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Electricity Supply Model of Conventional Residential Buildings in Tehran with Priority on Renewable Energy Using Adaptive Fuzzy-neural Inference System

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A B S T R A C T

Energy consumption in the building sector, especially in residential buildings, due to the development of urbanization, has taken the largest share among all consumption sectors. Therefore, it is very necessary to predict the energy consumption of buildings, which has been presented as a challenge in recent decades. In this research, adaptive fuzzy-neural inference system (ANFIS) and MATLAB software have been used for forecasting to supply electrical energy to residential buildings whit random data that collected based on the hourly electricity consumption of conventional residential buildings in Tehran. According to the applied settings for the solar and wind energy production has been done by solar panels and wind turbines. The use of renewable energy is one of the ways that can reduce the consumption of fossil fuels and also reduce environmental pollution. Statistical indicators such az MSE, RMSE, μ, σ, and R were used to evaluate the model performance . The obtained values well show the ability of this model to foresee the generation and utilization of energy in privat reresidential buildings with tall exactness of about 96% and 90%, respectively. Therefore, this model well show the ability of to the needed estimates in the mentioned buildings with high accuracy.

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1. INTRODUCTION

Nowadays, energy is one of the basic components in human life and indeed relations between nations. Pollution from fossil fuels and their limited resources have led all countries to add renewable energy to their energy portfolio. One of the biggest energy customers, particularly in created nations, is buildings. Therefore, using renewable energy converters for residential buildings can be vital to reduce fossil fuels, reducing fossil fuel pollution, and reducing energy consumption.

Subsequently, different strategies have been utilized to decrease and optimize energy utilization. Buildings are one of the biggest sources of energy utilization. If excessive energy consumption continues and fuels the energy crisis within the world, it will too worsen natural contamination. For this purpose, one of the best ways is to control and anticipate the generation and administration of energy utilization within the building utilizing renewable energy.

Therefore, due to the limitation of energy resources and its very important role in the economic development of a country, paying attention to how to reduce energy consumption and optimizing it is a necessity in every country today [1].

Among several method to present a model for suitable strategy foreseeing and supply of energy in private buildings, the ANIFS is one of the most careful measuring tools for obscure and nonlinear concepts. Adaptive fuzzy-neural inference system (ANFIS), which best coordinating the highlights of fuzzy frameworks and neural systems, is specifyed by Bektas Ekici and Teoman Aksoy [2]. As a structure, ANFIS incorporates if-else rules and employments fuzzy match input-output information and neural network learning algorithms for preparing. An adaptive fuzzy-neural inference framework simulates complex nonlinear mapping utilizing neural arrange learning and fuzzy inference strategies. The ANFIS structure comprises of two models, ANN, and fuzzy logic, and can work with vague

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clamor and wrong situations. ANFIS is utilized within the neural network preparing handle to alter the participation work and parameters related to the information in question. It has more precise comes about than the normal squares error degree since it can abuse expert decisions. ANFIS learning calculation may be a hybrid learning calculation employing a post-diffusion learning algorithm and the least-squares strategy [2].

Due to the existence of uncertainties in the real world, it is very vital and important to use more efficient methods such as ANFIS. Therefore, this study aim to present a model for the foremost suitable strategy for foreseeing the utilization and supply of energy in private buildings with a sustainable development approach due to uncertainties in the real world using fuzzy-comparative neural inference system (ANFIS) and Using MATLAB software.

2. RESEARCH BACKGROUND

Nowday for dubious and unstable demand as well as the advancement of alternative energy sources, numerous energy firms (Oil, gas and electricity) have been forced by awesome weight to speed up the interest of efficiency in this climate, in this way boosting generation, reducing costs, and optimizing benefits. To assist in this interest, the application of modern techniques in this industry is rapidly advancing at present [3]. Energy is one of the foremost critical components that influence the solidness of any system, and hence, managing with distinctive energy systems is exceptionally critical to attain the most prominent conceivable advantage from energy sources [4]. Energy sources are partitioned into conventional and renewable sources, and both sorts take part in securing the essential vitality to total the prerequisites of the different bulding. Nowday, residential buildings are expected to be designed and built in a way that minimizes the use of materials and energy consumption, and at the same time maximizes the safety and health of their residents. It is very natural that in order to achieve this very important goal, new buildings with energy efficiency should be built and existing buildings should be strengthened and renovated. For this reason, a significant share of research has been focused on the issue of energy performance of buildings (EPB) due to the negative environmental effects and energy loss [5].The results of an important part of the current research show that one way to diminish the ever-augmenting require for additional energy supply is, in this manner, to supply more energy-efficient building plans with altered energy-saving properties [6].

