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# Buildings' Heating and Cooling Load Prediction for Hot Arid Climates: A Novel Intelligent Data-Driven Approach

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**Abstract:** An important aspect in improving the energy efficiency of buildings is the effective use of building heating and cooling load prediction models. A lot of studies have been undertaken in recent years to anticipate cooling and heating loads. Choosing the most effective input parameters as well as developing a high-accuracy forecasting model are the most difficult and important aspects of prediction. The goal of this research is to create an intelligent data-driven load forecast model for residential construction heating and cooling load intensities. In this paper, the shuffled shepherd red deer optimization linked self-systematized intelligent fuzzy reasoning-based neural network (SSRD-SsIF-NN) is introduced as a novel intelligent data-driven load prediction method. To test the suggested approaches, a simulated dataset based on the climate of Dhahran, Saudi Arabia will be employed, with building system parameters as input factors and heating and cooling loads as output results for each system. The simulation of this research is executed using MATLAB software. Finally, the theoretical and experimental results demonstrate the efficacy of the presented techniques. In terms of Mean Square Error (MSE), Root Mean Square Error (RMSE), Regression (R) values, Mean Absolute Error (MAE), coefficient of determination (R2), and other metrics, their prediction performance is compared to that of other conventional methods. It shows that the proposed method has achieved the finest performance of load prediction compared with the conventional methods.

**Keywords:** energy consumption; data-driven; prediction; building; heating load; cooling load; optimization

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## 1. Introduction

The proportion of residence structures has grown during the last ten years of global concern about climate change, worldwide carbon emissions, global warming, urbanization, and rapid construction development [1]. Many procedures and technologies in residential and commercial buildings serve to keep the environment at a pleasant and favorable level, but they cost energy, which adds to the heating and cooling burden [2]. A lot of studies have been conducted on the energy profile of buildings, as well as many elements of efficient building development [3,4]. In Saudi Arabia, numerous residential buildings are attached or semidetached, which require more cooling and heating than ordinary flat residences [5]. Temperature, humidity, the operations of sunlight devices, and the construction and design elements of buildings all have a role in the heating and cooling of structures [6].

The material used in wall surfaces, the relative compactness of building structures, the glazed windows region, the ceiling dimensions, the outer layer and density of the building, the outer layer and density of the wall, the roof height, the number of wall surfaces and their region, the orientation of the halls and the building, and the stand over height are all involved in construction and relate to the environment. However, several aspects of the building design and layout have a significant effect with regard to the building's warming and chilling load, which has a direct impact on the building's overall performance [7]. Thus, by alleviating the computational load for optimum design, which includes multiple building feature subsets, an accurate and rapid forecast of space heating as well as cooling loads improves energy saving and carbon emission mitigation [8]. Developing machine learning techniques for predicting heating and cooling needs can assist in improving the effectiveness and precision in real time [9]. Conventional heating and cooling predictive modeling algorithms include the minimax probability machine regression (MPMR) [10], deep neural network (DNN) [11], Gaussian process regression (GPR) [12], and gradient boosted machine (GBM) [13]. Moreover, artificial neural networks (ANN) [14], categorization and regression trees (CART) [15], general linear regressions (GLR) [16], and chi-squared automated interaction detectors (CHAID) [17] were used to forecast the cooling and heating requirements of the building.

As a result, various hybrid methodologies based on ANN and meta-heuristic schemes have been developed for forecasting a building's heating and cooling demand efficiency, including the imperialist competitive algorithm (ICA) [18], artificial bee colony (ABC) [19], genetic algorithm (GA) [20], whale optimization [21], bat optimization [22], and particle swarm optimization (PSO) [23]. However, such factors have been utilized in certain studies with little benefit. Meteorological parameters were employed as an indication and input for estimating apartment building cooling/heating demands in the majority of the preceding academic studies [24]. Environmental and climatic conditions do not affect the cooling/heating loads of residential construction; this is indisputable. However, sudden weather changes might cause sustainable models to be disrupted, lowering the reliability factor and enhancing the error in the process [25].

This research focuses on the construction and design characteristics of the building, as well as their effects on heating/cooling loads. Besides constructing supervised classification forecasting models, the research applied in-depth testing on structural features for building energy. The quantity of the cooling/heating load was regarded as an outcome parameter, although a collection of information on the structural attributes of the structure was regarded as an input parameter. The following are the main research contributions:

- A dataset was produced in the Dhahran area of Saudi Arabia for estimating power requirements based on building attributes in a dry climate.
- After collecting the data, the preprocessing and feature extraction function is applied for improving the prediction model using a knowledge-based approach.
- Then, to predict building heating/cooling demands, the SSRD-SsIF-NN technique is presented with various parameter tunings.
- Building energy demand simulations are conducted to anticipate heating and cooling demands in dry climates. In contrast to various studies, the prediction methods depend on the characteristics of the study instead of on previous results on energy usage.
- A simulation analysis is conducted by varying the input parameters.
- The actual performance and the theoretical load prediction of the existing structure are compared.

The rest of the essay is organized as follows. The definition of investigation gaps is given in Section 2, along with a short assessment of the relevant publications. Section 3 describes how the issue is stated. Section 4 includes detailed explanations of the suggested technique. Section 5 discusses the experimental outcomes as well as the efficiency comparison with state-of-the-art frameworks. Section 6 is the paper's conclusion.

## 2. Related Work

The heating/cooling loads in buildings are closely connected to energy performance, and various studies have been undertaken in this area. Because cooling/heating loads are considered key factors for examining building energy efficiency, the necessity to anticipate and assess them for residential structures appears to be unavoidable. As a result, Xu, Yuanjin, Fei Li, and Armin Asgari [26] sought to optimize the multi-layer perceptron-based neural network utilizing a variety of optimization techniques in order to anticipate the heating/cooling of energy-efficient architecture. The database used for this investigation is made up of eight different variables, such as total area, space limitations, wall region, and so on. Optimizing has the highest accuracy in both the learning and test data for cooling/heating loads. The normed RMSD, RMSD, and MAE have the lowest values, as well as adjusted R2, as per the study findings.

The multi-target forecasting of heating/cooling loads through HVAC systems uses hybrid intelligent methodologies: the wind-driven-based optimization (WDO), grasshopper optimization algorithm (GOA), and biogeography-based optimization (BBO) were employed by [27]. Some swarm-based rounds are carried out to optimize the applicable methods, and the optimum design for each simulation is provided. In regard to the heating load, the suggested WDO-ANN offered an accurate forecast, while in terms of cooling capacity, it provided the finest forecast.

While earlier research has focused on point forecasts, Rana and Mashud [28] focused on predicting prediction pauses for the building cooling/heating load in this work. A data-driven technique for predicting prediction periods for building cooling demand is provided here, which initially employs a machine learning subset of feature techniques to find a limited but useful collection of factors. The findings demonstrate that the suggested method may yield a narrow and trustworthy forecasting period while fulfilling the penetration probabilities that have been defined.

To determine the energy requirement of the structures for heating and cooling, Li, Xinyi, and Runming Yao [29] combined the physical analytical model with the data-driven technique. The severity of heating/cooling energy consumption was then predicted using a variety of machine learning algorithms (EUI). The findings reveal that machine learning methods can accurately estimate building heating and cooling EUI. At the single-cell level, the most accurate method is quadratic kernel-based supported vectors extraction, while the Gaussian perceptron support-vector training has the highest accuracy at the inventory levels. Kim, Daeung Danny, and Hye Soo Suh [30] used the statistical technique to design a forecast model for energy usage in residential structures. The links between the design elements and heating/cooling load of energy usage in residential structures were detailed utilizing the response surface approach. To establish a prediction model for the heating/cooling load of energy usage, the connection has validated the dependencies of the energy consumption on key design factors of exterior technologies in residential structures. With only a few design factors, the created model can provide a quick energy estimate for apartment structures. Additionally, it may quickly determine the most significant design component for creating a more efficient energy residential building layout.

