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Prediction model of electrical energy consumption in conventional residential buildings using ANN and ANFIS

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Abstract

The energy consumption of a residential building is considered in terms of energy use and efficiency. Therefore, forecasting the energy consumption of buildings has been raised as a challenge in recent decades. In a residential home, electricity consumption can have recognizable patterns daily, monthly, or yearly depending on living conditions and daily habits and events. In this research, artificial neural network (ANN) and adaptive fuzzy-neural inference system (ANFIS) have been performed using MATLAB software to predict building energy consumption. Also, random data collected based on the criteria obtained from the hourly electricity consumption of conventional residential buildings in Tehran has been used. In order to evaluate and measure the performance of this model, statistical indicators have been used. According to the applied settings (type of learning, number of steps, and error tolerance), the system error rate is calculated based on MSE, RMSE, μ, σ, and R statistical indicators and the results of energy consumption forecast in three buildings with high accuracy and correlation coefficient. R is more than 98%. The output of this research is an intelligent combined system of ANN and ANFIS. The obtained values well show the ability of this model to estimate energy consumption in the mentioned buildings with high accuracy.

Keywords: residential buildings, electricity consumption, Artificial Neural Network (ANN), Adaptive Neural Fuzzy Inference System (ANFIS)
2020 MSC: 93C42, 62F86, 68M10

1 Introduction

Energy conservation is now recognized as one of the most significant challenges in the world. Over recent years, growing concerns about the environmental consequences of energy consumption and global warming have also doubled the importance of this point; therefore, fundamental steps have been taken in nearly all industrial countries to change consumption patterns using different tools, including the development of rules and regulations. In this respect, the building sector consumes about 40% of available energy and produces 30% of the world's greenhouse gases [6]. Respecting the undeniable role of energy in the development and economic cycle of a country along with the limited energy resources and given the outstanding share of energy produced in a country spent on cooling and heating for residential buildings, addressing methods for reducing energy consumption and achieving optimization is today a necessity in each country [6].

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Limited fossil resources, high annual growth of energy consumption, technical and economic inefficiency of energy consumption, about one-third of total energy loss in consumption processes, and growing environmental problems in Iran reveal the need to manage energy consumption and efficiency much more. Over recent years, some awareness and attention to uncontrolled increase in energy consumption and the existence of various restrictions on the development of production resources have led to comprehensive studies around the world on ways to diminish energy consumption and at the same time not to toughen development and growth in countries. In developing countries, factors such as rapid population growth, urban development, improved living standards, welfare, and industrial and commercial development have raised the need to expand energy consumption. Nowadays, energy conservation in residential complexes is one of the most critical concerns in all countries. Because of limited available resources and growing needs for energy consumption, studying new methods to reduce and optimize energy consumption becomes of utmost importance. In this respect, different factors can affect energy consumption in a building, varying from climate to climate. This makes it very complicated to perform calculations theoretically and manually [6].

This study aims to present a combined model of the most appropriate method for predicting the energy consumption of residential buildings with a sustainable development approach due to uncertainties in the real world using artificial neural network (ANN) and fuzzy-neural inference system. Comparative (ANFIS) and using MATLAB software.

2 Research background

Li et al. proposed a model for predicting the cooling energy of an entire building using an artificial neural network due to the existence of an intelligent network in energy consumption [17]. Shaikh et al. have investigated intelligent, multi-purpose optimization for energy and comfort management [14]. Amber et al. have examined intelligent techniques for predicting the electricity consumption of buildings [4]. Ahn et al. have examined the energy cost analysis of an intelligent building network by adopting the concept of heat trading in a district heating model [1]. Raatikainen et al. have examined the intelligent analysis of energy consumption in school buildings [25]. Ascione et al. have presented simulations based on the control model of building energy performance and thermal comfort prediction using a multi-objective optimization method, genetic algorithm, and MATLAB and building automation systems [5]. This issue has also been mentioned in the research of Nguyen et al. [22]. Delgarm et al. have presented an efficient method for multi-objective simulation-based optimization using ENERGYPLUS to increase building energy performance in four areas: building direction, window size, wall specifications, and cladding [12]. Due to the incredible popularity of artificial intelligence methods and especially artificial neural networks in building energy analysis, there was a need to review different methods to achieve this. Kumar et al. reviewed these methods and examined the potential of the artificial neural network as a design tool in a wide range of buildings [26]. The application of an artificial neural network in simulating the behavior of building shells in summer conditions with a new glass system to evaluate and improve energy performance was investigated by Buratti et al.. The climatic conditions and thermal characteristics of the building shell were assumed as the input and the temperature of the interior space of the building as the network output. The results showed that artificial neural networks could be used as a powerful tool in simulation [9].

The prediction of energy consumption of a residential building with the approach of artificial neural networks was discussed by Biswas et al.. The best error criterion was reached by selecting the appropriate number of hidden layer neurons. The network results were statistically satisfactory in comparison to previous studies [8]. Chabaud et al. (2014) studied the management of energy resources in buildings in the south of France with energy storage systems from renewable energy production and modeled them using TRNSYS software and found that savings can be made by changing Acquired some internal loads from peak load periods to off-peak periods [10]. Lee et al. review the use of the artificial neural network to predict user-based energy consumption, consider 5240 male and single female households, and calculate the corresponding energy consumption using Energy Plus and users' activities and features. They analyzed the energy consumption of the building [16] Amara et al. propose an adaptive circle conditional expectation method (ACCE) based on circle analysis to define sub-action plans. As a result, an adaptive linear model (LM) method is used to predict the demand for residual components using the results of the ACCE process in each time window. After that, the projected balance is used to comparatively improve the performance forecast of total electricity demand. The accuracy of the prediction results is evaluated using the mean normalized absolute error. As a result, the proposed approach to modeling periodic residual demand on the daily horizon leads to a good 23% accuracy [3]. Ciancio et al. measured discrepancies between energy consumption in a residential building and seasonally analyzed and compared the energy needs of buildings with ENERGYPLUS and the WRF forecast model for two airports in Rome. [11]. Malik et al. to accurately predict the energy consumption of residential and commercial buildings and optimize the energy consumption of intelligent buildings for the required management, use the PSO particle swarm optimization algorithm with neural networks and create PSO-NN neural networks in order to increase the accuracy of forecasting [18]. Alobaidi et al. (2018) provide a framework using a vital regression component to predict each household's average daily energy consumption [2]. Accurate estimation of energy efficiency of residential buildings based on the calculation of HL heating load and CL cooling load is an important task. Nilashi et al. presented an efficient method for predicting the energy performance of residential buildings using the adaptive neural-fuzzy inference system. The mean absolute error of MAE of HL and CL predictions is 0.16 and 0.52, respectively, which shows the method's effectiveness in HL and CL predictions [23]. Naji et al. propose a new method for estimating building energy consumption based on ELM. The Extreme Learning Machine method is applied for the thickness of building materials. Estimates and predictions obtained by the ELM model are compared with genetic programming and artificial neural network models for predictive accuracy [20]. Ahmad et al. predicted energy consumption in a residential building with the Markov model. The Markov-based algorithm predicts energy consumption in Korean residential buildings using data collected through smart meters and four cases of multi-story buildings in Seoul. The prediction results of the proposed model were compared with three well-known prediction algorithms: Support vector machine and artificial neural network and regression classification were compared, and the prediction accuracy was acceptable [28].

Yu et al., based on the backpropagation (BP) neural network model, examined the energy consumption forecast of residential buildings in Chongqing, China, and obtained good results [30]. Yang et al. used simulated (artificial) and measured data using artificial neural networks to predict building energy and obtained acceptable results compared to actual data [29]. Mocanu et al. (2016) examined two reinforcement learning algorithms to model building energy consumption. As a core theoretical contribution, a Deep Belief Network (DBN) is included in each algorithm. The methods are then developed in the MATLAB environment and tested on an actual database recorded over seven years at hourly resolution. Experimental results show that the RMSE energy prediction accuracy intervals are 91.42% [19]. According to Tian et al., data sets do not have much value in predicting building energy consumption time series. Moreover, it still requires accurate building information, which may lack existing buildings—proposed a parallel forecast of building energy consumption using hostile GAN generating networks. The results showed that the proposed method has the best performance compared to existing methods such as information dissemination technology, Trend-Diffusion (HMTD) Mega experimental method, and Bootstrap method. The proposed parallel forecasting scheme can be extended to other time series forecasting problems, such as electrical load forecasting and traffic flow forecasting [27]. Jang et al. (2019) created an artificial neural network. A model predicts when the heating system should work to reduce energy consumption in winter mornings. BEMS experimental data and artificial neural network model predictive performance were approximately 13.13% better than CVRMSE and 0.197% better than MBE. This study helps reduce energy consumption in buildings and helps to provide pleasure [15].