Recent studies have attempted to model the energy performance of buildings by predicting and using soft computing methods. Basically, it is stated that the cornerstone of energy efficient building design is the modeling of heating load (HL) and cooling load (CL), because it determines the heating and cooling equipment requirements needed to maintain indoor air conditions. For this purpose, many simulation tools are widely used [7]. Deb et al. [8] used ANN to forecast the diurnal CL for institutional buildings. Yokoyama et al. [9] used ANN coupled with an optimization method in order to estimate the CL demand.

Li et al. [10] For predicting the cooling energy of the whole building utilizing an counterfeit neural network for the presence of an intelligent network in energy utilization. Hameed et al. [11] have examined brilliantly, multi-purpose optimization for energy and consolation administration. Delgarm et al. [12] 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. Acording to the extraordinary ubiquity of artificial intelligence technique and particularly manufactured neural systems in building energy investigation, there was a got to audit diverse strategies to attain this. The application of an counterfeit neural network in simulating the behavior of building shells in summer conditions with a modern glass framework to assess and make strides energy execution was examined by Buratti et al. [13]. The climatic conditions and warm characteristics of the building shell were expected as input and temperature of the insides space of the building the yield of the arrange. The results showed that ANN can be utilized as a effective apparatus in simulation [13]. The forecast of energy utilization of a private building with the approach of counterfeit neural organize MLP was examined by Biswas et al. [14]. The finest mistake model was come to by selecting the fitting number of covered up layer neurons. The results arrange comes about were factually palatable in comparison to past ponders [14]. Amara et al. [15] proposed an adaptive circle conditional desire Technique (ACCE) based on circle investigation to characterize sub-action plans. As a result, an adaptive linear model (LM) technique is utilized to anticipate the demand for leftover components utilizing the comes about of the ACCE handle in each time window. After that, the anticipated adjust is utilized to comparatively move forward the execution estimate of add up to power request. The precision of the forecast comes about is assessed utilizing the the mean normalized absolute error (NMAE). As a result, the proposed approach to model intermittent remaining demand on the every day skyline leads to a great 23% exactness [16]. Simulate energy consumption in an hourly regime, perform calculations on residential buildings, and analyze and compare regularly between the energy needs of the building reenacted by EnergyPlus, with climatic inputs related to two air terminals in rurals Rome and with Entries. The information displayed by the WRF estimate model for the center of Rome show a few errors. Ciancio et al. [17] measured these discrepancies. Alobaidi et al. [18] provide a framework using a vital regression component to predict each household's average daily energy consumption. Exact estimation of energy productivity of private buildings based on the calculation of HL heating load and CL cooling stack is an vital assignment. Nilashi et al. [19] displayed an proficient strategy for foreseeing the vitality execution of private buildings utilizing the ANFIS versatile neural-fuzzy deduction framework. 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 [19]. Ullah et al. [20] anticipated energy utilization in a private building with the Markov model. The Markov-based calculation predicts energy utilization in Korean private buildings utilizing data collected through smart meters and four cases of multi-story buildings in Seoul. The forecast comes about of the proposed model were compared with three well-known expectation algorithms: SVM back vector machine and ANN counterfeit neural network and regression classification, and the forecast exactness were satisfactory [20].

Mocanu et al. [21] started a study by using two reinforcement learning models to modeling energy consumption in buildings. As a centeral hypothetical , a Deep Belief Networkze (DBN) is used in each calculation. The Techniques are at that point created within the MATLAB environment and tried on an genuine database recorded over seven years at hourly determination. Exploratory comes about appear that the RMSE energy expectation exactness interims are 91.42%. [21]. Jang et al. [22] made an ANN artificial neural network. A demonstrate predicts when the warming system ought to work to decrease energy utilization in winter mornings. BEMS exploratory information and ANN demonstrate prescient execution were roughly 13.13% superior than CvRMSE and 0.197% superior than MBE. This investigation consider a difference decrease energy utilization in buildings and makes a difference to supply satisfaction [22]. Qiao et al. [23] audit different model and procedures for anticipating building energy utilization based on existing information collections and systematically demonstrate application areas. It also offers a all encompassing see of building energy utilization [23]. Naji et al. [24] utilized the whole energy necessities of the building is influenced by different components such as the environment, climatic conditions, building materials, separator, etc., using the fuzzy-neural network system ANFIS and Energy Plus and soft computational method with Matlab/Simulink. They have examined he energy utilization of the building [24]. Predicting the energy required by the mansions in the early stages of design using the ANFIS adaptive fuzzy-neural inference framework model was examined by Ekici and Aksoy [2] to anticipate the building energy utilization. Baheri et al. [1] examined the expectation of electricity and gas utilization in a private building complex within the cold region of Iran, the city of Tabriz employing a neural network and genetic algorithm.