Tran et al. [31] developed an evolutionary Neural Machine Inference Model (ENMIM) for predicting energy usage using actual data from residential structures. Their novel ensembles model combines the Radial Basis Function Neural Network and the Least Squares Support Vector Regression (LSSVR), two separate supervised learning devices (RBFNN). For forecasting resource usage, the created model is more accurate than previous comparable artificial intelligence systems.

In the study that was conducted by Zhou et al. [32], the artificial bee colony (ABC) and particle swarm optimization (PSO) metaheuristic algorithms were used to optimize the MLP neural network. This was done in order to make accurate predictions regarding the heating and cooling loads of energy-efficient buildings that are used for residential purposes. In order to do this, they made use of a dataset that had eight independent variables. According to the findings of their study, making use of the ABC and PSO algorithms makes the MLP perform better. In addition to this, they came to the conclusion that, in terms of MLP performance improvement, PSO was superior to ABC.

In order to study how well machine learning can estimate the heating and cooling loads of buildings, Seyedzadeh et al. [33] created two datasets using two distinct kinds of modelling software. In order to investigate the different permutations of the model parameters, a gridsearch and a cross-validation approach were used. The findings revealed that, among the five models that were investigated, the Gradient Boosted Regression Trees

(GBRT) deliver the most accurate forecast predictions depending on the RMSE. On the other hand, NNs were shown to be the most effective at dealing with complicated datasets.

Sharif and Hammad [34] centered on the creation of an ANN model with the goal of predicting energy consumption using a big and difficult dataset supplied by the SBMO model. According to the results of this research, the ANN models that were recommended were able to yield accurate predictions. These scenarios included the building envelope, HVAC, and lighting systems.

In a work by Singaravel et al. [35], 201 design scenarios were used to evaluate the deep learning model against a simulation of a building's functionality. With an R2 of 0.983, the deep learning model demonstrated remarkable accuracy for cooling predictions. With additional heating data from a more accurate sample model, the model's R2 of 0.848 inaccuracy for heating predictions may be eliminated. According to the research, deep learning simulation results may be obtained in 0.9 s, which is regarded as a high calculation speed for simulating structure efficiency.

The cooling demand of big industrial structures was predicted by Gao et al. [36] using a hybrid forecasting model based on the random forest-improvement parallel whale optimizing-extreme learning machine neural network (RF-IPWOA-ELM). The experimental findings demonstrate that the RMSE and MAPE of the RF-IPWOA-ELM model accurately estimate the cooling demand for these two structures. The suggested hybrid model may be used as a trustworthy tool for cooling load prediction in the administration and energy saving of air conditioning systems.

Wei et al. [37] used seven common machine learning techniques to determine the best prediction method in a local heating load sample from Shanghai, China. To evaluate the model's effectiveness, data from a power transmission sensor, a heat sensor, and the current weather are merged into several input options. The findings demonstrate that SVR outperforms all others in MAPE. Further analysis reveals that the continual lengthening of previous datasets does not affect performance. The preceding literature analysis demonstrates the successful application of data-driven algorithms to handle building heating/cooling load forecast issues. Nevertheless, subsequent research deficiencies have been identified:

- The majority of the research is being undertaken in non-arid regions such as Canada, Greece, the United States, and China.
- The benchmark dataset of the conventional technique is used in many studies that employ building attributes as inputs to the forecasting model. Some self-generated statistics are kept secret and cannot be replicated experimentally.
- There is some advice on how to utilize deep learning techniques and how to modify them for the highest predicted accuracy and completeness for the assigned task. While most research includes machine learning techniques, deep learning, as well as optimization, are infrequently employed.
- As a result, utilizing a bigger, accessible self-generated database in Dhahran, a typical desert climatic zone, this research sets out an applicable strategy for adapting smart data-driven frameworks to building energy performance data.

## 3. Problem Statement

Predictive cooling/heating load is an effective method for ensuring future energy use. A significant number of academics are investigating the strategies and models for predicting cooling/heating demand in green buildings using machine learning and artificial intelligence techniques. Due to numerous issues that the researchers encountered, linked to building features, weather conditions, and data produced by the process control itself, the proposed methodologies differ in their ability to produce precise and reliable outcomes. Because linear regression is often utilized, it is more difficult to describe the function that connects to the aforementioned issue than the cooling/heating load. Furthermore, the non-linear structure of building systems complicates the connection.

The forecasting models require a lot of specific details from the building features, which might be difficult to assess and calculate. The operations and conduct of the residents within the building are predictable, since their behavior does not follow a specific order and varies irregularly. Thus, this research proposed an intelligent data-driven approach to anticipate the cooling and heating load in Dhahran buildings in response to the aforementioned issues.

## 4. Proposed Framework

This research is focused on thermal load characteristics for residential structures, as their real-world activities are heavily influenced by building design requirements. Building design rules attempt to decrease energy usage by taking into account two main terms of heating/cooling load. The proposed framework of a predictive model is illustrated in Figure 1. Some procedures were followed in the current investigation. The factors of the residential building layout were first discovered. The buildings in Dhahran, Saudi Arabia, were chosen for the data collection on design characteristics. The initial step in data preparation is to filter the data. Furthermore, by obtaining relevant features for validation, feature extraction methods may be utilized to improve the prediction performance of the proposed model. A prediction model for the cooling and heating load of the development of a domestic structure's energy usage uses SSRD-SsIF-NN. Following that, the proposed models anticipate the study's outputs of heating and cooling demand. In the last phase, the suggested models' error efficiency is measured using the leftover 30% of the test data depending on the discrepancies between the true calculated data and the anticipated values derived from the developed model. Then, the performance analysis is performed for the effective measurements.

