5 \bar{w}_i f_i = \frac{\sum_i^5 w_i f_i}{\sum_i^5 w_i} \qquad (6)$$

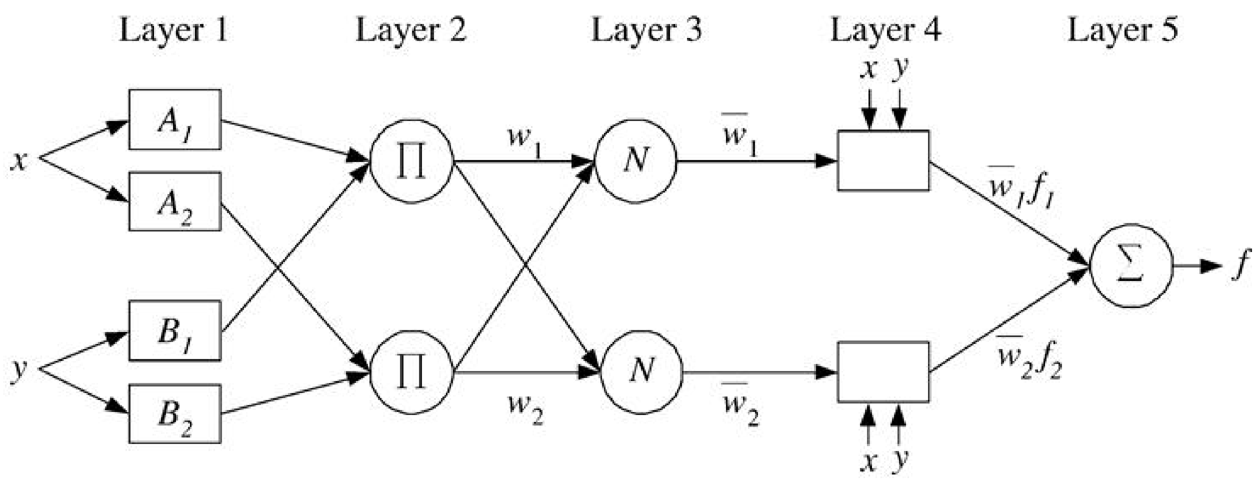


Fig. 2. ANFIS structure

3.2.2. Training and testing of the model

To ensure optimal performance and enhance the accuracy of the *ANFIS* model, a hybrid learning algorithm was employed for training. This approach integrates the back-propagation method with the least squares estimation, leveraging the advantages of both techniques as demonstrated in prior studies (Çaydaş *et al*., 2009; Ekici and Aksoy, 2011; Li *et al*., 2011; Aramesh *et al*., 2014; Naji *et al*., 2016).

The hybrid training process involves two main stages:

- Forward pass: In this phase, the consequent parameters of the fuzzy rules are identified using the least squares estimation method.
- Backward pass: Here, the error signals—calculated as derivatives of the squared error with respect to each output node—are propagated backward through the network to update the premise parameters using gradient descent (back-propagation).

The dataset used for model development comprised 1200 *LHS*-generated samples.

To ensure robust model generalization and reliable performance evaluation, the dataset was partitioned into training and validation subsets using an 80-20 split. Specifically, 960 samples (80%) were randomly allocated for training the ANFIS model, while the remaining 240 samples (20%) were reserved for validation. This split ratio aligns with standard practices in machine learning for building energy prediction, where 70-30 or 80-20 partitions are commonly employed to balance computational efficiency and the prevention of overfitting (Al-Shargabi *et al*., 2022; Olu-Ajayi *et al*., 2022). The relatively larger training set enables the model to effectively learn complex nonlinear patterns within the data, while maintaining a statistically significant validation subset ensures a rigorous assessment of the model's predictive performance on unseen data, thereby reducing the risk of overfitting and enhancing generalization.

3.2.3. Model performance evaluation

To assess the predictive performance of the ANFIS models for both cooling and heating load estimation, the Coefficient of Variation of the Root Mean Square Error (CV-RMSE) and the Coefficient of Determination (R^2) were employed as evaluation metrics. These performance indicators were selected due to their widespread recognition in energy prediction research (Al-Shargabi *et al*., 2022; Qin *et al*., 2024) and their specific recommendation by ASHRAE Guideline 14 (2023) for evaluating building energy models (Amasyali and El-Gohary, 2018; Chen *et al*., 2023). CV-RMSE provides a normalized measure of prediction accuracy by expressing the RMSE relative to the mean of observed values, thus facilitating comparison across different scales and datasets. In parallel, the coefficient of determination (R^2) quantifies the proportion of variance in the observed data that is explained by the model, indicating its goodness of fit. Together, these statistical indicators offer robust and complementary measures of accuracy and consistency between the ANFIS-predicted and simulated energy load values.

$$CV\ (RMSE) = \frac{1}{M}\sqrt{\frac{\sum_{i-1}^{n}(M_i \quad P_i)^2}{n}}\ (\%) \tag{7}$$

Where M_i and P_i are the measured and predicted value, n is the total number of data values used for the calculation, and M is the average of all measured data.

$$R^2 = 1 - \frac{SSres}{SStot} = 1 - \frac{\sum_{i=1}^{n}(M_i - P_i)^2}{\sum_{i=1}^{n}(M_i - \bar{P})^2} \quad (8)$$

Where $SSres$ is the sum of squares of residuals, $SStot$ is the total sum of squares, M_i is measured value, P_i is the predicted value of M_i, and $\bar{P}$ is the mean of M_i values.