Edwards et al. From an artificial neural network to predict energy consumption in buildings. Energy consumption patterns may differ significantly in residential buildings, evaluating seven different machine learning algorithms into a new residential data set, which includes sensor measurements collected every 15 minutes. In order to determine which technique is most successful for predicting the hourly consumption of a residential building. [13]. Giao et al. have reviewed various techniques and strategies for predicting building energy consumption based on existing knowledge collections and have systematically demonstrated application areas. They also offer a very holistic view of the building's energy consumption [24]. Shahaboddin et al. Using the total energy requirements of the building are affected by various factors such as the environment, climatic conditions, building materials, insulation, etc., using the fuzzy-neural network system ANFIS and Energy Plus and soft computational method with Matlab/Simulink have examined the energy consumption of the building [21]. Predicting the energy required by the building in the early stages of design using the ANFIS adaptive fuzzy-neural inference system model was studied by Ekici et al. to predict the building energy consumption [7]. Baheri et al. investigated the prediction of electricity and gas consumption in a residential building complex in the cold region of Iran in the city of Tabriz using a neural network and genetic algorithm [6].

According to the review of research literature, it is observed that no research has attempted to provide multi-criteria decision-making methods to select energy supply methods in residential buildings with a sustainable development approach. However, paying attention to the existing criteria for choosing an efficient method to manage energy consumption optimally is very important in management decisions.

3 Background of applications of neural network models and adaptive fuzzy-neural inference system

Building energy consumption is a critical variable, not only in scientific analysis but also in cost analysis. Therefore, high accuracy in developing the energy consumption model is essential because underestimating energy consumption can lead to potential outages that can be detrimental to social and economic lifestyles. In contrast, overestimation leads to unnecessary unemployment capacity. And as a result, wasted financial resources. Therefore, several studies have been performed to predict energy consumption with different statistical models and approaches accurately. Because conventional statistical models require a significant amount of collected data and are relatively accurate for linear data, neural network models can calculate nonlinear data. Properties are observed at different electrical loads by urban meter readings [8].

Artificial neural networks are generalized to the human nervous system by mathematical models. The concept of neural network analysis was discovered about five decades ago. However, its applications have become more widespread and famous in the last two decades. Significant technological advances have become a challenging problem with higher processing speed and higher computing capacity. The artificial neural network has succeeded in overcoming the research process to find its place in real-time schedules in various industries, including aerospace, robotics, energy, medicine, economics, psychology, and neurology. This concept was used to model energy consumption in individual buildings and began with commercial buildings during the last decade of the 20th century. Several researchers have shown that because of their ability to manage nonlinear patterns with high computational speed and high accuracy, they can be more reliable in predicting energy consumption in buildings than other traditional statistical approaches. Such traditional statistical approaches, which are usually static models, include the use of simple or multiple linear regression to find the relationship between output and input parameters and the variable base degree-day method and point-of-change models [8].

Adaptive fuzzy-neural inference system (ANFIS), which best integrates the features of fuzzy systems and neural networks, is defined by Jang. As a structure, ANFIS includes if-else rules and uses fuzzy pair input-output data and neural network learning algorithms for training. An adaptive fuzzy-neural inference system simulates complex nonlinear mapping using neural network learning and fuzzy inference methods. The ANFIS structure consists of two models, ANN, and fuzzy logic, and can work with indistinct noise and inaccurate environments. ANFIS is used in the neural network training process to adjust the membership function and parameters related to the data in question. It has more accurate results than the average squares error measure because it can exploit expert decisions. ANFIS learning algorithm is a hybrid learning algorithm using a post-diffusion learning algorithm and the least-squares method [7].

4 Modeling approach

4.1 Artificial Neural Network (ANN)

In its simplest form, shown in Figure 1, it is an artificial neural network model consisting of simple single elements known as neurons. Each neuron n has a p input, a weight function w, and a bias function b to generate the result a.

$$a = f(wp + b) \tag{4.1}$$

Where $f(\ )$ is an activation function to scale or convert the number of neurons to values of meaningful results for further analysis, the activation function can be a linear function, which can be $y = x$, or a sigmoid logarithmic function, which can be given by Ref [8].

$$\frac{1}{1+e^{-x}} \tag{4.2}$$

A typical network consists of an input layer, one or more hidden

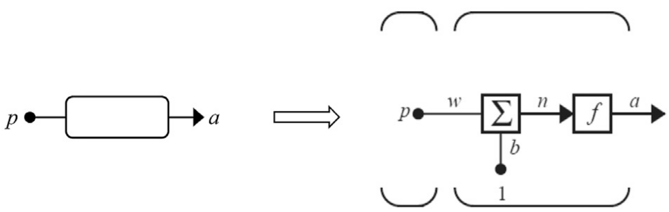


Figure 1: Example of simple element called a neuron with an input layer of one variable. [8]

A typical network consists of an input layer and more hidden layers. Each layer has more than one neuron in which they work and an output layer of one or more outputs represented by neurons.

Different types of neural networks can be used according to the research objectives. In this study, a feedforward neural network was used. Typically, these networks consist of sensory units (primary neurons) that make up the input layer, one or more hidden layers, and an output layer. The front is spread layer-by-layer. This type of network is commonly referred to as the multilayer perceptron (MLP). Such as forecasting, classification, and modeling and can learn.

4.2 Adaptive fuzzy-neural inference system

Various structures have been proposed to implement a fuzzy system by neural networks. The difference between a fuzzy-neural network principle and an artificial neural network is that the weights and values of the neural network input and output are defined as fuzzy numbers.

The neural-fuzzy inference system is one of the most accurate measuring tools for ambiguous and nonlinear concepts. In recent years, robust fuzzy inference systems based on the ANFIS adaptive neural network have been used in various sciences. Using the training power of neural networks and the capabilities of fuzzy systems, these types of systems have been able to use the advantages of these two in analyzing potent complex processes. And modeling. ANFIS model is very suitable for describing and interpreting nonlinear systems.

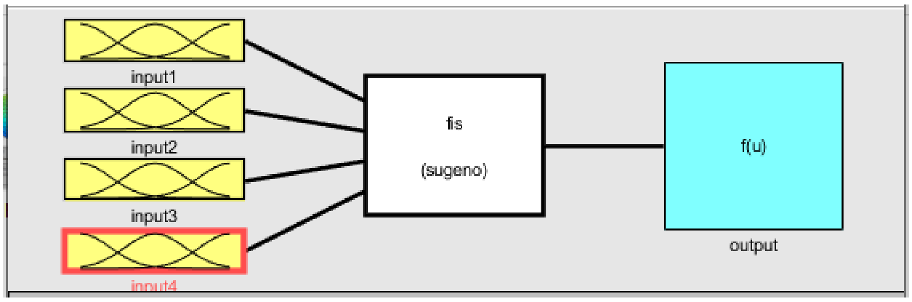


Figure 2: Overview of the fuzzy inference system

5 Research methods

According to the purpose of this research, the application type (using the model to predict energy consumption during the year for residential buildings) and multi-criteria decision-making methods have been used. The optimization section is presented using multi-objective optimization algorithms of ANN artificial neural network and ANFIS adaptive fuzzy-neural inference system and MATLAB software.

5.1 Input data

Electricity consumption in residential buildings is defined depending on year-day, i.e., $365 * 24$ position of the year. Provide a database whose content is the amount of energy consumed during this period when it should have 8760 lines (per year).

Hourly energy consumption recording of residential buildings in Tehran is not available, and only electricity consumption bill is available monthly or bi-monthly for each branch. By examining the sample operation of urban electricity meters of residential units (as an example, in Table 1, the five-year operation of the municipal electricity meter of a residential unit is given), household consumption interval was recorded at different hours of the day, including mid-load and low load and peak energy consumption. Then, using MATLAB software, a data random function is defined. Random amounts of energy consumption per energy consumption of three conventional residential buildings in Tehran are prepared. Conventional buildings are buildings up to 7 floors, including most urban buildings in Tehran. This data is related to three residential apartment buildings in Tehran and has been prepared for three years, including a four-unit residential building and two eight-unit residential buildings. According to the study of consumption tables and the amount of hourly consumption during the day and night of buildings, in the case of the first four units, the maximum energy consumption is about 12 kWh. In two buildings of eight units, the maximum energy consumption is 25 kWh. The available data are presented in three Excel files (for each house) that represent each residential unit's energy consumption. These files have three columns (for each year of data recording) and 8670 rows (for each hour of the day during 365 days of the year) and show the amount of energy consumption of each residential building in watts per hour.

Also, by knowing the average energy consumption in the building and general information about the deviation from the criterion of that index, it is possible to replace the actual data with the appropriate accuracy of a random number generator with normal distribution. Here neural networks can predict the exact amount of energy consumption.