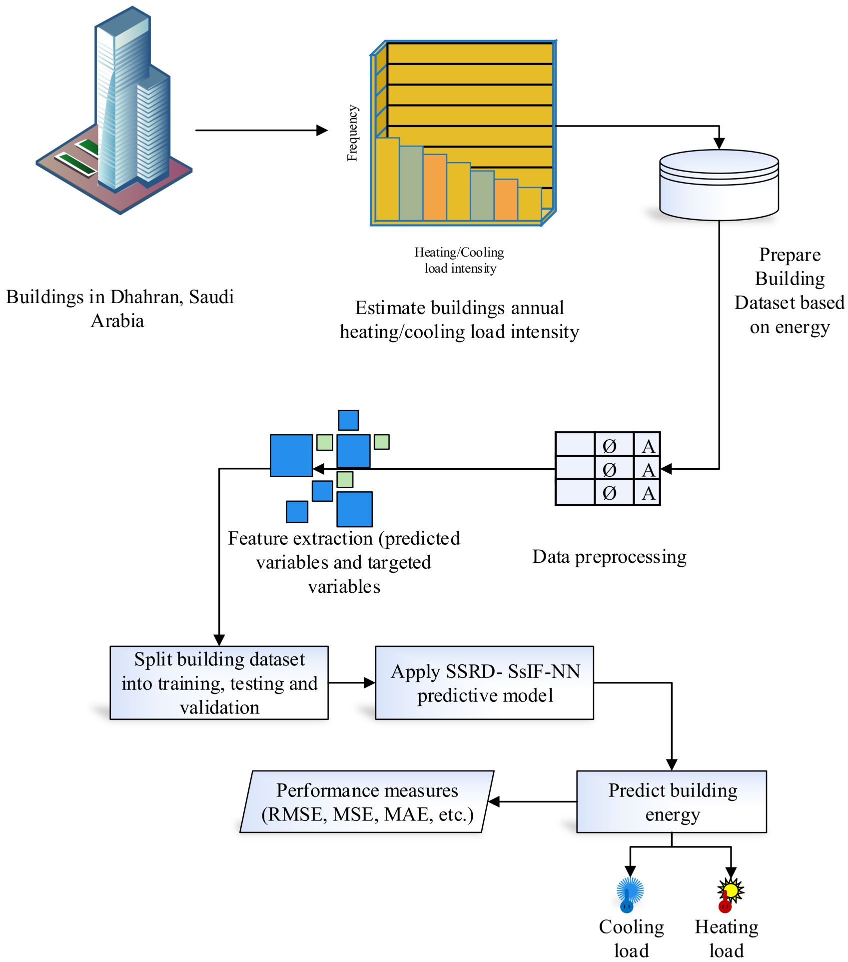


**Figure 1.** Proposed framework of the predictive model.

### 4.1. Pre-Processing and Feature Extraction

Filtering the data is the initial step in data preparation. The information is organized by the date-time index in order of decreasing importance. Data that are erroneous, anomalous, or duplicated are found and deleted. The missing data are again filled using knowledge-based interpolation. The method of translating raw information into information features that can be examined while keeping the information from the source dataset is carried out by feature extraction. It produces better outcomes than applying prediction techniques to raw information automatically. By splitting the inputs and predicting the aim, a singular sample is produced after the feature extraction procedure.

The acquired dataset of the heating and cooling loads is arbitrarily split into two different portions—the training data and the testing data—in this stage. Additionally, 70% of the entire data are utilized for building the model in order to develop a good prediction model and to develop the link across both the heating and cooling objectives and their significant components, according to a well-delivered train/test database selection. In order to test and validate the model, the other 30% of the information would be employed.

### 4.2. SSRD-SsIF-NN-Based Prediction

A quantitative performance indicator is assessed for validity. SSRD-SsIF-NN is the combination of a self-systematized intelligent fuzzy reasoning-based neural network and a hybrid meta-heuristic optimization approach. The parameters of SsIF-NN are tuned by the SSRD optimization technique.

#### 4.2.1. SsIF-NN Methodology

These tools are frequently used to represent difficult engineering problems. By generating non-linear relationships, this artificial intelligence (AI)-based approach will attempt to build a link between a sequence of given input layers and one or more output neurons. A fuzzy inference system layer, four hidden layers, and a defuzzification layer make up the SsIF-NN structure. Figure 2 depicts the suggested predictive model. The fuzzification layer transforms the feature selection's sharp input into a fuzzy collection of values. Floors Area, Number of flats, Gross Area, Roof Area ($m^2$), Study Area, Module Orientation, Parapet Wall Height (m), Annual Consumption (kWh), and Utilization Factor are the inputs of the SsIF-NN structure. The heating and cooling load is the output of the proposed approach. The input activation function and layer result were both specified in Equations (1) and (2), correspondingly.

$$Input = a\left[z_1^{(s)}, z_2^{(s)}, \ldots z_n^{(s)};\ b_1^{(s)},\ b_2^{(s)},\ \ldots . b_n^{(s)}\right] \tag{1}$$

$$Output = F_o^{(s)} = f_a(input) = f_a^{(a)} \tag{2}$$

where the inputs to this unit are $z_1^{(s)},\ z_2^{(s)}, \ldots \ldots ..z_n^{(s)}$ and the link weights are $b_1^{(s)}, b_2^{(s)}, \ldots \ldots b_n^{(s)}$. The layer number is denoted by $f_a^{(.)}$ and the superscript in the overhead equation is denoted by $(s)$. The activation function is described as follows: each node's second function is to create an activation value based on its primary input.

The following six stages of the prediction model are explained. There are no computations performed by this layer. This layer's terminals, each of which corresponds to a certain input factor, only transmit data to the following layer. This is accurate, and the first layer connection weight factor is $\left[b_i^{(1)}\right]$ one, according to Equation (3).

$$a = z_1^{(s)}\ and\ f_a^{(1)} = aa = z_1^{(s)}\ and\ f_a^{(1)} = a \tag{3}$$

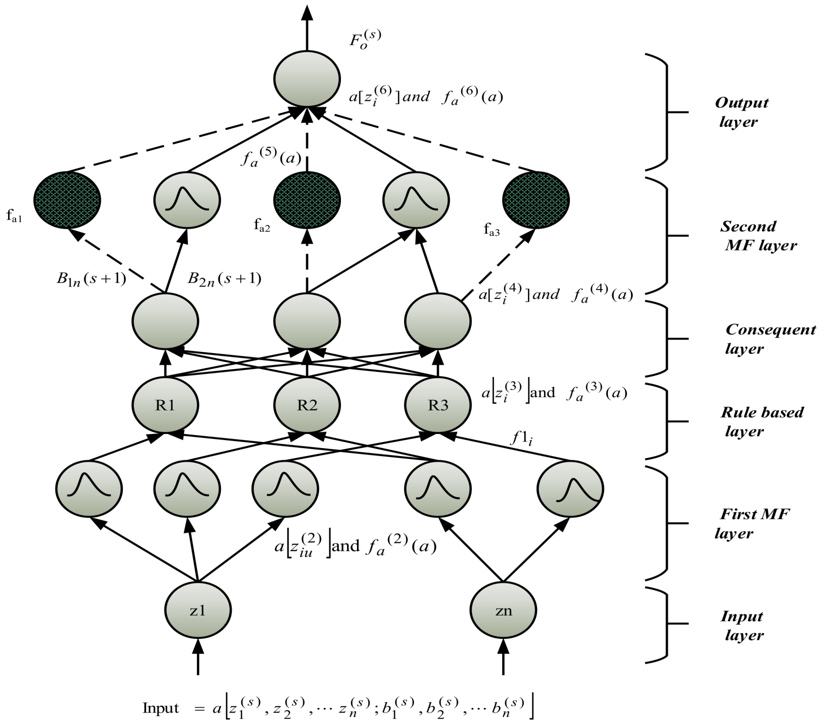


**Figure 2.** The proposed model of the SsIF-NN method.

Fuzzification is achieved in the second layer by finding the membership function parameters of an input to a group of Gaussian MFs. Each component in this provided a good one to one of the linguistic values of the input variables in the first layer (medium, small, large, etc.). This research makes use of a Gaussian membership characteristic, which has been proved to be a global prediction technique of any dynamic function on the basis of Equation (4).

$$a\left[z_{iu}^{(2)}\right] = -\frac{\left[z_i^{(2)} - f_{iu}\right]^2}{\sigma_{iu}^2} \; and \; f_a^{(2)}(a) = t^a \tag{4}$$

where the Gaussian MF of the $u_{th}$ element of the $i_{th}$ input factor has a mean and variance of $f_{iu}$ and $\sigma_{iu}$, respectively. As a solution, the weight of a second-layer link may be expressed as $f_{iu}$. Equation (5) may be used to compute the normalized fuzzy closeness between a fresh fuzzy sample $z_{1f}$ and $u_{th}$ the stored characteristic $L_1(u)$,

$$N_u = \frac{\|z_{1f} - L_1(u)\|_g}{\sum_{u=1}^{n} \|z_{1f} - L_1(u)\|_g} \tag{5}$$

Here, g-norm is the abbreviation for $\|.\|_g$. The g-norm $\|d\|_{g+z} \leq \|d\|_g$ for $d \in \Re^n$, $u \geq 1$, $g \geq 0$ of each given vector $\|d\|_g$ does not expand with $g$; all other norms are lower-bounded by the 1-norm. As a consequence, the Euclidean system was implemented $g = 2$ Radial basis models may also be used to determine rule neuron activation thresholds. Equation (6) is used in this section.