4. Results

4.1. Selection of influential variables for cooling energy loads

The Standardized Regression Coefficients (*SRCs*) for cooling energy loads, as illustrated in Fig. 3, highlight six primary design variables that exert the greatest influence on building cooling demand. These are: the living room window-to-wall ratio (*X16*), window type (*X18*), solar absorptance of the external wall (*X14*), insulation thickness of the external wall (*X8*), bedroom window-to-wall ratio (*X17*), and building orientation (*X1*). Among these, all variables showed a positive correlation with cooling energy demand—except for insulation thickness of the external wall (X8), which exhibited a negative impact.

As detailed in Fig. 3 and Table 2, these findings underline the significant role of the transparent envelope components—particularly window design factors—in influencing cooling loads for multifamily social residential buildings in the hot and arid climate of Biskra. Additionally, external wall insulation thickness, wall color (solar absorptance), and orientation are also critical considerations in reducing cooling energy requirements during the design phase.

4.2. Selection of influential variables for heating energy loads

The Standardized Regression Coefficients (*SRCs*) for heating energy loads, presented in Fig. 4, identify six key design variables that significantly impact heating demand. These include: insulation thickness of the external wall (*X8*), insulation thickness of the floor (*X9*), window type (*X18*), solar absorptance of the external wall (*X14*), thermal conductivity/density of the floor block (*X6*), and building orientation (*X1*). Among these, only window type (*X18*) and floor block thermal conductivity/density (*X6*) showed a positive correlation with heating loads, whereas the others demonstrated negative influences.

As illustrated in Fig. 4 and detailed in Table 2, insulation levels within the building envelope, particularly for the external wall and floor, as well as window characteristics, play the most critical role in reducing heating energy demand. Additionally, wall color (solar absorptance) and building orientation also contribute to improved energy efficiency in heating-dominant periods, especially within the hot and dry climatic conditions of Biskra.

4.3. Selection of influential variables for total cooling and heating energy loads

Fig. 5 presents the Standardized Regression Coefficients (*SRCs*) for the total annual energy loads, combining both heating and cooling demands. The analysis highlights five primary design variables with the strongest influence: window type (*X18*), living room window-to-wall ratio (*X16*), insulation thickness of the external wall (*X8*), bedroom window-to-wall ratio (*X17*), and thermal conductivity/density of the external wall block (*X5*). Among these, only the insulation thickness of the external wall (*X8*) exhibited a negative correlation with energy loads, indicating that increased insulation contributes to reduced overall demand. The other four variables had positive correlations, suggesting their increase leads to higher energy loads.

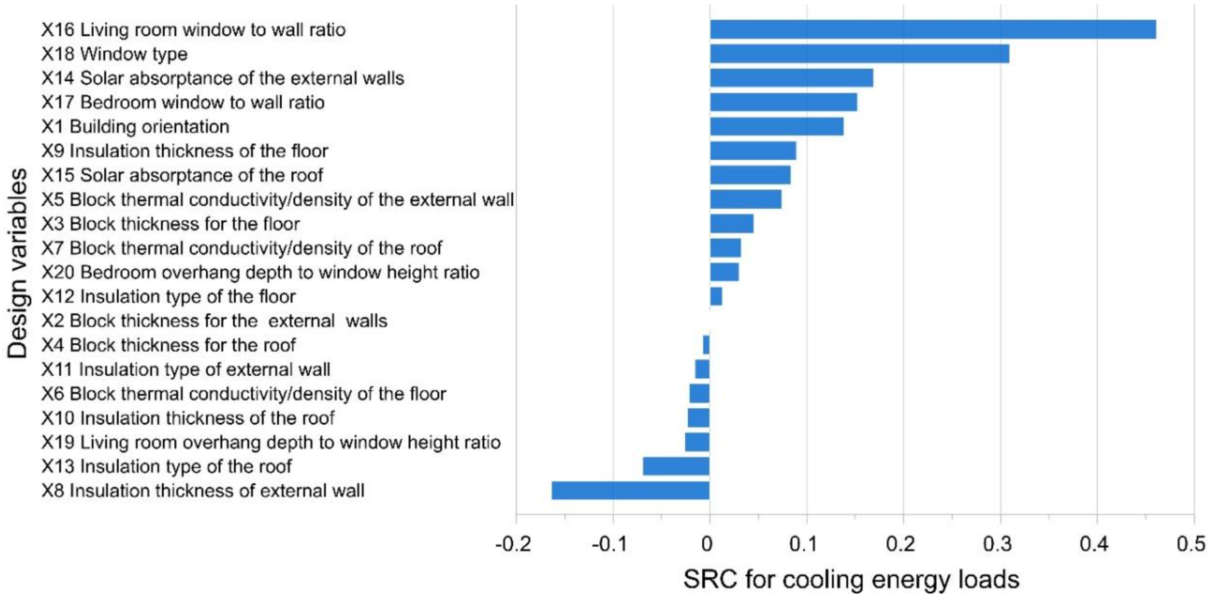


Fig. 3. Sensitivity ranking of Standard Regression Coefficients (*SRCs*) for annual cooling energy loads of the selected building.