Table 1: Sample of five-year energy consumption values of a residential unit in kWh

Date	**number of days**	**Average monthly consumption**	**Shoulder**	**Peak**	**Off-peak**
2021/10/27	57	308.95	315	75	197
2021/8/31	56	336.43	409	87	132
2021/7/6	57	310.53	316	124	150
2021/5/10	77	259.48	419	57	190
2021/2/22	64	329.06	440	79	183
2020/12/20	62	203.23	235	59	126
2020/10/19	56	197.68	209	54	106
2020/8/24	51	324.71	328	82	142
2020/7/4	59	315.76	372	93	156
2020/5/6	73	300.41	454	113	164
2020/2/23	57	325.26	389	77	152
2019/12/28	59	298.47	348	77	162
2019/10/30	64	306.56	384	82	188
2019/8/27	56	325.18	345	87	175
2019/7/2	58	336.72	371	101	179
2019/5/5	82	308.41	508	110	225
2019/2/12	57	321.05	377	71	162
2018/12/17	57	345.79	409	76	172
2018/10/21	55	316.36	343	77	160
2018/8/27	56	196.07	235	42	89
2018/7/2	58	174.83	203	38	97
2018/5/5	87	284.48	465	131	229
2018/2/7	52	318.46	300	105	147
2017/12/17	57	302.11	312	109	153
2017/10/21	59	305.08	337	104	159
2017/8/23	52	314.42	295	97	153
2017/7/2	61	318.69	340	121	187
2017/5/2	83	265.3	412	138	184
Total	1722	8249	9870	2466	4519
Average	62	295	353	88	161

5.2 Mackey-Glass equation

The Mackey Glass equation is a nonlinear time-delay differential equation according to Equation (5.1).

$$\frac{dx}{dt} = \beta \frac{x_\tau}{1 + x_\tau^n} - \gamma x, \quad \gamma, \beta, n > 0. \tag{5.1}$$

The ANN artificial neural network and the ANFIS adaptive neural-neural inference system are used to prepare a time series prediction model generated by the McKee-Glass time-delay differential equation.

In predicting time series, known values of time series t are used to indicate the deal at a future point $t + p$. When forecasting, it is assumed that the behavior of this system is constant at different times, and not much change in the conduct of the system should be observed. Moreover, that is why there is predictability. Based on the past behavior of the system and using mathematical tools and statistical analysis, the future of the system can be estimated. This system also has Markov properties, and by referring to the little part of the system, it offers a formula for predicting the future. The general concept of this system is given in Figure 4.

$$X(t) = f\big(x(t-1), x(t-2), \cdots, x(t-d)\big) \quad \text{Nonlinear Differential Equation} \tag{5.2}$$

In the time series prediction structure, using an estimated function $f(\cdot)$ Moreover, using past time data, the future is predicted so that the prediction error is minimized. In this case, it is necessary to use the approximate functions of Approximation of functions (regression, ANN, ANFIS, Fuzzy, ... The artificial neural network ANN and ANFIS have been used in this study.

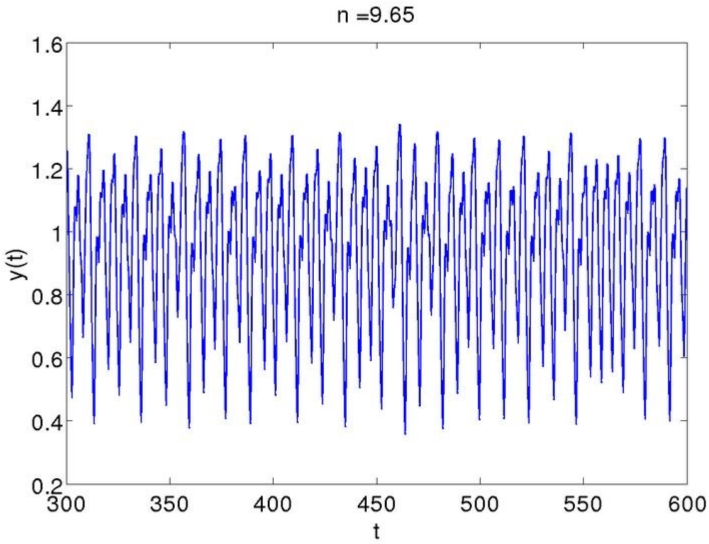


Figure 3: Dynamics in the Mackey-Glass equation, Equation (5.1), for $\gamma = 1,\ \beta = 2,\ \tau = 2$ and $n = 9.65$

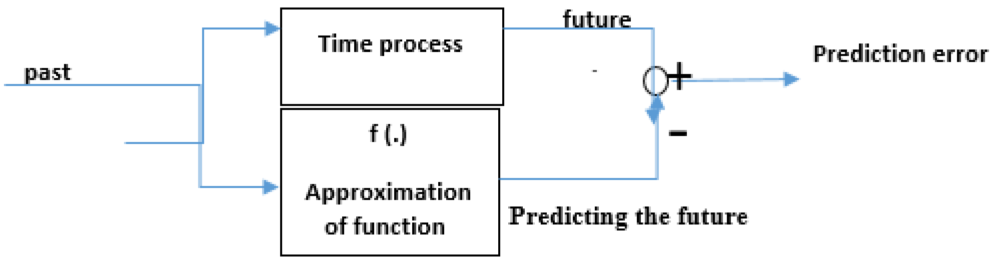


Figure 4: Time series prediction structure and prediction error determination

5.3 Features and specifications of artificial neural network (ANN)

In this study, the artificial neural network of the feeder, according to the programs written in MATLAB software, is responsible for predicting (modeling) the amounts of energy consumption over time. Among the various training methods, the Lundberg-Marquardt algorithm has been used to train the network and optimize the weights of the multilayer MLP perceptron neural network due to faster convergence in the training of medium-sized networks. In this system, a round of training and moving forward outputs in the last layer are calculated. Then, the error value is calculated by comparing the actual and desired output value by the mean of the squares. The error ratio is distributed on the previous steps in the reverse path, and the error value is corrected using the descending slope method. Also, the energy consumption of the building corresponding to the input data in a specific time has been used as the target vector.

In this study, 70% of the input data was used for network training, 15% as test data, and 15% for network evaluation. It is proved that each function can be approximated with a maximum of three hidden layers. In this paper, the number of hidden layers is 2, the first layer contains ten neurons, and the second layer contains five neurons. Neurons can use different stimulus functions to produce output. This study uses the Tansig hyperbolic function in Hidden layer neurons and the Purelin linear function for output layer neurons. The objective or fit function for the model presented in this research is to minimize the mean squares of the MSE error, which is calculated from the following equation.

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(x_{\mathrm{real}_i} - x_{\mathrm{forcast}_i})^2 \quad \text{mean square error} \tag{5.3}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_{\mathrm{real}_i} - x_{\mathrm{forcast}_i})^2} \quad \text{root mean square error} \tag{5.4}$$

$$\sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \mu)} \tag{5.5}$$

$\mu =$ Mean of empirical data $\quad \sigma =$ Standard deviation of empirical data

Other parameters are considered during the neural network training process, such as the number of repetitions of Epochs training, which is 1000 here, and the minimum acceptable max-fail efficiency, which is 100 here. In neural network training, *efficiency* is defined as the difference between the output's sum and the desired output's sum. We have declared an acceptable value equal to 1e-8 of the sum of the output values. For example, for a neural network that is supposed to predict the amount of energy consumption per hour, the above value is considered the maximum acceptable error for the network in all outputs. According to the following figure, two hidden layers are used in the presented model, the first layer has ten neurons, and the second layer has five neurons and one output layer.

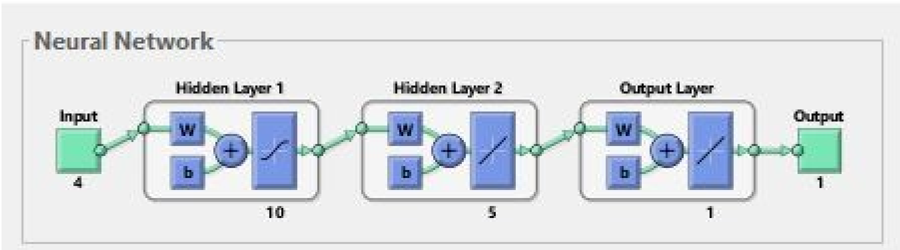


Figure 5: ANN model of error backpropagation method, Lunberg-Marquardt algorithm in all three buildings

5.4 Features and specifications of the fuzzy-neural adaptive inference system (ANFIS)

In this research, the adaptive fuzzy-neural inference system, according to the programs written in MATLAB software, is responsible for predicting (modeling) energy consumption values over time. This system uses 70% of the input data for network training and 30% for test data. Here, three types of genes are used to design ANFIS, which include:

genfis1 (Grid Partition): The data generates a single-output fuzzy inference system of the Sugeno type using a network partition on the data. The number of membership functions is five, the type of Gaussian input function is gaussmf (Gaussian membership function), and the type of membership function is linear output.

genfis2 (Sub Clustering): A Sugeno-type FIS structure created using differential clustering. Moreover, it requires separate input and output data sets as input arguments. Its penetration radius in this program is equal to 0.2.

genfis3 (FCM): Using fuzzy c-means clustering, FCM generates a FIS by extracting a set of rules that models data behavior. Since there is only one output, genfis3 has been used to create an initial FIS for training. The number of clusters is equal to 10, the number of partitions of matrices is equal to 2, the maximum number of iterations is equal to 100, and the minimum amount of system improvement is equal to 1e-5.