$$f1_i = 1 - N_u \tag{6}$$

where $f1_i,\ N_u \in [0,1]$. This threshold controls the model's sensitivity to the generation or modification of rule neurons $q \in [0,1]$. With higher scores, larger numbers of hidden neurons and attributes are feasible. Assume that the threshold value is set at 0.3 by default, which was created in each of the iterations. If the number of neurons develops at a faster pace than the set rate, the number of neurons grows at a slower rate $F > \varepsilon$, and the number of neurons increases at $F > \varepsilon$

$$\text{If } F > \varepsilon\ ,\ q \text{ is reduced, } q(n+s) = \left[1 + \frac{F - \varepsilon}{s}\right] q(n) \tag{7}$$

$$\text{If } w < \beta,\ q \text{ is increased, } q(n+s) = \left[1 + \frac{\varepsilon}{s}\right] q(n) \tag{8}$$

This layer's nodes also each have one fuzzy inference system rule and execute prerequisite testing. For the third layer part, the AND function was utilized, as seen below

$$a\left[z_i^{(3)}\right] = \prod_i z_i^{(3)} = t^{-[R_i(z-f_i)]q[R_i(z-f_i]}\ and\ f_a^{(3)}(a) = t^a \tag{9}$$

The number of second layers is stated as being engaged in the IF component of the fuzzy rule, and the diagonals are written as

$$R_i = d\left(\frac{1}{\sigma_{i1}}, \frac{1}{\sigma_{i2}}, \ldots\ldots\ldots \frac{1}{\sigma_{in}}\right)\ and\ f_i = d(f_{i1}, f_{i2}, \ldots\ldots\ldots f_{in})^T$$

In the third layer, there is just one weight connection, $\left[b_i^{(3)}\right]$. The firing intensity of the connected fuzzy rule is reflected in the third layer consequences. The subsequent layer has the same number of components as the third layer, the firing strength estimated in the third layer is normalized in this layer by Equation (10), and the weighted link in the fourth layer is also one $\left[b_i^{(4)}\right]$.

$$a\left[z_i^{(4)}\right] = \sum_i z_i^{(4)}\ and\ f_a^{(4)}(a) = \frac{z_i^{(4)}}{t^a} \tag{10}$$

A discriminative method that estimates the probability and a sample from training data rather than the prediction model delivers superior results that accurately depict the data distribution. The purpose of generative training is to reduce the chances of people making poor decisions. The second MF layer has two distinct modes, which are shown in Figure 2 as blank and shaded circles, respectively. The basic node, denoted by empty circles, is a fuzzy set specified by the Gaussian membership degree of the outcome variable. In the local mean of maximum (LMOM)-based defuzzification approach, the center of each Gaussian membership value is simply relayed to the next layer, while the width is just employed for output grouping. The activation of the winning neuron is propagated by Equation (11), using a saturated scaling factor of the type

$$G_{max} = \begin{cases} 0 & if G(F_{max})B_2 < 0 \\ 1 & if G(F_{max})B_2 > 1 \\ G(F_{max})B_2 & otherwise \end{cases} \tag{11}$$

Furthermore, $G_{max}$ is the neuron with the highest membership value and $G(F_{max})$ is the activation. The error $e^*$ among the actual fuzzy outcome vector $z_{1f}$ and $G(F_{max})$ is contrasted to a threshold $q$. If the mistake exceeds the threshold, a rule neuron is formed. Meanwhile, the leading neuron weight parameters $w_1$ and $w_2$ are generated from Equation (12) for the shaded and blanked portion,

$$B_{1n}(s+1) = B_{1n}(s) + \mu_1(z_i - B_{1n}) \tag{12}$$

$$B_{2n}(s+1) = B_{1n}(s) + \mu_2 G_{max} e^* \tag{13}$$

Here, $\mu_1$ and $\mu_2$ are the constant learning values, and $z_i$ is the $i^{th}$ input vector. The same fuzzy numbers can be given for various rules if many fourth-layer terminals are linked to the same fifth-layer empty element. By integrating these two components in the fifth layer, the whole function provided by this layer can be explained.

$$f_a^{(5)}(a) = \left(\sum_i z_{iu} z_u + f_{a0j} + B_{1n}(s+1) + B_{2n}(s+1)\right) z_j^5 \quad (14)$$

The mean of the Gaussian MF is expressed. Only when the shaded element is necessary is it produced. The summing is over the important phrases associated with the darkened node alone, and $q_{xj}$ is the relevant variable. This layer's nodes each relate to a single output variable. The node collects all fifth-layer ideas and functions as a defuzzifier, predicting the proper outcomes.

$$a\left[z_i^{(6)}\right] = \sum_i z_i^{(6)} and\ f_a^{(6)}(a) = a \quad (15)$$

The output of the proposed algorithm provided the consequences of the heating and cooling load in residential buildings.

4.2.2. SSRD of Parameter Tuning

The SSRD optimization algorithm is a combination of the shuffled shepherd and red deer optimization algorithms. The fitness of both algorithms is considered for the parameter tuning of the proposed SsIF-NN predictive model in the residential building energy load. The purpose of optimization is to create a global solution that takes into account all of the problem's factors. Figure 3 also displays the flowchart for the suggested prediction system. The values of the fuzzy variable and $t^a$ parameters are to be optimized in this case.