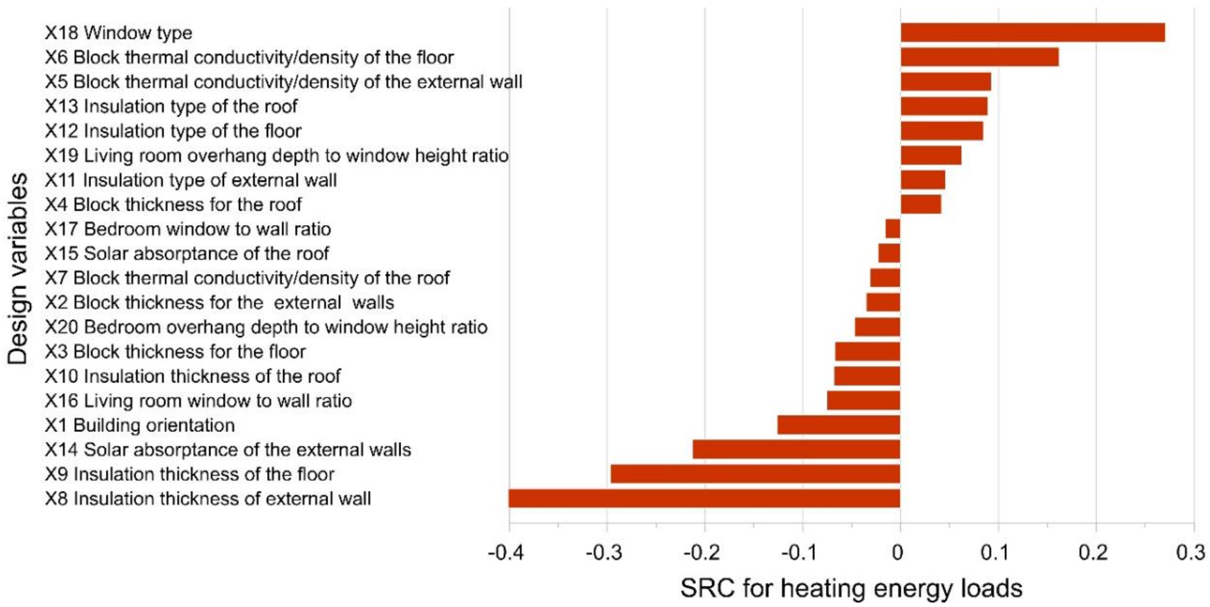


Fig. 4. Sensitivity ranking of Standard Regression Coefficients (*SRCs*) for annual heating energy loads of the selected building

As reflected in both Fig. 5 and Table 3, transparent envelope features, particularly window type and surface ratios, emerge as the dominant factors in managing total energy performance. This is followed by the role of insulation and material properties of the external wall. These insights emphasize the critical importance of early design decisions related to glazing and envelope configuration for improving energy efficiency in hot and arid climates like that of Biskra.

Table 2. Sensitivity analysis results using *SRC* for cooling and heating energy loads.

Design variables	Variables number	SRC for cooling energy loads	SRC for heating energy loads
Building orientation	X_1	0.138	-0.126
Block thickness for the external walls	X_2	-0.0004	-0.035
Block thickness for the floor	X_3	0.045	-0.067
Block thickness for the roof	X_4	-0.007	0.041
Block thermal conductivity / density of the external wall	X_5	0.074	0.092
Block thermal conductivity / density of the floor	X_6	-0.021	0.162
Block thermal conductivity / density of the roof	X_7	0.032	-0.031
Insulation thickness of external wall	X_8	-0.163	-0.401
Insulation thickness of the floor	X_9	0.089	-0.296
Insulation thickness of the roof	X_{10}	-0.023	-0.068
Insulation type of external wall	X_{11}	-0.015	0.045
Insulation type of the floor	X_{12}	0.013	0.085
Insulation type of the roof	X_{13}	-0.069	0.089
Solar absorptance of the external walls	X_{14}	0.168	-0.212
Solar absorptance of the roof	X_{15}	0.083	-0.022
Living room window to wall ratio	X_{16}	0.461	-0.075
Bedroom window to wall rat	X_{17}	0.152	-0.015
Window type (Window U value)	X_{18}	0.309	0.270
Living room overhang depth to window height ratio	X_{19}	-0.025	0.062
Bedroom overhang depth to window height ratio	X_{20}	0.030	-0.047