The situation and landscape of solar energy in Iran have been studied by Najafi et al. [25]. With current energy policies, investing in hybrid solar power plants, wind power plants are economically viable. Additionally, it requires more than $ 2800 million in venture amid 2010-2030. By measuring the eleven-year wind speed of the Iranian capital, Tehran, at the height of ten meters above the ground, Keyhani et al. [26] concluded that this area could be suitable for electrical and mechanical applications not connected to the grid, such as wind. Fazelpour et al. [27] examined the utilization of hybrid frameworks to supply energy to a family in Tehran, Iran. They utilized the photovoltaic system, wind turbine, diesel generator, and capacity battery, and made the wind- hydrogen-battery hybrid framework reasonable. They gotten the best economical system [27]. Tahani et al. [28] modeled a system using solar panels and wind and hybrid batteries optimized for a three-story building in Tehran, the capital of Iran, with the method of minimizing costs and obtaining desirable results. Shivam et al. [29] implemented a multi-objective predictive energy management strategy based on machine learning using solar panels, storage batteries, and neural networks. The resulting model provides a more than fifty percent good forecast [29]. Taghavifar and Zomorodian [30] considered installing a micro-hybrid system in grid mode to sell additional electricity and thus save electricity consumption of the building as a source of income. One system of PV and wind and national electricity network and the other system of PV and wind and national network and generator were examined from the technical-economic point of view in different inflation conditions [30]. Asrami et al. [31] inspected three scenarios for finding the leading arrangement for utilizing photovoltaic solar boards for private buildings in urban regions: lattice association with and without battery and total power supply.

Moreover, the genetic algorithm and TOPSIS method are used to determine the optimal response for each scenario. A residential complex in Tehran, Iran, was selected. As a result, the scenario of electricity transmission generated by renewable sources to the national grid and the use of electricity required from the national grid was selected as the optimal design [31]. Ehyaei and Bahadori [32] investigated the use of small gas turbines to supply electricity to residential buildings in Iran. They obtained good results. On the other hand reliable and exact forecast of electricity generation and consumption is subsequently imperative for Utilities Company and government to arrange for future control era and conveyance. Stack estimating can be classified into short-term stack estimating (STLF), medium-term stack determining (MTLF) and long-term stack determining (LTLF). Therefore, it is very important to use appropriate methods for this issue.

It can be seen from the above studies that various models have been used in this field. However, there are still some advanced computational frameworks including hybrid models and fuzzy logic-based models and their capacitates in electricity supply model of conventional residential buildings have not been widely studied. Considering the above gaps in the literature, this study was motivated to develop and applied of ANFIS versatile fuzzy-neural deduction system in electricity supply. This study is a long-term study that has not been used in many other studies.

3. FOUNDATION OF APPLICATION OF ANFIS VERSATILE FUZZY-NEURAL DEDUCTION SYSTEM

Building energy utilization may be a basic variable, not as it were in logical investigation but moreover in taken a toll examination. Subsequently, tall precision in creating the energy utilization is fundamental since belittling vitality utilization can lead to potential blackouts that can be negative to social and financial ways of life. In differentiate, overestimation leads to superfluous unemployment capacity. Besides, as a result, squandered monetary assets. Subsequently, a few considers have been performed to foresee vitality utilization with diverse factual models and approaches precisely. Since ordinary statistical models require a noteworthy sum of collected information and are moderately exact for straight information, neural organize models can calculate nonlinear information. Properties are watched at diverse electrical loads by urban meter readings [14].

Adaptive fuzzy-neural induction system (ANFIS), which best coordinating the highlights of fuzzy frameworks and neural networks, is characterized by Jang et al. [22]. As a structure, ANFIS incorporates if-else rules and employments fuzzy combine input-output information neural organize learning calculations for the preparation (Figure 1). An versatile fuzzy-neural deduction framework mimics complex nonlinear mapping utilizing neural arrange learning and fuzzy deduction strategies. The ANFIS structure comprises of two models, ANN and fuzzy rationale, and can work with ill defined commotion and wrong situations. ANFIS is utilized within the neural arrange prepare to alter the enrollment work and parameters related to the information in address. It has more exact comes about than the cruel square squared mistake degree since it can misuse master decisions. ANFIS learning calculation may be a crossover learning calculation employing a post-diffusion learning calculation and the least-squares strategy [2].