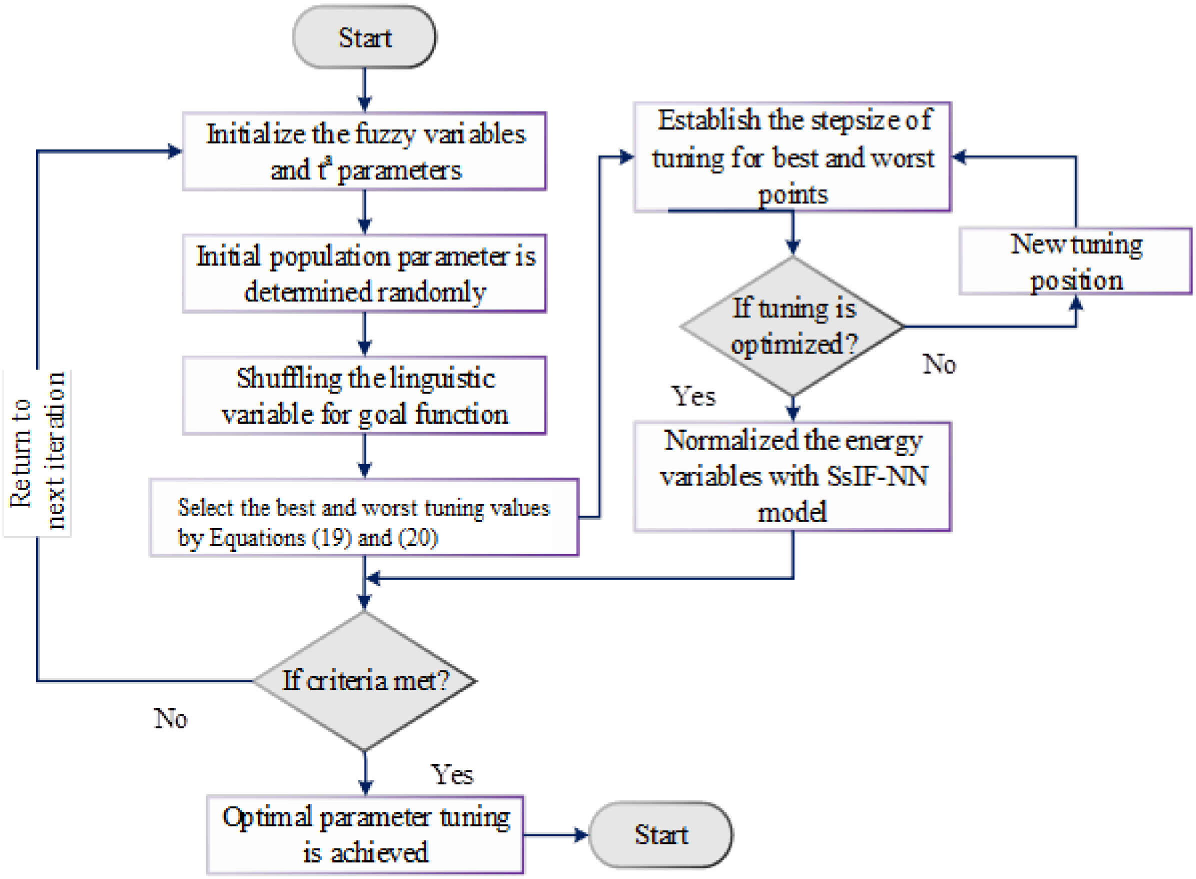


**Figure 3.** The flowchart of the proposed SSRD for SsIF-NN parameter optimization.

Initialization: The algorithm is initialized; the parameters in the array form Equation (16):

$$p(r) = f(t_1, t_2, \ldots\ldots. t_n) \quad (16)$$

In the solution space, the mathematical analysis initiates SSRD with a randomly determined beginning population parameter:

$$T^0_{q,w} = T_{min} + ran \times (T_{max} - T_{min});\ \ q = 1,2,\ldots\ldots\ldots x\ and\ w = 1,2,\ldots\ldots y \tag{17}$$

where $T_{min}$ and $T_{max}$ are the lowest and maximum fuzzy model parameter bounds, respectively; *ran* is a random variable formed between 0 and 1 for each element; $x$ is the number of persons in each parameter group; and $y$ is the total number of parameters in the groups.

Shuffling: According to their goal features, the initial point x of each population is randomly placed in the first column of the cross conditions (Equation (18)), as between members of each population. The subsequent members x are chosen in the same way as the previous step and are organized in a random order in the section to create the second column of the multi-community parameter. This procedure is continued y until the following multi-community matrix is created:

$$T_p = \begin{bmatrix} T_{1,1} & T_{1,2} & T_{1,y} & T_{1,y} \\ T_{2,1} & T_{2,2} & T_{2,y} & T_{2,y} \\ T_{q,1} & T_{q,2} & T_{q,w} & T_{q,y} \\ T_{x,1} & T_{x,2} & T_{x,w} & T_{x,y} \end{bmatrix} \tag{18}$$

It is worth noting that each row of the multi-community parameter reflects an individual from each group, with the top column being the best values from each group. Furthermore, the persons in the last segment are the weakest variables in the group.

Optimal value selection: After shuffling the variables, the best and worst values are selected for the finest tuning of the SsIF-NN model. Equations (18) and (19) are used to calculate the worst and best functions of the step size for adjusting the parameter

$$S^w_q, w = \alpha \times ran_1 \times \left(T_{q,w} - T_{q,w}\right) \tag{19}$$

$$S^f_q, w = \beta \times ran_2 \times \left(T_{q,f} - T_{q,w}\right) \tag{20}$$

Compared to $T_{q,w}$, $ran_1$ and $ran_2$ are random variables, with each component formed between 0 and 1, respectively; $T_{q,f}$ and $T_{q,w}$ are the superior and worse variables in terms of optimal value. To establish a specific step size for each member of the group, two factors are utilized. The functional form for the step size is as follows:

$$S_{q,w=S^w_{q,w}+S^f_{q,w}} \ldots .q = 1,2,\ldots\ldots\ldots x \text{ and } w = 1,2,\ldots\ldots y \tag{21}$$

The potential to explore more areas of the solution space is shown by the first variable $S^w_q, w$. The capacity to explore the surroundings of previously visited prospective solution space portions of the intensification approach is the second variable $S^f_q, w$.

It is worth noting that the $x^{th}$ community's initial parameter $T_{q,1}$ lacks an affiliate that is superior to it. As a result, $S^f_q, w$ has the same value as 0. As a result of the $x^{th}$ group's final parameters, $T_{q,y}$ does not have a worse parameter than itself. As a result, $S^w_q, w$ is also zero. Furthermore, α and β are the variables that have an impact on both exploration and exploitation.

New Tuning Position: If the neighbors' objective functions are better than the attained fuzzy values, the fuzzy values are replaced with the preceding ones. Allow all fuzzy values to modify their positions in reality. The following equation is presented to update the location of the fuzzy value:

$$S_{new} = \begin{cases} S_{old} + t_1 \times ((U - L) * t_2) + L) & if\ t_3 \geq 0.5 \\ S_{old} - t_1 \times ((U - L) * t_2) + L) & if\ t_3 < 0.5 \end{cases} \tag{22}$$

Limit the search field to where and when older value neighborhood responses are appropriate. As a result, they are the upper and lower boundaries of a random search, $U$ and $L$. $S_{old}$ denotes the current fuzzy scenario, whereas $S_{new}$ denotes the modified position. Homogeneity between 0 and 1 is employed to develop $t_1$, $t_2$ and $t_3$ for the randomization of nature's tuning mechanism.

Normalized Energy variables: The following expression can be used to calculate the general normalized power.

$$E_k = \left| \frac{P_k}{\sum_{i=C_1}^{N} P_i} \right| \quad (23)$$

where $p_k$ is the energy of the $k^{\text{th}}$ main node and $N_c$ is the number of variables. To find the nearest hind, divide the distance among an MF, which is estimated with the *i*th dimension.

Termination: After a chosen maximum iteration, the optimization procedure will be completed. If it is not, it goes back to step one for another round of repetitions.

## 5. Results and Discussion

The proposed prediction models were developed using the MATLAB 2019b software program and settings on a desktop PC with an Intel Core i-7 9700K processor, 16 GB RAM, and a 3.6 GHz clock speed, as well as the Windows 10 64-bit operating platform.

### 5.1. Case Study

The district meteorological station has been established in Al-Dhahran. The research employed the use of climatic variables from Al-Dhahran. In the Saudi Arabian metropolis of Al-Dhahran, the study area covers more than 100 km$^2$ and includes 33,000 residential properties. For more than a 38-year span, the average global temperature data were obtained. The hottest month is July, with the maxima reaching 49 °C and a mean high temperature of 43 °C. The coldest month is January, with a mean low temperature of 11 °C. Summers in Al-Dhahran are hot and muggy, with an estimated average of 100% relative humidity (RH) ranging between 61 and 90 percent and the daily total minimum RH ranging between 15 and 46 percent over the year. During the year, the area features clear skies with rare sandstorms that reduce sun irradiation. With a total surface area of 254 m$^2$, a 1.7 m-high parapet wall, and a PV utilization ratio of 0.13, the roof is rectangular. In addition, site inspections were made to further understand the roof's qualities and the nearby regions of 70 model buildings. To understand the differences in building features, specimens from several residential districts around the city were tested. The database includes 70 samples, each with nine characteristics, namely, z1, z2, z3, z4, z5, z6, z7, and z8, along with b1 and b2 as objective functions (see Table 1). Using the preceding properties as objective functions, this study tries to predict y1 as the heating load and y2 as the cooling load.