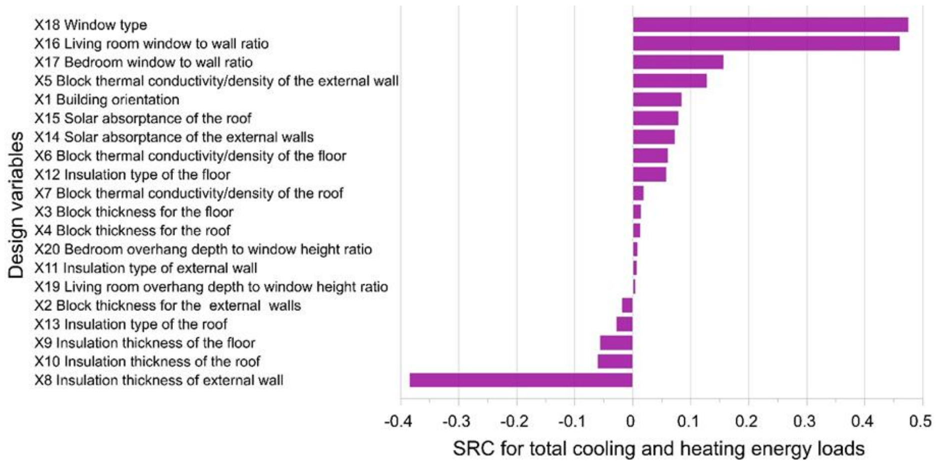


Fig. 5. Sensitivity ranking of Standard Regression Coefficients (*SRCs*) for total cooling and heating energy loads of the selected building.

4.4. Influential variables used for developing ANFIS model

Among the most influential variables identified for each energy load objective, only window type (*X18*) and insulation thickness of the external wall (*X8*) were common across all categories. However, the dominant variables influencing both cooling loads and total energy loads showed considerable overlap.

Given that Biskra's climate is primarily cooling-oriented, with a greater emphasis on achieving indoor comfort during the hot summer months, the analysis prioritized the cooling load-related variables for the next modeling phase.

Table 3. Sensitivity analysis results using SRC for total cooling and heating energy loads

Design variables	Variables number	SRC for total cooling and heating energy loads
Building orientation	X_1	0.084
Block thickness for the external walls	X_2	-0.018
Block thickness for the floor	X_3	0.014
Block thickness for the roof	X_4	0.013
Block thermal conductivity/density of the external wall	X_5	0.128
Block thermal conductivity/density of the floor	X_6	0.060
Block thermal conductivity/density of the roof	X_7	0.018
Insulation thickness of external wall	X_8	-0.384
Insulation thickness of the floor	X_9	-0.056
Insulation thickness of the roof	X_{10}	-0.060
Insulation type of external wall	X_{11}	0.006
Insulation type of the floor	X_{12}	0.058
Insulation type of the roof	X_{13}	-0.029
Solar absorptance of the external walls	X_{14}	0.072
Solar absorptance of the roof	X_{15}	0.079
Living room window to wall ratio	X_{16}	0.460
Bedroom window to wall rat	X_{17}	0.157
Window type (Window U value)	X_{18}	0.475
Living room overhang depth to window height ratio	X_{19}	0.004
Bedroom overhang depth to window height ratio	X_{20}	0.008

As a result, the six variables selected to construct the dataset for the ANFIS model include: living room window-to-wall ratio (*X16*), window type (*X18*), solar absorptance of the external wall (*X14*), insulation thickness of the external wall (*X8*), bedroom window-to-wall ratio (*X17*), and building orientation (*X1*). These features were deemed the most impactful in reducing cooling demands and therefore served as the input parameters for developing and training the *ANFIS* predictive models.

4.5. Proposed ANFIS prediction model

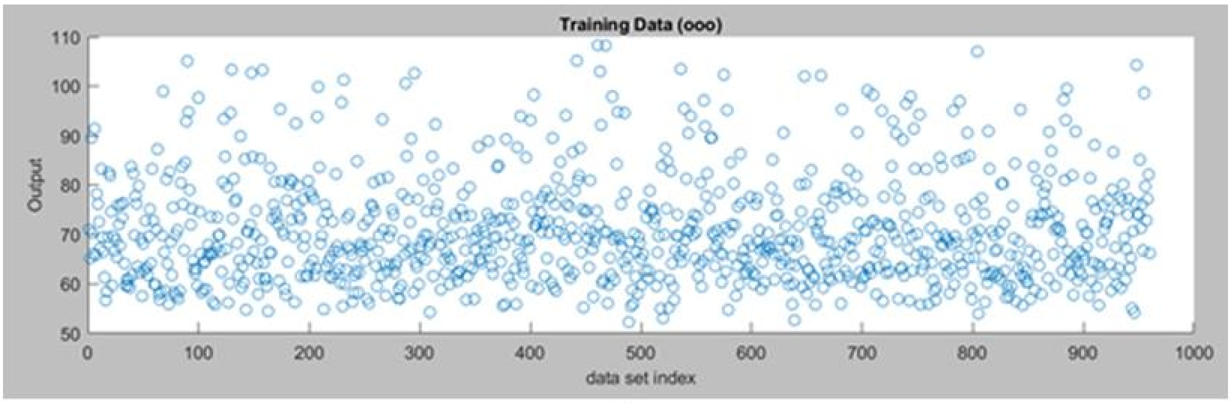
In the framework of this research, an Adaptive Neuro-Fuzzy Inference System (*ANFIS*) model was developed with the objective of predicting both cooling and heating energy loads for a representative multifamily social residential building located in Algeria. Two separate ANFIS models were constructed: one specifically tailored for predicting the cooling energy loads, and the other designed to estimate the heating energy loads of the building.