4. MODELING APPROACH

4. 1. ANFIS Adaptive Neural-fuzzy 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 robust complex processes and modeling. ANFIS model is very suitable for describing and interpreting nonlinear systems. According to Figure 1, the steps of designing the optimal fuzzy-neural are as follows:

1. Get preparing data.
2. Make a essential fuzzy system.
3. Altering the parameters of the essential fuzzy framework agreeing to the modeling blunder work by the optimization algorithm.
4. Return the fluffy framework with the finest values of the parameters as the ultimate result.

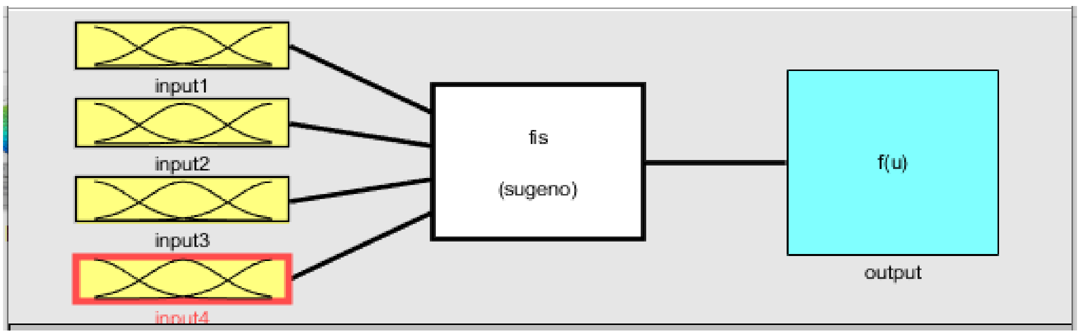


Figure 1. Overview of the fuzzy inference system

5. RESEARCH METHODOLOGY

Concurring to the reason of this investigate, the connected sort (utilizing the demonstrate to foresee energy consumption and generation amid the year for private buildings) and multi-criteria decision-making strategies have been utilized. The optimization segment is displayed utilizing ANFIS adaptive fuzzy-neural deduction framework calculation and MATLAB program.

5. 1. Input Data

5. 1. 1. Energy Load of a Residential Building As an essential parameter, electricity demand must be determined. Electric charge analysis is performed by considering the ordinary utilization of people within the chosen case consider. Family power request for each month is calculated based on its information. In arrange to supply comes about based on reality and, so, as much as conceivable, the foremost common sorts of cooling and warming frameworks within the city that evaporative cooling and water warming advances are considered. Also, the calculation of electric charge is done assuming standard equipment such as TVs, lamps, refrigerators, etc. Figure 2 shows the household electricity consumption index for a year. According to this figure, 3604 kWh of electricity is consumed by households during a year [31].

A parameter has been introduced for electricity consumption in residential houses, which varies depending on the year-day schedule, i.e., 24 * 365, the year's position. The substance of the database is the sum of energy utilization of a private building amid this period, i.e., 8760 lines (per year).

According to Figures 2 and 3, the average monthly consumption of each household in Tehran is 300 kWh, the minimum daily consumption is 300 Wh, and the maximum is 1.5 kWh. Using MATLAB software, datarand function are defined, and random amounts of energy consumption per energy consumption of three conventional residential buildings in Tehran are prepared. Conventional buildings refer to buildings up to 7 floors, which include the main urban buildings in Tehran that have access to renewable energy from wind and solar and the city's electricity source. This data is related to three apartment buildings of four, six, and eight units in Tehran and has been prepared for three years. According to Figures 2 and 3, the annual and seasonal electricity consumption of the building in Tehran, in the case of buildings 4, 6, and 8 units, energy consumption is estimated at 12,00, 18,00, and 25,00 kWh, respectively. The available data are presented in three Excel files (for each building), which include the amount of energy consumed by each building. 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 Wh. In the above three buildings, renewable wind and solar energies have been used by installing wind turbines and solar panels on their roofs.

5. 1. 2. Solar Radiation Solar radiation information for Tehran have been gotten from the Meteorological Organization. The worldwide solar radiation is flat for Tehran by year, hour, and day, as appeared in Figure 4. The crest of daylight is in June and July, whereas January has the least sum of solar radiation [27].