**Table 1.** Description of the case study's input and output data.

| Variables | Symbols | Values |
|---|---|---|
| Floors Area | z1 | 504 m$^2$ |
| Number of Flats | z2 | 14 |
| Gross Area | z3 | 254 m$^2$ |
| Roof Area (m$^2$) | z4 | 254 |
| Study Area | z5 | 100 m$^2$ |
| Module Orientation | z6 | Main elevation facing east |
| Parapet Wall Height (m) | z7 | 1.7 |
| Annual Consumption (kWh) | z8 | 188,740 |
| Utilization Factor, UF | z9 | 0.3 |
| Cooling Load | b1 | - |
| Heating Load | b2 | - |

### 5.2. Performance Analysis

The NMAE and NRMSE are context-independent and may be used to compare the performance of the model on building heating and cooling load strength with various input ranges. Smaller numbers for RMSE, like MSE, imply a better performance of the model. The correlation between the actual and predicted variables is measured by the R value. The nearer the R value is to 1, the greater the association is and the better the model's effectiveness is. R2 measures how much variance in the relying factor can be anticipated from the independent factors. The nearer the R2 number is to 1, the greater the relative value is and the better the model's performance is. The preceding formulae are used to compute each of the categories referenced, where $a_p$ and $b_p$ are the actual and anticipated values for sample $p$, respectively. Furthermore, $\overline{a}$ and $\overline{b}$ show the average of the actual and desired heating/cooling load intensity for a building, where M is the representative sample and $\overline{A}$ is a simulation run in MATLAB that represents the average of the building's initial heating and cooling load strength.

$$R = \frac{\sum_{p=1}^{M}\left(a_p - \overline{a}\right)\left(b_p - \overline{b}\right)}{\sqrt{\sum_{p=1}^{M}\left(a_p - \overline{a}\right)^2 \sum_{p=1}^{M}\left(b_p - \overline{b}\right)^2}} \tag{24}$$

$$R^2 = 1 - \frac{\sum_{p=1}^{M}\left(a_p - b_p\right)^2}{\sqrt{\sum_{p=1}^{M}\left(a_p - \overline{b}\right)^2}} \tag{25}$$

$$\text{RMSE} = \sqrt{\frac{1}{M}\sum_{p=1}^{M}\left(a_p - b_p\right)^2} \tag{26}$$

$$\text{MSE} = \frac{1}{M}\sum_{p=1}^{M}\left(a_p - b_p\right)^2 \tag{27}$$

$$\text{MAE} = \frac{1}{M}\sum_{p=1}^{M}\left|a_p - b_p\right| \tag{28}$$

$$\text{NRMSE} = \frac{RMSE}{\overline{A}} \tag{29}$$

$$\text{NMAE} = \frac{MAE}{\overline{A}} \tag{30}$$

During the training stage, Figure 4 shows a good correlation coefficient between the actual values and the projected value for the presented approach. Considering the massive correlation between the goal data and each channel's outcome, it is evident that all of these systems survived the training phase with excellent grades. Great training implies that the system can recognize statistical properties in the types of information and forecast new data using the learned structures, allowing each system to learn how much cooling and heating load is necessary for every building with unique features. Each model can anticipate the quantity of cooling and heating loads based on the test stage's data input with some of this training.

Each model is verified by early test data once it has been trained (30 percent of 100 percent). This is a form of a practice run for the training stage, which is handled entirely by the system. Figure 5 shows the forecast error in the testing or validation stage, which is one of the foremost essential metrics in assessing the outcomes, in a histogram manner, for the SSRD-SsIF-NN. The minimal and largest prediction errors are indicated by the error histogram framework's error. This indicates that the number of inaccuracies that all of the trained systems can have in forecasting the cooling and heating loads for such a testing set is equivalent to the quantity stated in the statistics.

It can be inferred by examining and analyzing each of the above statistics, which reflect the effectiveness of each system throughout the first training stage as well as the testing stage, that the suggested techniques' training has been well verified using the needed data. It is worth mentioning that, whenever a model is trained with extreme accuracy, it is well built, and the number of failures in the validation as well as the first testing procedure is more dependent on the data quality. It also indicates that the system will be able to examine and forecast new and untested data with accuracy. During training, each system is preserved as a black box. During the training stage, the system was able to recognize trends inside this black box. New and untested data must first be utilized to evaluate these systems and forecast cooling and heating loads for buildings. To accomplish this, 15% (five samples) of the information, which was preserved as unidentified and unique data, was employed. Figure 6a,b demonstrate the outcomes of predicting heating and cooling loads for updated information by trained SSRD-SsIF-NN models.

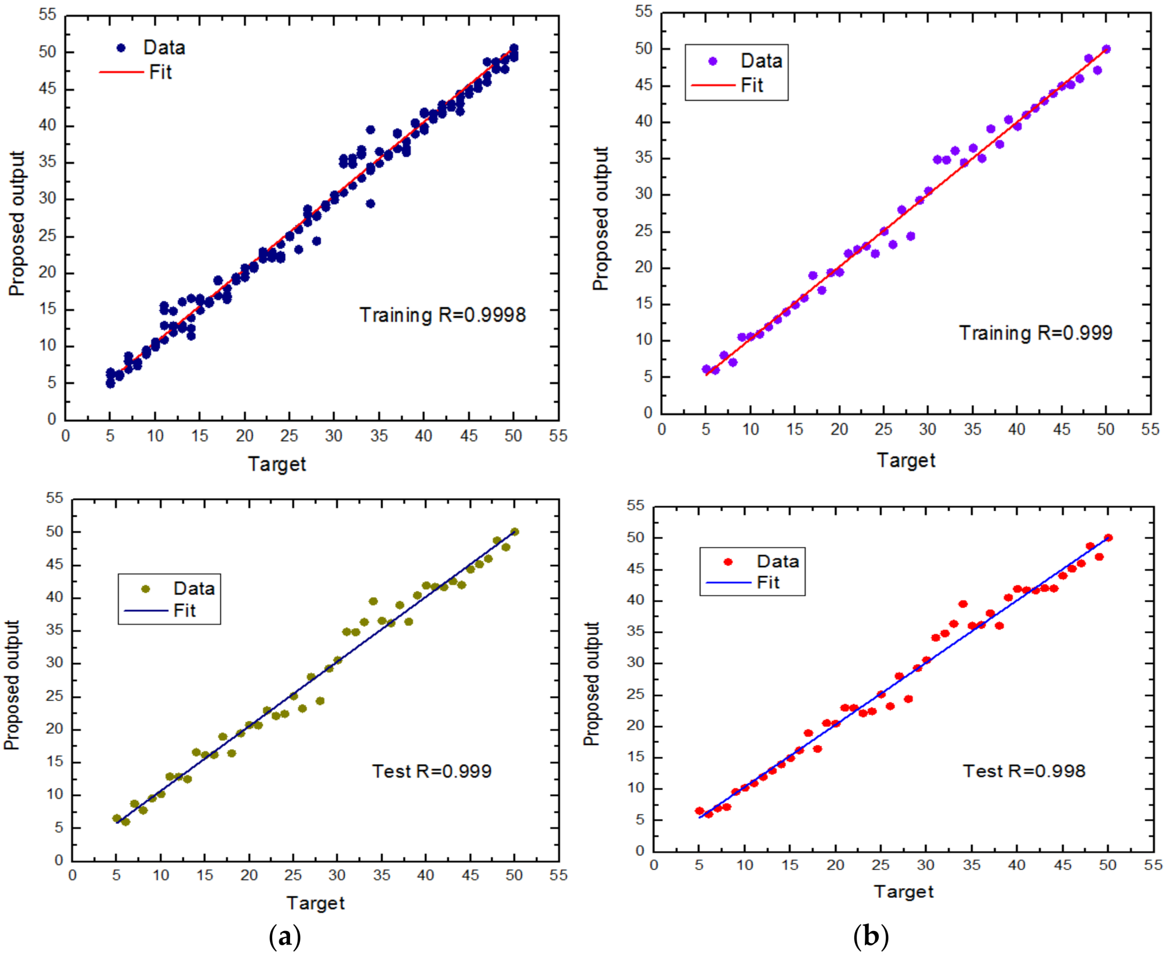


**Figure 4.** The training and testing phases of the proposed model's correlation coefficient. (**a**) Heating load, (**b**) cooling load.