Each of these *ANFIS* models comprises a total of 1,503 nodes structured across five layers. The model architecture integrates six input variables; each associated with three Gaussian membership functions. This configuration leads to the generation of 729 fuzzy inference rules, with each rule corresponding to a unique combination of input membership functions. Consequently, there are 729 output membership functions, culminating in a single output node that yields the predicted energy load. Furthermore, the models incorporate 729 linear parameters related to the consequent part of the fuzzy rules and 36 nonlinear parameters that define the shape and characteristics of the Gaussian membership functions used in the input layer.

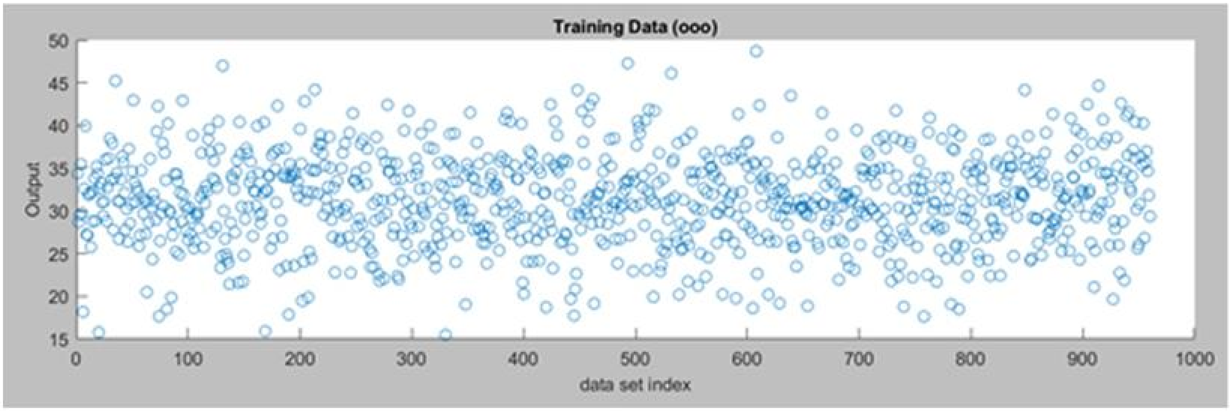
The training process of the *ANFIS* models is illustrated in Fig. 6, which displays the training data points for both cooling and heating energy predictions. The training dataset consisted of 960 cases, representing 80% of the total simulation data generated through Latin Hypercube Sampling (*LHS*). The training process was conducted over 1,000 epochs to ensure sufficient learning and convergence of the model.

Following the training phase, the relationship between the input variables and the predicted outputs was visualized using response surface plots, as shown in Fig. 7. These plots highlight the complex nonlinear interactions captured by the ANFIS model. In the presented figure, the surface plot demonstrates the influence of two selected inputs—window type and building orientation—on the energy load outputs. The x-axis and y-axis represent the normalized values of the two input parameters, while the z-axis illustrates the normalized energy load predictions.

As outlined in the methodology, the accuracy and performance of both ANFIS models were evaluated using two well-established statistical indicators: the Coefficient of Variation of the Root Mean Square Error (CV-*RMSE*) and the coefficient of determination (R^2). The evaluation results are summarized in Table 4.



(a)



(b)

Fig. 6. Training data of obtained ANFIS model. (a) for cooling energy loads, (b) for heating energy loads

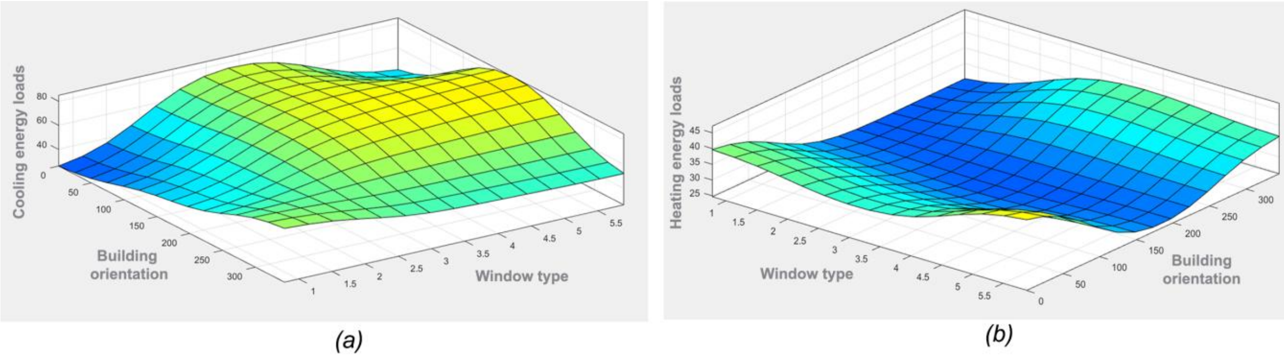


Fig. 7. Predicted *ANFIS* relationships between different combinations of input parameters. (a) for cooling energy loads, (b) for heating energy loads