The number of repetitions of Epochs training here is 100, the target for error rate is zero, the initial step size is 0.01, the step size reduction rate is 0.9, and the step size increase rate is 1.1.

5.4.1 Output membership function type

This method is suitable for multi-input and multi-output calculations with any level of complexity, and by determining the number of clusters purposefully, the amount of error can be reduced. The following figure shows the user-software relationship based on the choice of each of the genfis methods. (The following is the choice for the FCM method).

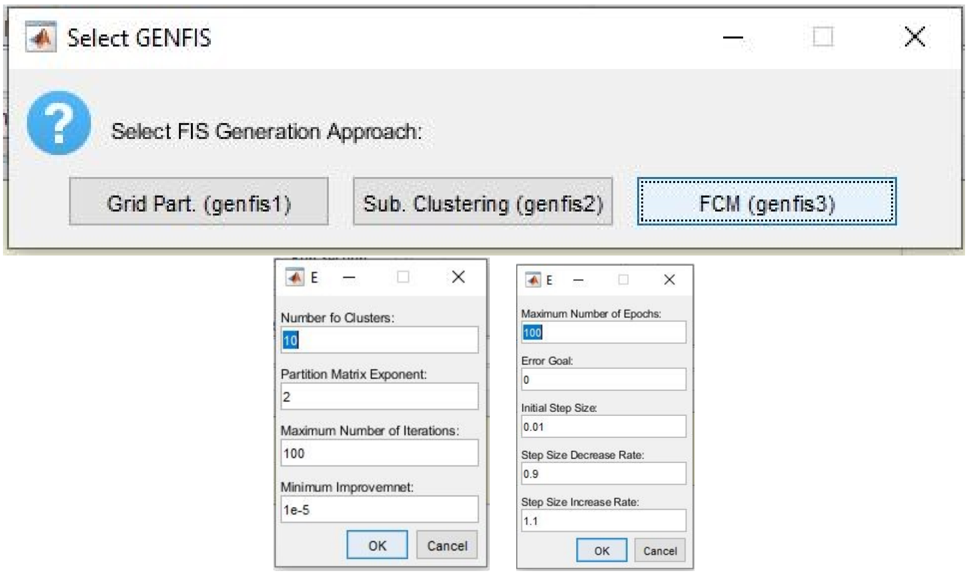
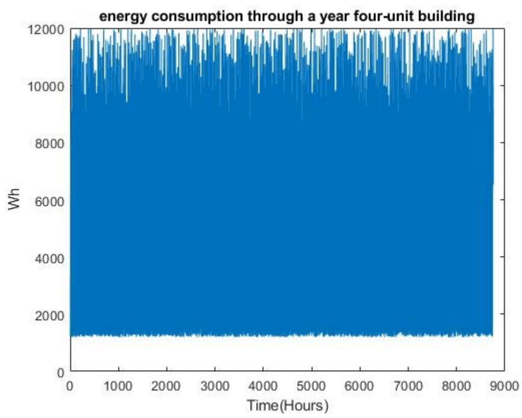


Figure 6: Applied relationship for selecting FCM design method in ANFIS in all three buildings

6 Findings and research results

In this research, an artificial feed neural network with ANN error propagation algorithm and ANFIS adaptive fuzzy-neural inference system has been used to calculate the prediction of energy consumption in the building. One of the most important findings of this research is to prepare a model for predicting energy consumption using the above tools. The results show that the error of both networks is acceptable, and the speed and ability to learn and their efficiency in estimating the energy consumption of a residential building have very high accuracy. First, the results obtained from the ANN artificial neural network are examined:



The energy consumption of buildings in Figures 7 and 8 is very similar to the Mackey Glass chart. Of course, the energy consumption of the second 8-unit buildings is identical. By performing training and testing processes and evaluating the ANN system in all three buildings according to the applied settings (type of learning, number of steps, and error tolerance), the system error rate is calculated based on statistical indicators MSE, RMSE, μ, σ and R Has been.

By implementing the general forecasting processes of the ANN system in all three buildings according to the applied settings and also according to the obtained results, the statistical distribution of energy consumption values in all three buildings is entirely consistent with the normal distribution. The system error rate is calculated based on MSE, RMSE, μ, σ and R statistical indices. The energy consumption forecast results in three buildings with high accuracy and an R correlation coefficient of more than 98% have been obtained.

According to the evaluations performed in the ANN system, the research validation at this stage is based on the difference between model outputs and the input data in three buildings. The values of the R correlation coefficient in