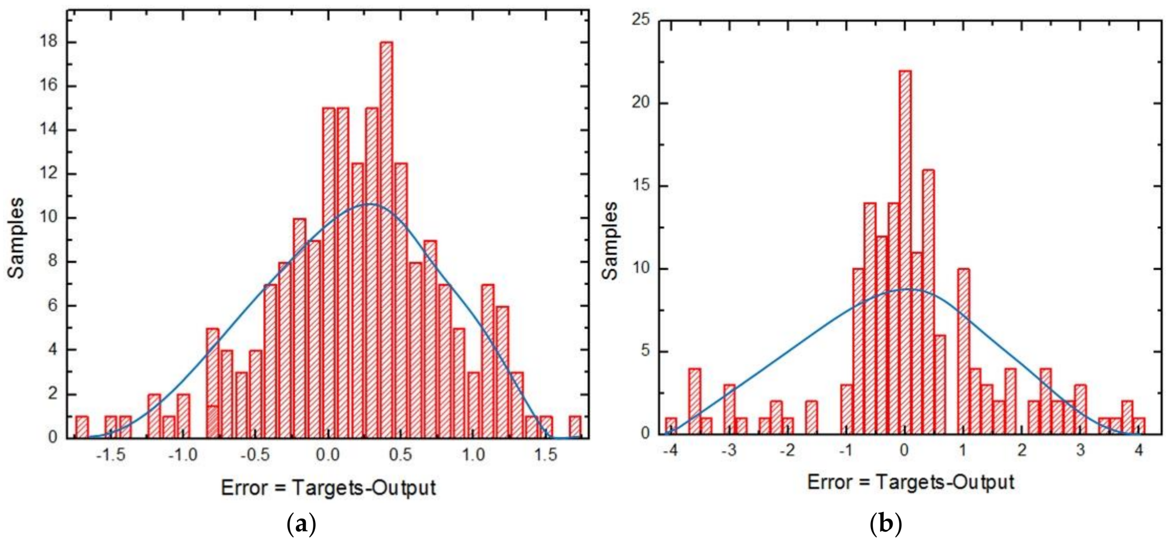


**Figure 5.** Heating load and cooling load histogram testing error. (**a**) Heating load, (**b**) cooling load.

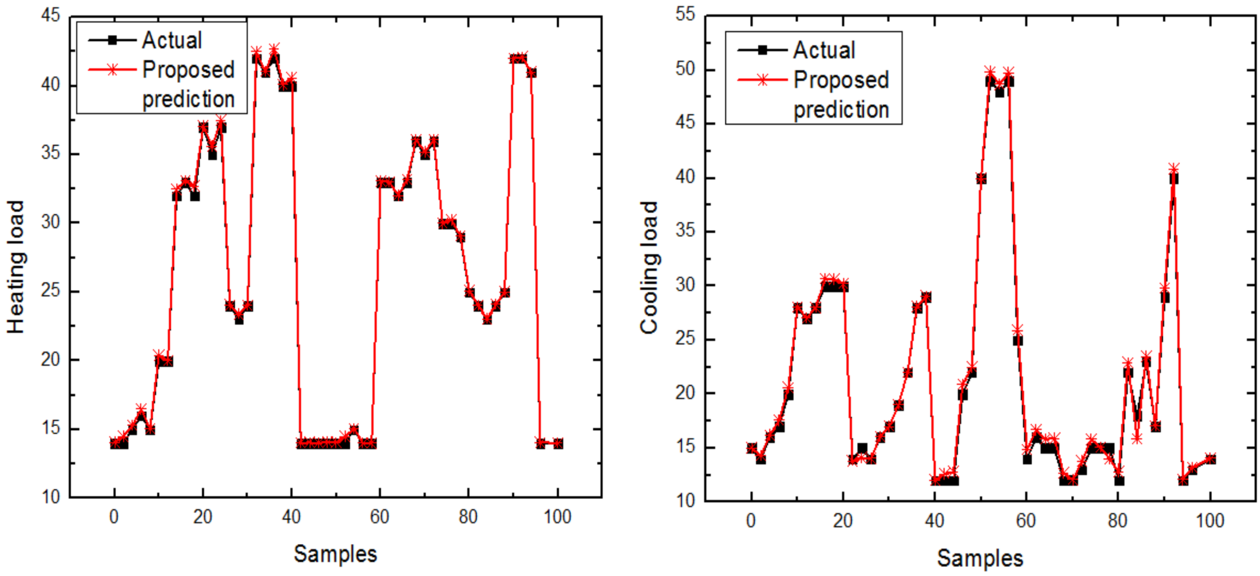


**Figure 6.** Forecasting heat load and cooling load using the proposed method. (**a**) Heating load, (**b**) cooling load.

In the log scale, Figure 7 shows the MSE effectiveness of the proposed models for the training, validation, and test datasets. The best performing network on the validation dataset is the completed system. As a result of training, the system can now predict simultaneous heating and cooling needs. The MSE of the developed framework reduced quickly, resulting in lower error levels. Using the validation sample, the suggested framework predicted the heating load with an MSE of 0.01530 at epoch 115 (Figure 7a) and the cooling load with an MSE of 0.148 at epoch 110 (Figure 7b).

Figure 8 depicts the forecasting accuracy of models tuned using training/testing sets with various sample sizes. When the sample size is increased from 50 to 250, the criteria for evaluating prediction performance drop considerably. When the sample size exceeds 250, meanwhile, the process of diminishing prediction standard evaluation metrics decreases or, indeed, reverses.

Table 2 shows the R, R2, RMSE, MSE, MAE, NRMSE, and NMAE performance evaluations of the proposed approaches. The best prediction was connected to the forecast of the heating load by the suggested technique, which had the greatest value of R (0.9998) and the lowest errors of MSE (0.01530), RMSE (0.21), MAE (0.2), NRMSE (1.5), and NMAE (0.2).

The suggested strategy in the prediction of the cooling load was likewise linked to the best ratings of MSE & RMSE prediction errors. The kind of data input has a significant impact on the application of proposed algorithms and the outcomes. There is indeed a difference in the outcomes of each platform's prediction of cooling and heating loads, and the heating load is anticipated with a high degree of accuracy. This disparity arises from a lack of connection between the data input and the degree of cooling load in comparison to the number of the heating load.

### *5.3. Comparative Analysis*

It is vital to compare the findings acquired with the findings of earlier research to assess the usefulness of the offered approaches in this study. Using identical datasets, comparisons must be conducted with caution. For that purpose, some studies with similar findings for estimating cooling and heating loads were chosen for comparison. The findings of numerous tests conducted to estimate cooling and heating loads by relevant metrics were compared with the experimental results obtained in this paper to represent the efficacy of the data structure in the accuracy of the results. This comparison is made in Table 3.