Table 4. ANFIS prediction training and testing errors for cooling and heating energy loads

Proposed ANFIS model	For cooling energy loads			For heating energy loads		
Data	Training	Testing	All	Training	Testing	All
R^2	0.9	0.87	0.89	0.89	0.84	0.88
CV-RMSE	2.09	2.34	2.14	1.51	1.76	1.56

Fig. 8 presents a comparative analysis between the cooling energy loads predicted by the *ANFIS* model and the reference values obtained through EnergyPlus simulations. The results indicate that the model achieved an R^2 of 0.90 on the training data, 0.84 on the testing data, and 0.89 when considering the entire dataset. These high values of R^2 confirm a strong correlation between the predicted and simulated energy loads. This is further validated by the low CV-*RMSE* values, which demonstrate the model's precision. Notably, the difference between the CV-*RMSE* values for the training and testing sets was minimal—approximately 0.25, reflecting the robustness and generalization capability of the *ANFIS* model for cooling load prediction.

Similarly, Fig. 9 illustrates the comparison between predicted and simulated heating energy loads. The *ANFIS* model yielded an R^2 of 0.89 for the training data, 0.84 for the testing data, and 0.88 for the entire dataset. These findings reveal a high degree of alignment between the predicted values and the EnergyPlus simulation outputs, again supported by low CV-*RMSE* values. The small discrepancy (about 0.25) between the training and testing CV-*RMSE* confirms the reliability of the model and its ability to generalize beyond the training set.

5. Discussion

In this study, an Adaptive Neuro-Fuzzy Inference System (*ANFIS*) was developed and implemented to forecast the cooling and heating energy loads of residential buildings by focusing on the most influential passive envelope design variables. The following sections summarize the key findings, evaluate the strengths and limitations of the research, and provide implications for practice and future research directions.

5.1. Summary of main findings

The results demonstrate that building envelope design parameters exhibit varying degrees of influence on cooling and heating energy loads, often acting in opposing ways. According to the sensitivity analysis conducted on a representative multifamily social residential building located in Biskra (classified under climate zone D in Algeria), the living room window-to-wall ratio (*WWR*) emerged as the most influential variable for cooling loads, whereas external wall insulation thickness was found to be the dominant factor affecting heating loads.

Interestingly, the living room *WWR* showed a positive correlation with cooling energy demands and a negative correlation with heating demands. While maintaining a low WWR can effectively reduce cooling energy consumption by minimizing solar heat gain, thereby improving summer thermal comfort, this approach simultaneously increases heating demands. Therefore, selecting an optimal WWR that balances both heating and cooling needs represents a key passive design strategy for minimizing overall building energy consumption. However, it is essential to note that WWR also significantly impacts indoor natural lighting, which was not taken into account in this study. Thus, although a lower WWR may benefit cooling performance, its final determination should account for daylighting requirements in practice.

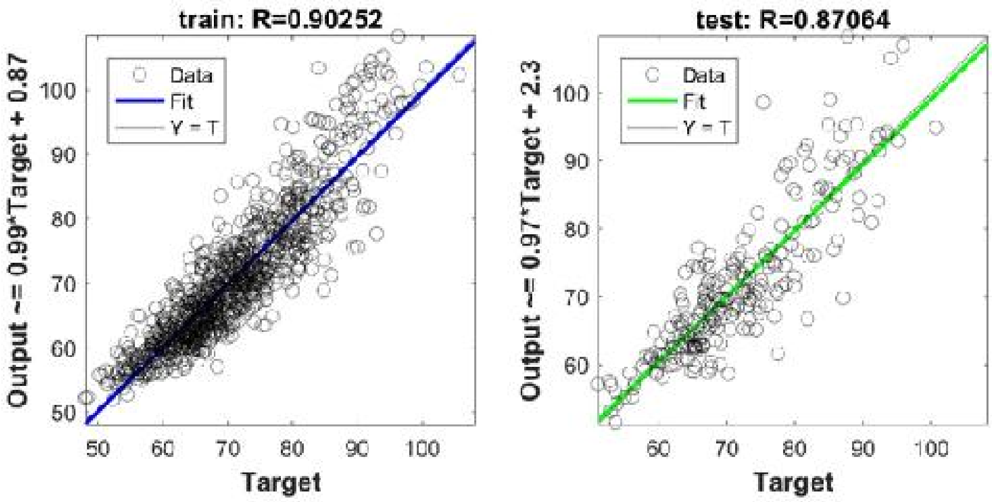


Fig. 8. Regression between *ANFIS* predicted and EnergyPlus simulated cooling energy loads