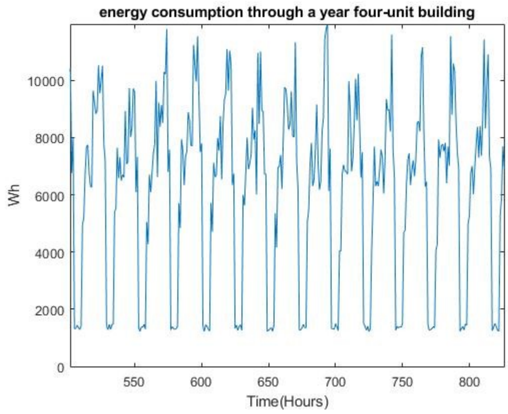


Figure 7: Building energy consumption of 4 units per year and in a period

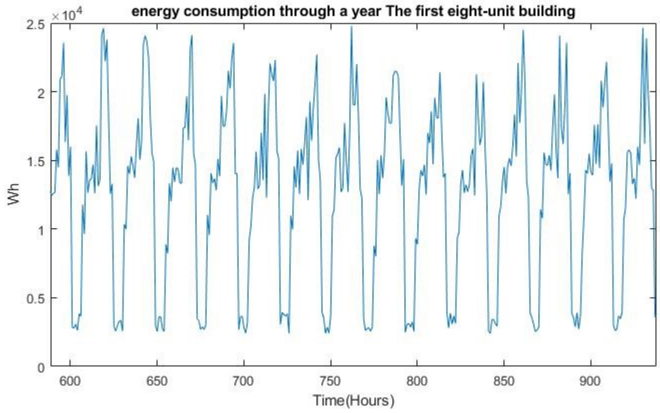


Figure 8: Energy consumption of the first eight units of a building in a period

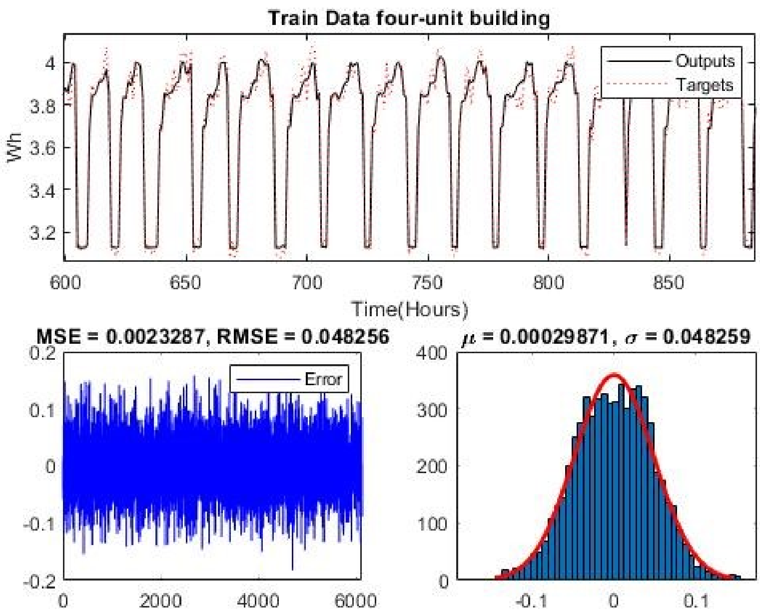


Figure 9: Training results of a 4-unit building system using the ANN

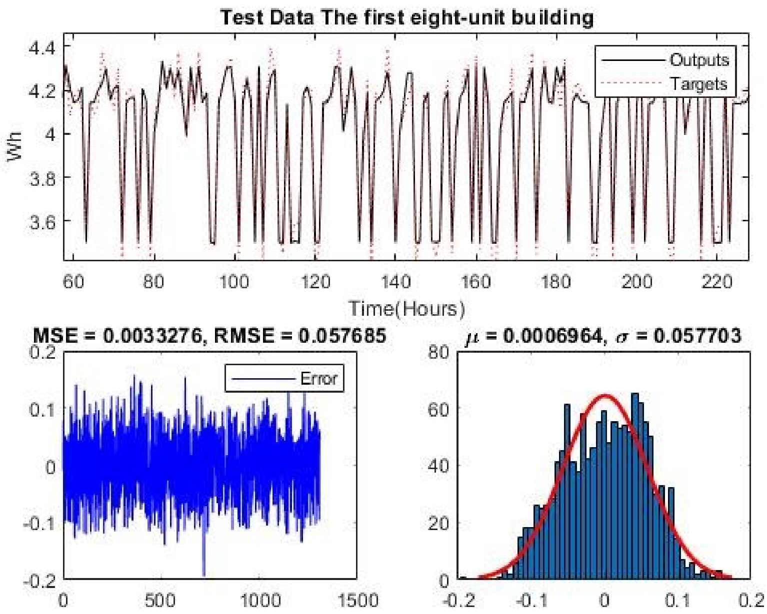


Figure 10: Test results of the first 8-unit building system using the ANN

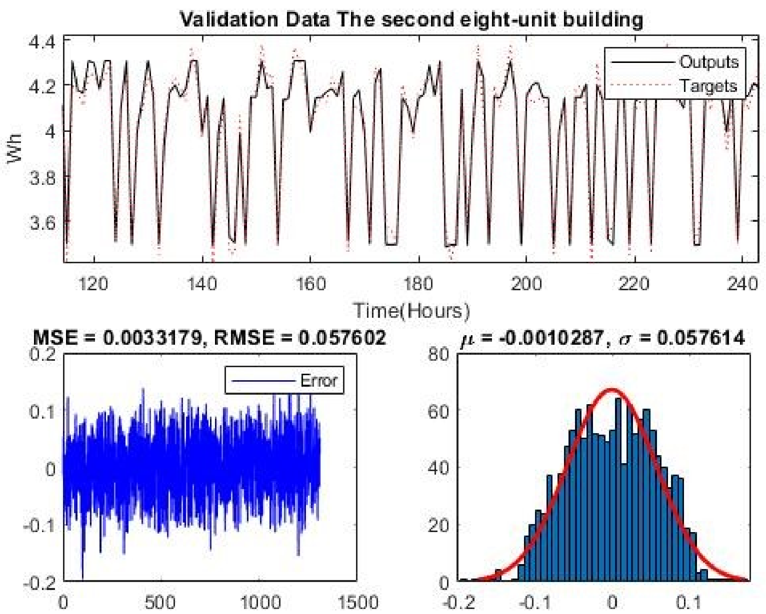


Figure 11: Evaluation results of the second 8-unit building system using ANN

the obtained results are more than 98%, which is a sign of the proper performance of the designed model.

Due to the large number of results obtained, the different stages and ANN network outputs related to all three buildings are presented in Table 2.

Here we review the results obtained from the ANFIS fuzzy-neural inference system. Table 3 provides information about the ANFIS system and its genfis type in each of the studied residential buildings.

In Figures 16, 17, 18 and 19, as examples of ANFIS system outputs, the structure model and membership function model and fuzzy role representation, and input and output representation are given.

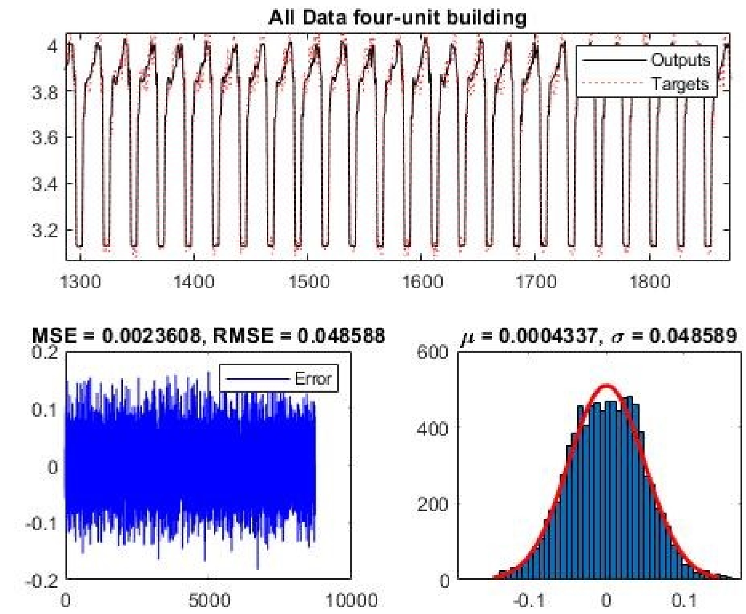


Figure 12: Results of forecasting energy consumption of a 4-unit building using ANN

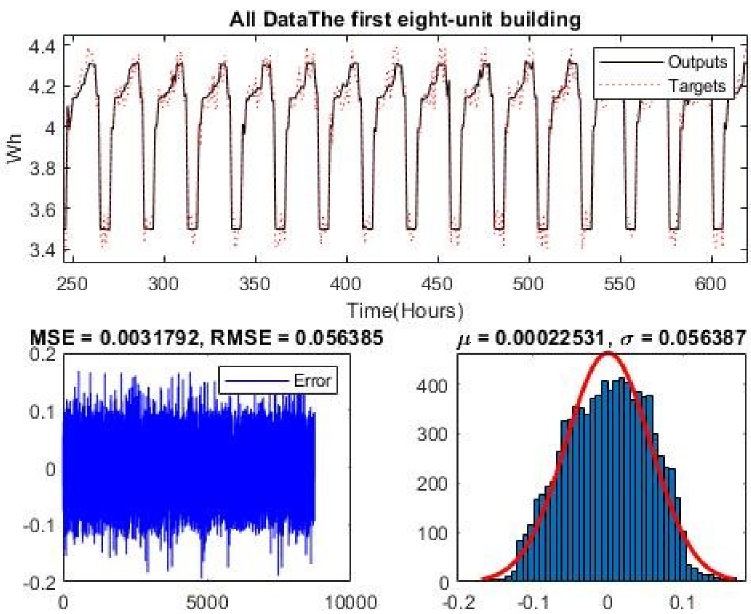


Figure 13: Results of forecasting energy consumption of the first 8-unit building using ANN

Table 2: Statistical index of MSE, RMSE, R, μ and σ in ANN system in all three residential buildings

Statistical index	4-unit building				The First 8-unit building				8-unit second building			
	All Data	Train	Test	Vallidation	All Data	Train	Test	Vallidation	All Data	Train	Test	Vallidation
MSE	0.00236	0.00232	0.00246	0.00242	0.00317	0.00311	0.00332	0.00336	0.00321	0.00317	0.00312	0.00331
RMSE	0.04559	0.04826	0.04956	0.04914	0.05638	0.05575	0.05768	0.05801	0.0567	0.05632	0.05755	0.0576
R	0.9896	0.9897	0.9894	0.9892	0.9835	0.9839	0.9828	0.9825	0.9834	0.9837	0.9826	0.9832
μ	0.00043	0.00029	0.0022	0.0007	0.0002	0.00024	0.00069	0.00069	0.00022	0.00014	0.00124	0.00102
σ	0.04859	0.04826	0.04953	0.04916	0.05638	0.05575	0.0577	0.05802	0.05671	0.05632	0.05756	0.05761

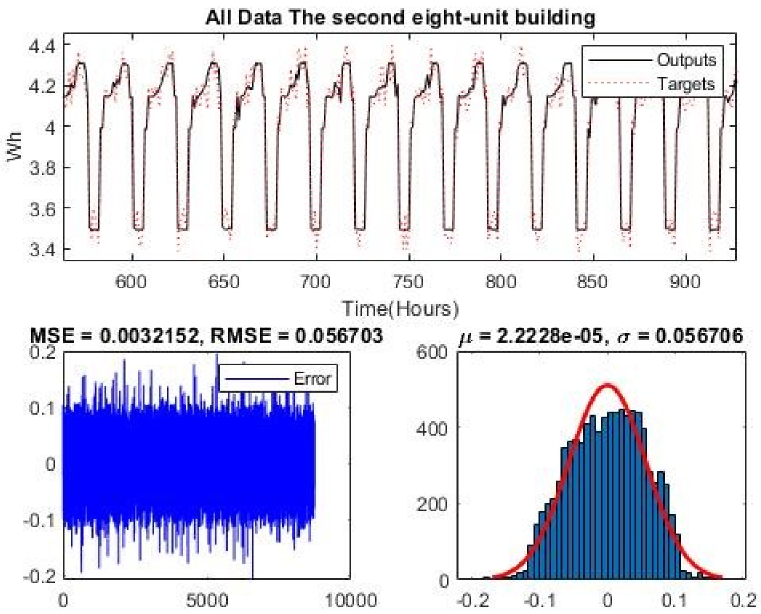


Figure 14: Results of forecasting energy consumption of the second 8-unit building using ANN

Table 3: Specifications of ANFIS system and its genfis type in all three residential buildings

ANFIS information	4-unit building			The First 8-unit building			8-unit second building		
Genfis type	1	2	3	1	2	3	1	2	3
Number of nodes	55	147	107	55	197	107	55	217	107
Number of linear parameters	80	70	50	80	95	50	80	105	50
Number of nonlinear parameters	16	112	80	16	152	80	16	168	80
Total number of parameters	96	182	130	96	247	130	96	273	130
Number of training data pairs	6115	6115	6115	6115	6115	6115	6115	6115	6115
Number of checking data pairs	0	0	0	0	0	0	0	0	0
Number of fuzzy rules	16	14	10	16	19	10	16	21	10

By performing training and testing processes and evaluating the ANFIS system and in all three studied buildings according to the applied settings (type of learning, number of steps, and error tolerance), the system error rate based on statistical indicators MSE, RMSE, μ and σ and R is calculated based on the following outputs.