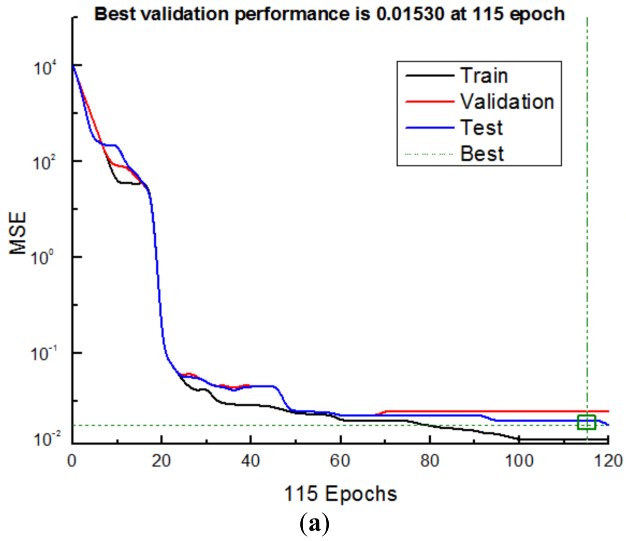


**Figure 7.** Analysis of the best performing model in terms of prediction using the MSE metric. (**a**) Heating load, (**b**) cooling load.

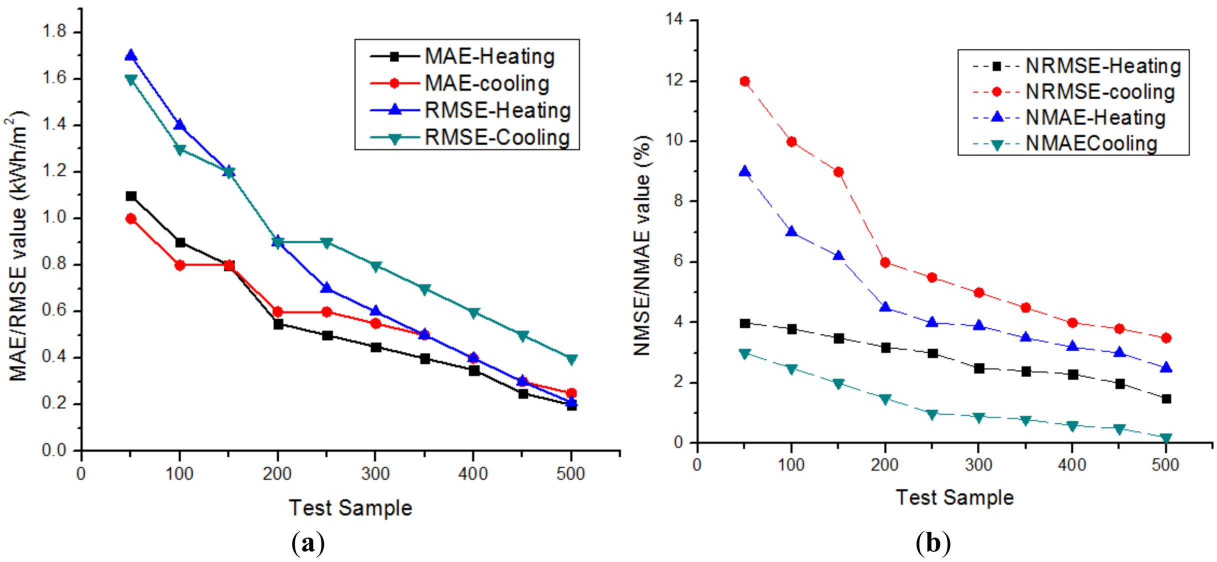


**Figure 8.** (**a**,**b**) Developed model performance using varying sample sizes in the training and testing sets.

**Table 2.** The suggested approach results in terms of predicting heating and cooling loads.

| Loads | Performance Metrics | | | | | | |
|---|---|---|---|---|---|---|---|
| | R | R2 | RMSE (kWh/m$^2$) | MSE (kWh/m$^2$) | MAE (kWh/m$^2$) | NRMSE (%) | NMAE (%) |
| Heating load | 0.9998 | 0.9987 | 0.21 | 0.01530 | 0.2 | 1.5 | 2.5 |
| Cooling load | 0.999 | 0.9978 | 0.4 | 0.148 | 0.25 | 3.5 | 0.2 |

The comparison in Table 3 demonstrates the precision and robustness of the proposed approaches in this research for projecting a building's cooling and heating demands. In residential structures, the use of the proposed SSRD-SsIF-NN methods and the choice of the most appropriate approach for energy prediction and energy-efficient technologies are highly beneficial in reducing energy consumption. With their great accuracy, the chosen approaches were able to accomplish the objective of the study and achieve this key goal. Finally, it is worth noting that the presented techniques may be applied to real-world data as well. The SSRD-SsIF-NN approach was used to forecast the yearly spatial heating/cooling of load intensities in individual groups in this study. Meanwhile, the database of annual residential heating and cooling load intensities created in this study will be a useful resource of household energy statistics for traditional research on WDO-ANN [27], RF-IPWOA-ELM [31], and SVR [32] approaches. Compared to conventional methods, the developed model has achieved much fewer errors of MSE, RMSE, and other significant metrics. The MATLAB simulation is used to create the information on the building structures' heating and cooling of load intensities for this study.

**Table 3.** Comparative analysis of the proposed method and conventional approaches.

| Loads | Performance Evaluation | Model | | | |
|---|---|---|---|---|---|
| | | **WDO-ANN [27]** | **RF-IPWOA-ELM [31]** | **SVR [32]** | **Proposed SSRD-SsIF-NN** |
| Heating load | R | 0.99 | 0.9978 | 0.997 | 0.9998 |
| | R2 | 0.97 | 0.987 | 0.991 | 0.9987 |
| | RMSE (kWh/m$^2$) | 0.2476 | 0.146 | 0.3458 | 0.21 |
| | MSE (kWh/m$^2$) | 0.1459 | 0.01597 | 0.26 | 0.01530 |
| | MAE (kWh/m$^2$) | 0.28 | 0.39 | 0.85 | 0.2 |
| | NRMSE (%) | 1.16 | 2.04 | 1.89 | 1.5 |
| | NMAE (%) | 2.92 | 3.18 | 2.987 | 2.5 |
| Cooling load | R | 0.9987 | 0.99 | 0.9912 | 0.999 |
| | R2 | 0.8931 | 0.928 | 0.948 | 0.9978 |
| | RMSE (kWh/m$^2$) | 0.599 | 0.492 | 0.643 | 0.4 |
| | MSE (kWh/m$^2$) | 0.234 | 0.285 | 0.68 | 0.148 |
| | MAE (kWh/m$^2$) | 0.396 | 0.46 | 0.26 | 0.25 |
| | NRMSE (%) | 4.2 | 4.6 | 3.9 | 3.5 |
| | NMAE (%) | 0.39 | 0.52 | 0.4 | 0.2 |

## 6. Conclusions

The necessity of energy protection and sustainability has created several obstacles in predicting a building's heating and cooling needs. Numerous strategies and techniques for estimating heating and cooling loads are offered by most experts in this subject to improve predictive performance. In this research, SSRD-SsIF-NN is offered as a method for predicting a residential structure's cooling and heating demands. In this work, considerable improvements can be made by including additional values in constructing structural features and switching from a shallow to a profound design-based forecasting model. During the training stage, after developing each of the proposed frameworks, the essential features of a residence were utilized as sources, and the heating/cooling loads were utilized as the output results of each system. To validate the trained networks and anticipate the heating and cooling needs, unique and unidentified information was employed. In forecasting the heating load, this proposed model had an MSE of 0.01530, an MAE of 0.2, an RMSE of 0.21, and an R and R2 both as great as 0.998, and in forecasting the cooling load, it had an MSE of 0.148, an MAE of 0.25, an RMSE of 0.4, and an R and R2 both as great as 0.99. Because the generated prediction methods were dependent on the building attributes, the findings of the study may be useful for developers during the pre-design phase of the energy-efficient heating/cooling of residential buildings.

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