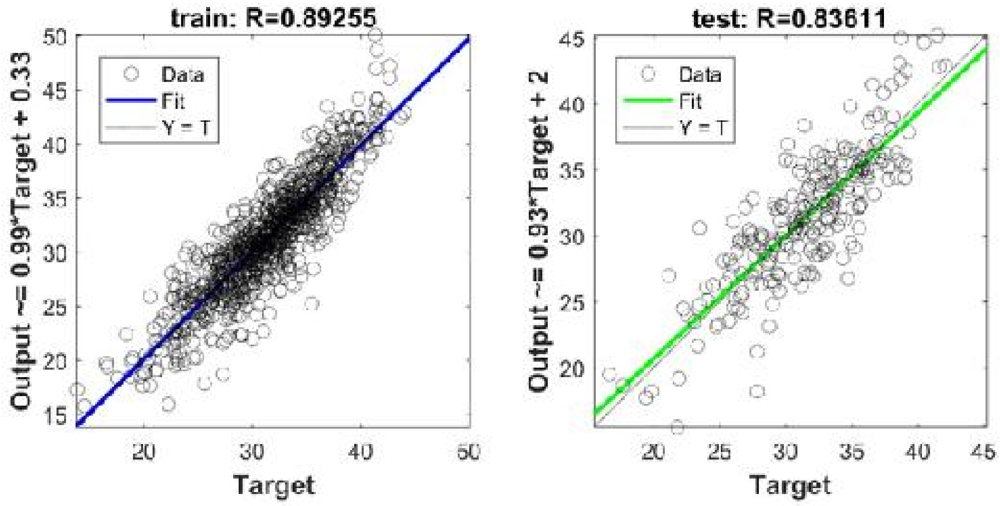


Fig. 9. Regression between *ANFIS* predicted and EnergyPlus simulated heating energy loads

On the other hand, the insulation thickness of the external walls consistently showed a negative correlation with both cooling and heating loads, confirming that enhanced thermal insulation in the building envelope improves the building energy performance and indoor comfort in hot arid climates.

Moreover, low window U-values (window type) consistently improve indoor thermal comfort and enhance energy performance for both cooling and heating by reducing heat transfer. Additionally, the solar absorptance exhibited opposing effects: negative for heating loads (reducing winter heat retention) but positive for cooling loads (increasing summer heat gain). Given that the studied city lies in a cooling-dominated climate, using light-colored surfaces (low solar absorptance) on building walls can significantly improve summer thermal comfort and reduce cooling energy consumption. Other key variables influencing cooling energy loads included the bedroom window-to-wall ratio, and building orientation.

Regarding prediction accuracy, the *ANFIS* models developed for both cooling and heating loads achieved high levels of precision. The coefficient of determination (R^2) was 0.90 for the cooling model and 0.89 for the heating model, indicating strong predictive performance and close alignment with simulated results. Furthermore, the models achieved exceptional precision, as evidenced by CV-RMSE values of 2.09% (cooling) and 1.51% (heating), significantly surpassing ASHRAE Guideline 14's recommended threshold of 15% for hourly data.

The performance of the proposed ANFIS model is compared with prior studies that employed different machine learning methods to predict heating and cooling energy loads in residential buildings based on envelope measures. As shown in Table 5, the proposed model achieves higher accuracy and robustness in predicting both cooling and heating demands compared to the listed models. Additionally, it is worth noting that the presented approach can be used for real-world data.

Table 5. Performance comparison between proposed ANFIS model and prior works

Reference	*Models*	*Error statistics*			
		R^2		*CV-RMSE*	
		CL	*HL*	*CL*	*HL*
(Boukarta 2021)	LR	0.895	0.885	-	-
(Chaganti *et al.*, 2022)	MLP	0.777	0.849	-	-
	LR	0.887	0.896	-	-
(Goyal and Pandey, 2021)	MLR	0.852	0.885	-	-
	SVR	0.893	0.823	-	-
(Huang and Li, 2021)	ACO-WNN	0.866	0.866	-	-
(Afzal *et al.*, 2024)	RSM	0.878	0.897	-	-
(Gao *et al.*, 2019)	LMSR	0.851	0.857	-	-
	Lazy LWL	0.819	0.815	-	-
The current study	ANFIS	0.90	0.89	2.09	1.51

5.2. Strength and limitations

This research successfully applied an AI-based approach for accurately forecasting heating and cooling energy requirements in the early design stages of buildings under Algerian climate conditions. Two *ANFIS* models were developed using input datasets generated from simulations of a calibrated representative multifamily residential building. This represents a novel application in the Algerian context, where most prior studies relied on statistical or bottom-up methods for regional or national energy forecasting (e.g., Ouahab, 2015; Ghedamsi *et al*., 2016), and few employed Artificial Intelligence (*AI*), with existing efforts mainly focusing on Artificial Neural Networks (*ANNs*) (Mordjaoui *et al*., 2017).