By performing the general prediction processes of the ANFIS system in all three buildings according to the applied settings and the obtained results, the statistical distribution of energy consumption in all three buildings is entirely consistent with the normal distribution and the system error rate. They are calculated based on MSE, RMSE, μ, σ and R statistical indices. The values of correlation coefficient R in the outputs are more than 98%. And this is a sign of the proper performance of the designed model.

Due to the large number of results obtained, the results of different stages and the outputs of the ANFIS fuzzy-neural inference system related to all three buildings are presented in Tables 4, 5 and 6.

Table 4: Statistical characteristics of MSE, RMSE, R, μ and σ in ANFIS system and genfis type 1 in all three residential buildings

Statistical index	4-unit building			The First 8-unit building			8-unit second building		
	All Data	Train	Test	All Data	Train	Test	All Data	Train	Test
MSE	0.00248	0.00247	0.00249	0.00343	0.00344	0.00341	0.00353	0.00345	0.00372
RMSE	0.04981	0.04978	0.04989	0.05859	0.05867	0.05840	0.05947	0.05881	0.06098
R	0.9891	0.9892	0.9890	0.9822	0.9823	0.9821	0.9818	0.9822	0.9809
μ(mean)	0.00004	0.00003	0.00013	0.00041	0.00006	0.00136	0.00052	0.00001	0.00173
σ(std)	0.04982	0.04978	0.04990	0.05859	0.05868	0.05840	0.05947	0.05881	0.06096

One of the most important findings of this study is the design and presentation of a model for predicting energy

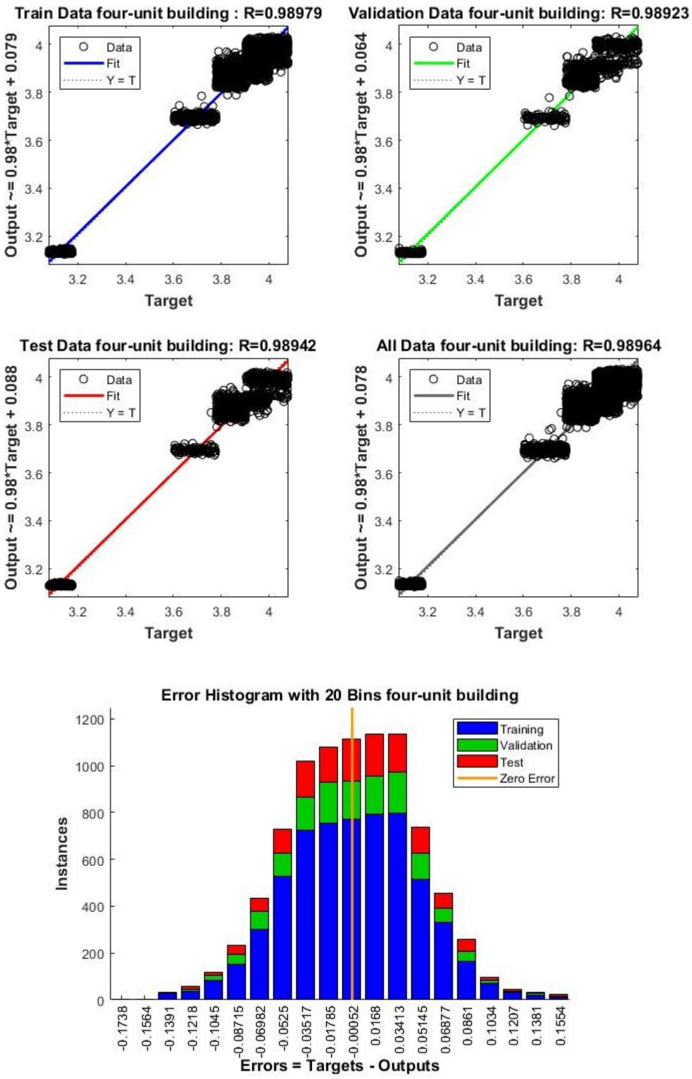


Figure 15: Predictive validation for a 4-unit building using ANN

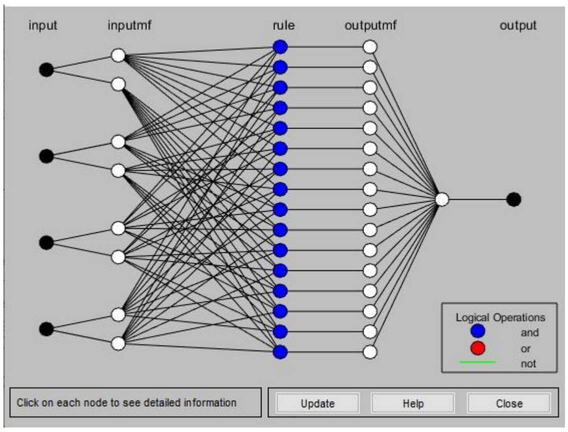


Figure 16: ANFIS structure model (genfis 1) of a 4-unit building

consumption in conventional residential buildings in Tehran with a focus on innovation using ANN artificial neural network and fuzzy-comparative neural inference system. ANFIS was prepared with high accuracy and validity. The

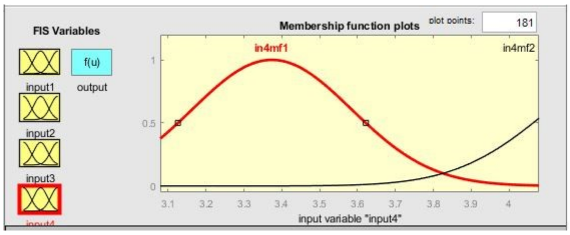


Figure 17: ANFIS membership function model (genfis 1) 4-unit building

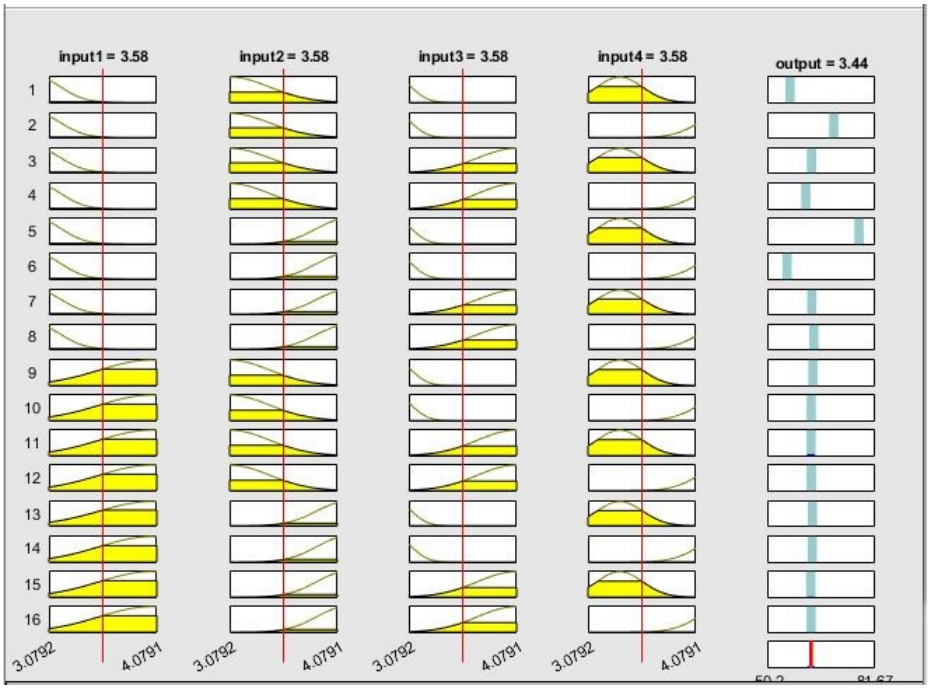


Figure 18: Display of roles in ANFIS (genfis 1) 4-unit building

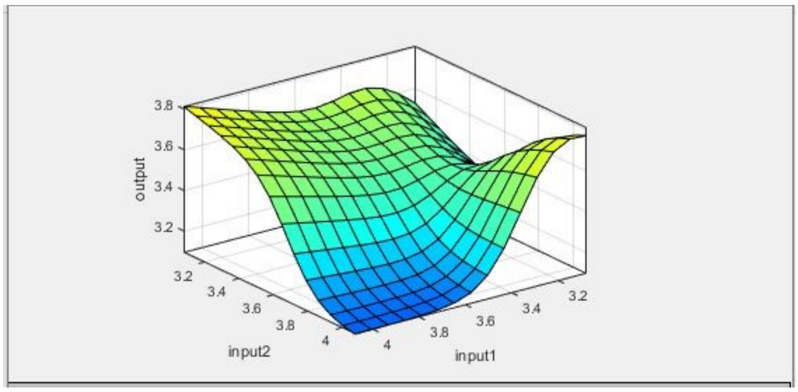


Figure 19: Three-dimensional display of input and output in ANFIS (genfis 1) 4-unit building

output of this research is an intelligent combined system of ANN and ANFIS.