The ANFIS technique, which effectively handles nonlinear relationships and captures data-driven patterns, proved particularly suitable for the complexity of building energy behavior (Shamshirband *et al*., 2015; Naji *et al*., 2016; Mardani *et al*., 2019). The dataset used in model development was derived from a dynamically simulated and calibrated building model, enhancing the robustness and reliability of the predictions.

The proposed *ANFIS* models also offer a practical solution for professionals such as architects and engineers by enabling rapid, simulation-free evaluations of energy performance during early design stages. This helps overcome challenges related to the time, expertise, and resources required to conduct traditional Building Performance Simulations (*BPS*).

Moreover, the use of data-driven training enables the automatic optimization of membership functions (*MFs*), avoiding reliance on expert knowledge. However, a few limitations remain. The most notable limitation is that the model was trained on simulated data, although this was mitigated by the use of a well-calibrated building model. Additionally, the number and shape of membership functions were not optimized experimentally but selected from the literature. These parameters significantly affect the computational complexity and prediction accuracy of the *ANFIS* model.
Due to time constraints and computational limitations, a comparative sensitivity study on MF configurations was not performed. Future work should explore this aspect to determine the most effective *MF* structures.

5.3. Implication on practice and research

This study provides actionable insights for residential building stakeholders (Policy-makers, designers, owners, and users) in arid climates. By quantifying energy reduction potential and identifying key parameters that should be considered prior to construction, it enables more informed, energy-efficient decisions about materials, dimensions, and design features. Moreover, the findings of this research can support the revision of Algeria's building thermal regulations to enhance energy efficiency, in collaboration with key stakeholders such as the Ministry of Housing, Urban Planning, and the City (MHUV) and the National Center for Integrated Building Studies and Research (CNERIB). Finally, it is worth noting that the findings are likely applicable across MENA countries, given their shared climatic and building conditions with Algeria.

The developed *ANFIS* prediction models can serve as valuable decision-making tools for building professionals seeking to estimate the heating and cooling energy loads of residential buildings in Algeria quickly and efficiently. With the integration of a user-friendly interface, the tool could be particularly beneficial for architects and professionals working on early-stage design.

Future research should prioritize optimizing the number and type of membership functions to enhance the model's accuracy. It would also be beneficial to benchmark the ANFIS model against other AI-based techniques such as Artificial Neural Networks (*ANN*), Genetic Programming (*GP*), and Support Vector Machines (*SVM*) to highlight its comparative strengths. Furthermore, extending the model to predict indoor thermal comfort conditions could broaden its applicability and provide deeper insights for energy-efficient building design in hot and arid climates.

6. Conclusion

Accurate prediction of energy consumption at the early design stages of residential buildings is crucial for supporting sustainable design decisions, enhancing energy efficiency, and minimizing environmental impact through reduced greenhouse gas emissions. In the context of Algeria's hot and arid climate, where residential energy demands are heavily influenced by passive design strategies, this study proposed a novel modeling framework using the Adaptive Neuro-Fuzzy Inference System (*ANFIS*) to estimate heating and cooling loads with high precision.

The *ANFIS* models developed in this research were specifically tailored to a representative typology of Algerian multifamily social housing. The models incorporated only the most significant passive design variables, carefully identified through a robust global sensitivity analysis. This approach not only ensured computational efficiency and simplicity but also grounded the model in physically meaningful architectural parameters.

To ensure reliability and relevance, the models were trained and validated on a comprehensive dataset of 1200 simulation cases generated via EnergyPlus, using a calibrated building model and real meteorological data from Biskra (2003–2017). The *ANFIS* predictions showed excellent agreement with EnergyPlus simulation results, reflected by high R^2 values and low CV-*RMSE*, underscoring the model's effectiveness as a fast and accurate alternative to conventional simulation tools during the conceptual design phase.

Beyond accuracy, the flexibility and interpretability of ANFIS make it particularly valuable for practitioners. When embedded within a user-friendly interface, the model can empower architects, engineers, and decision-makers to rapidly assess design alternatives and optimize building envelope configurations without the need for time-consuming simulations or deep expertise in energy modeling.

Nevertheless, this research also highlights opportunities for refinement. Future improvements could include the systematic optimization of *ANFIS* architecture—specifically, the number and shape of membership functions—through comparative testing and advanced tuning techniques. While Gaussian functions were used in this study for their balance of generalization and performance, exploring alternative configurations may yield further accuracy gains.

Moreover, while this work represents a pioneering application of *ANFIS* for

Algerian residential buildings, future research should consider benchmarking its predictive capabilities against other *AI* techniques such as Artificial Neural Networks (*ANN*), Support Vector Machines (*SVM*), and Genetic Programming (*GP*) under identical conditions. Such comparative studies would deepen our understanding of the most effective tools for energy prediction and facilitate the development of hybrid or ensemble approaches for even greater robustness.

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