Also, by knowing the forecast values of energy in the building, all builders and mass builders of housing, especially managers of energy supply in the country, will have the appropriate tools to plan for the energy supply needed by the city's housing sector or country. In addition, with the development of this model in the commercial and industrial sectors, other results can be achieved in future research.

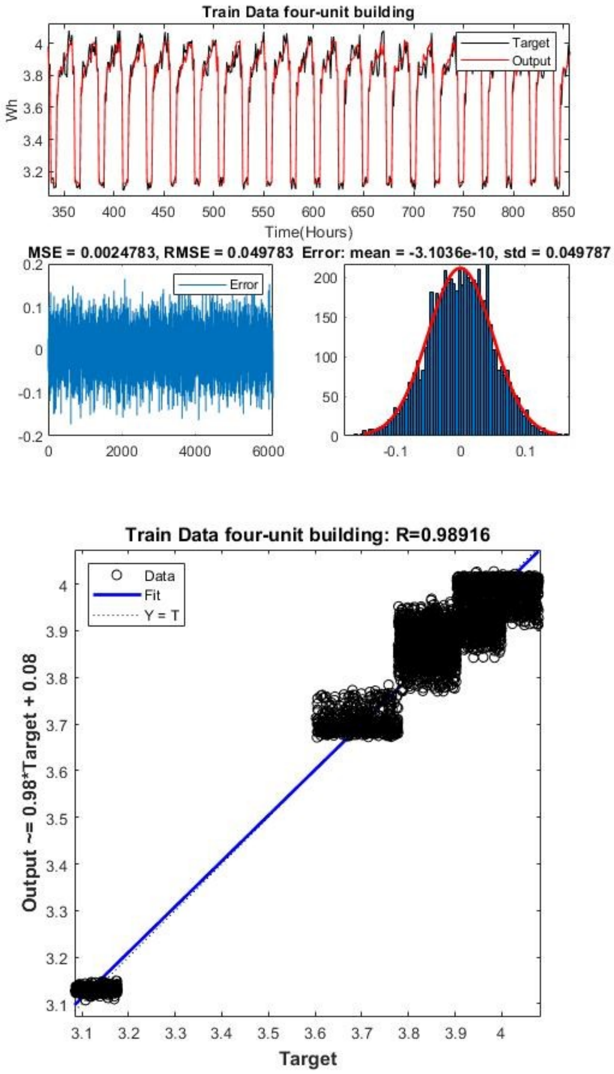


Figure 20: System training results in ANFIS (genfis 1) 4-unit building

Table 5: Statistical characteristics of MSE, RMSE, R, μ and σ in ANFIS system and genfis type 2 in all three residential buildings

Statistical index	4-unit building			The First 8-unit building			8-unit second building		
	All Data	Train	Test	All Data	Train	Test	All Data	Train	Test
MSE	0.00224	0.00223	0.00224	0.00312	0.00309	0.00317	0.00313	0.00306	0.00328
RMSE	0.04729	0.04725	0.04738	0.05583	0.05562	0.05631	0.05591	0.05530	0.05732
R	0.9902	0.9902	0.9901	0.9838	0.9841	0.9834	0.9839	0.9842	0.9831
μ(mean)	0.00001	0.00008	0.00004	0.00039	0.00001	0.00131	0.00038	0.00007	0.00126
σ(std)	0.04730	0.04726	0.04739	0.05583	0.05563	0.05631	0.05592	0.05531	0.05731

Table 6: Statistical characteristics of MSE, RMSE, R, μ and σ in ANFIS system and genfis type 3 in all three residential buildings

Statistical index	4-unit building			The First 8-unit building			8-unit second building		
	All Data	Train	Test	All Data	Train	Test	All Data	Train	Test
MSE	0.00227	0.00227	0.00228	0.00318	0.00318	0.00317	0.00315	0.00312	0.00322
RMSE	0.04766	0.04761	0.04779	0.05638	0.05642	0.05629	0.05612	0.05583	0.0568
R	0.9900	0.9901	0.9899	0.9835	0.9836	0.9834	0.9838	0.9839	0.9834
μ(mean)	0.00005	0.00006	0.00018	0.00042	0.00005	0.00141	0.00043	0.00004	0.00144
σ(std)	0.04766	0.04761	0.04780	0.05638	0.05643	0.05629	0.05613	0.05583	0.05679

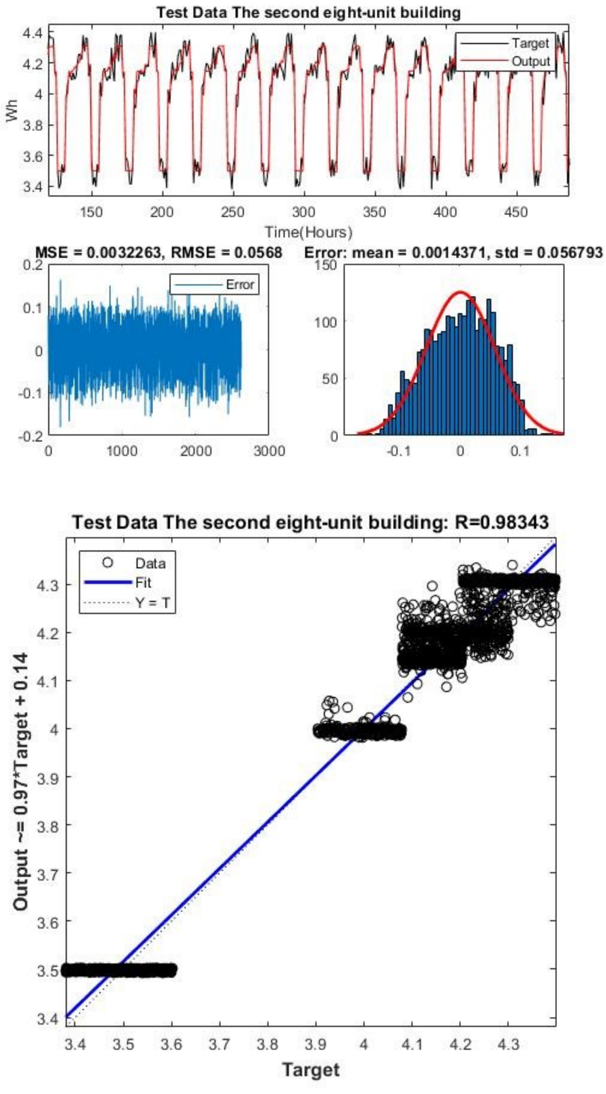


Figure 21: System test results in ANFIS (genfis 3) second 8-unit building

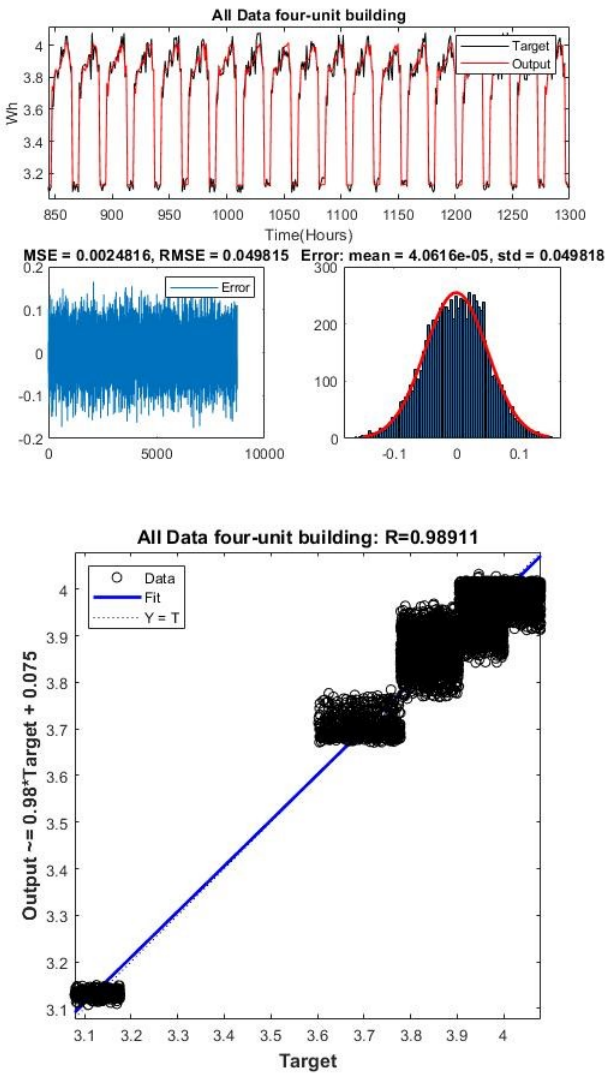


Figure 22: Energy consumption forecast results in ANFIS (genfis 1) 4-unit building

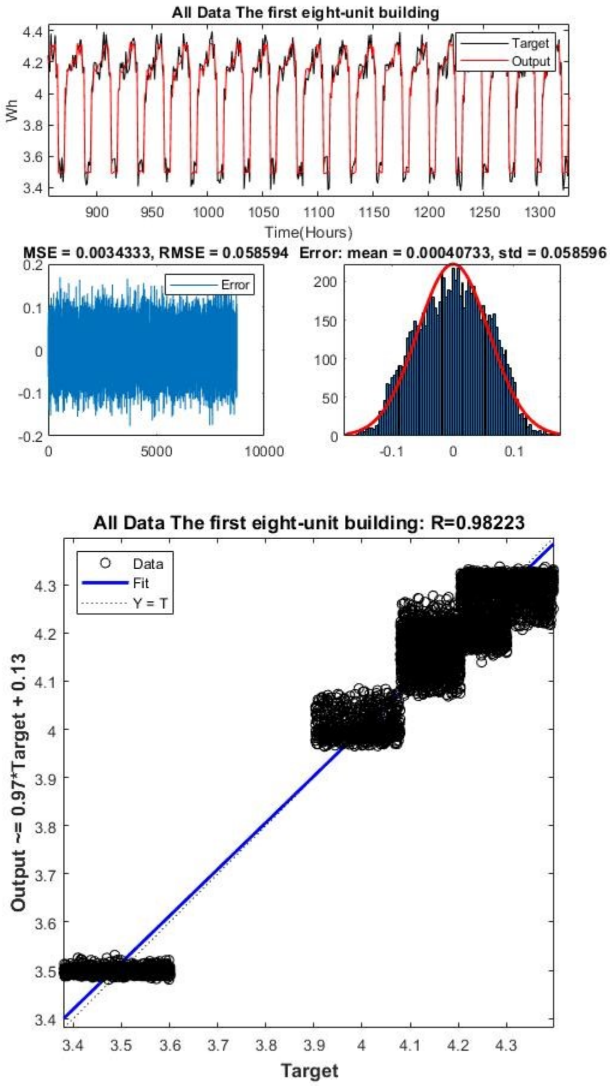


Figure 23: Results of energy consumption forecast in ANFIS (genfis 1) of the first 8-unit building

References

[1] J. Ahn, D.H. Chung and S. Choa, *Energy cost analysis of an intelligent building network adopting heat trading concept in a district heating model*, Energy **151** (2018), 11–25.

[2] M.H. Alobaidi, F. Chebana and M.A. Meguid, *Robust ensemble learning framework for day-ahead forecasting of household based energy consumption*, Appl. Energy **212** (2018), 997–1012.

[3] F. Amara, K. Agbossou, Y. Dubé, S. Kelouwani, A. Cardenas and S.S. Hosseini, *A residual load modeling approach for household short-term load forecasting application*, Energy Build. **187** (2019), 132–143.

[4] K.P. Amber and M.W. Ahmad, *Intelligent techniques for forecasting electricity consumption of buildings*, Energy **157** (2018), 886–893.

[5] F. Ascione, N. Bianco, C. De Stasio, G.M. Mauro and G.P. Vanoli, *Simulation-based model predictive control by the multi-objective optimization of building energy performance and thermal comfort*, Energy Build. **111** (2016), 131–144.

[6] A.R. Baheri, M. Najafi, A. Azimi and C. Aghanajafi, *A simplified model to predict and optimize the energy consumption of residential buildings in the cold climate regions of Iran*, Energy Sources, Part A: Recovery, Util. Envir. Effects **2020** (2020), 1–19.

[7] B. Bektas Ekici and U. Teoman Aksoy, *Prediction of building energy needs in the early stage of design by using ANFIS*, Expert Syst. Appl. **38** (2011), no. 5, 5352–5358.

[8] M.R. Biswas, M.D. Robinson and N. Fumo, *Prediction of residential building energy consumption: A neural network approach*, Energy **117** (2016), 84–92.

[9] C. Buratti, E. Lascaro and D. Palladino, *Building behavior simulation by means of artificial neural Nnetwork in summer conditions*, Sustain. **6** (2014), no. 8, 5339–5353.

[10] A. Chabaud, J. Eynard and S. Grieu, *A new approach to energy resources management in a grid-connected building equipped with energy production and storage systems: A case study in the south of France*, Energy Build. 99 (2015), 9–31.

[11] V. Ciancio, S. Falasca, I. Golasi, G. Curci, M. Coppi and F. Salata, *Influence of input climatic data on simulations of annual energy needs of a building: Energy Plus and WRF modeling for a case study in Rome (Italy)*, Energies **11** (2018), no. 10, 2835.

[12] N. Delgarm, B. Sajadi, F. Kowsary and S. Delgarm, *Multi-objective optimization of the building energy performance: A simulation-based approach by means of particle swarm optimization (PSO)*, Appl. Energy **170** (2016), 293–303.

[13] R.E. Edwards, J. New and L.E. Parker, *Predicting future hourly residential electrical consumption: a machine learning case study*, Energy Build. **49** (2012), 591–603.

[14] P. Hameed, *Intelligent multi-objective optimization for building energy and comfort management*, J. King Saud Univ. Engin. Sci. **30** (2018), no. 2, 195–204.

[15] J. Jang, J. Baek and S.B. Leigh, *Prediction of optimum heating timing based on the artificial neural network by utilizing BEMS data*, J. Build. Eng. **22** (2019), 66–74.

[16] S. Lee, S. Jung and J. Lee, *A Prediction model based on an artificial neural network for user-based building energy consumption in South Korea*, Energies **12** (2019), no. 4, 608.

[17] X. Li, J. Wen and E.W. Bai, *Developing a whole building cooling energy forecasting model for online operation optimization using proactive system identification*, Appl. Energy **164** (2016), 69–88.

[18] S. Malik and D.H. Kim, *Prediction-learning algorithm for efficient energy consumption in smart buildings based on particle regeneration and velocity boost in particle swarm optimization neural networks*, Energies **11** (2018), no. 5, 1–22.

[19] E. Mocanu, P.H. Nguyen, W.L. Kling and M. Gibescu, *Unsupervised energy prediction in a Smart Grid context using reinforcement cross-building transfer learning*, Energy Build. **116** (2016), 646-655.

[20] S. Naji, A. Keivani, S.Shamshirband, U.J. Alengaram, M.Z. Jumaat, Z. Mansor and M. Lee, *Estimating building*

energy consumption using extreme learning machine method, Energy **97** (2016), 506-516.

[21] S. Naji, Sh. Shamshirband, H. Basser, U. Afram Keivanid, J. Alengaram, M. Zamin Jumaat and D. Petkovic, *Application of adaptive neuro-fuzzy methodology for estimating building energy consumption*, Renew. Sustain. Energy Rev. **53** (2016), 1520-1528.

[22] A.T. Nguyen, S. Reiter and P. Rigo, *A review of simulation-based optimization methods applied to building performance analysis*, Applied Energy, **113** (2014), 1043–1058.

[23] M. Nilashi, M. Dalvi-Esfahani, O. Ibrahim, K. Bagherifard, A. Mardani and N. Zakuan, *A soft computing method for the prediction of the energy performance of residential buildings*, Meas. J. Int. Meas. Confed. **109** (2017), 268–280.

[24] Q. Qiao, A. Yunusa-Kaltungo and E. Rodger, *Towards developing a systematic knowledge trend for building energy consumption prediction*, J. Build. Engin. **35** (2021), 101967.

[25] M. Raatikainena, M. Pekka, S. Kauko and L. Mikko, *Intelligent analysis of energy consumption in school buildings*, Appl. Energy **165** (2016), 416–429.

[26] R. Kumar, R.K. Aggarwal and J.D. Sharma *Energy analysis of a building using artificial neural network: A review*, Energy Build. **65** (2013), 352-358.

[27] C. Tian, C. Li, G. Zhang and Y. Lv, *Data drove parallel prediction of building energy consumption using generative adversarial nets*, Energy Build. **186** (2019), 230–243.

[28] I. Ullah, R. Ahmad and D.H. Kim, *A prediction mechanism of energy consumption in residential buildings using hidden Markov model*, Energies **11** (2018), no. 2, 1–20.

[29] J. Yang, H. Rivard and R. Zmeureanu, *On-line building energy prediction using adaptive artificial neural networks*, Energy Build. **37** (2005), no. 12, 1250–1259.

[30] W. Yu, B. Li, Y. Lei and M. Liu, *Analysis of a residential building energy consumption demand model*, Energies **4** (2011), no. 3, 475–487.