In this research, one of the foremost common sorts of solar boards accessible within the Iranian advertise, to be specific the sharp of panel, model ND-240QCJ, has an output power of 240 watts and has dimensions of 994× 1640× 46 mm. Due to the application of the

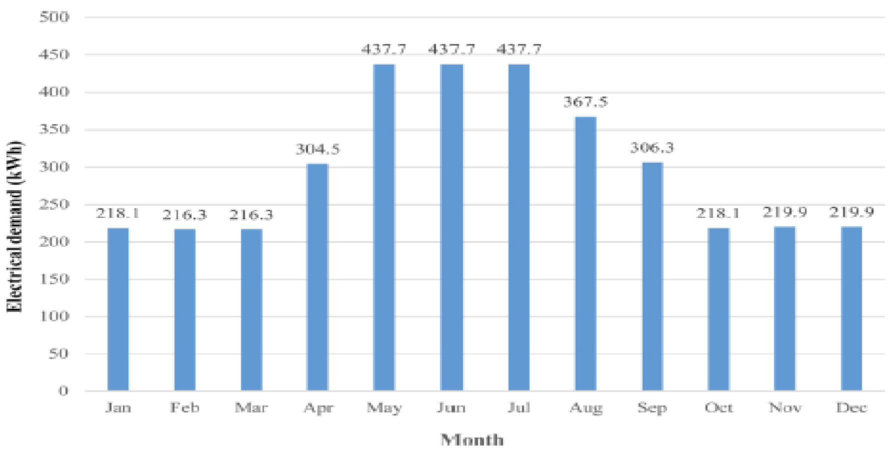


Figure 2. Details of household electricity consumption (energy load) during a year in Tehran [33]

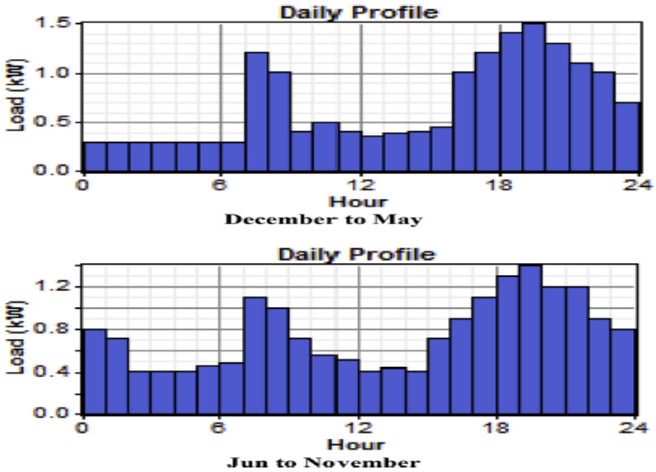


Figure 3. Seasonal household energy consumption in Tehran [27]

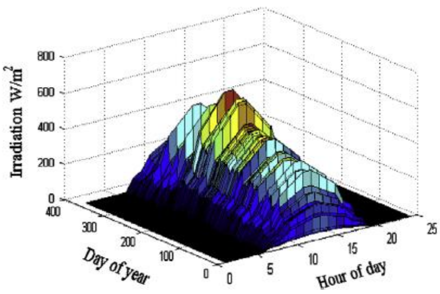


Figure 4. Hourly and daily horizontal solar radiation for Tehran, Iran [29]

manufacturer's output error (about 5%) and the effect of pollution and dust (equivalent to 5%) and the effect of daily temperature (12.5%) and loss coefficient in system cables (5%) and converter efficiency (92%), The output power output of the panel is reduced. In Tehran, the number of hours in which the amount of solar radiation energy is equal to one KWh/m^2 is equal to 5, which is defined as Peak Sun Hours (PSH). Therefore, the maximum amount of daily energy produced by each panel with the above specifications is calculated as follows:

$$240 \times 0.95 \times 0.95 \times 0.875 \times 0.95 \times 0.92 \times 5 = 0.828\ KWh$$

On the roofs of 4, 6, and 8 unit buildings, twelve, eighteen, and twenty-four panels with the above specifications and an angle of 30 degrees, which according to Table 1, have the highest efficiency during the year, have been installed respectively. Using MATLAB software, a datarand function is defined, and arbitrary values of solar electricity generation based on generation at distinctive hours of the day and distinctive months of the year (Table 1) in Tehran were prepared. The available data are presented in the form of three Excel files (for each building) that represent the solar energy production values. 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 energy production values of each residential building in Wh.

5. 1. 3. Wind Speed Tehran's 10-year average wind speed information are gotten based on month to month values given by the Meteorological Organization of Iran and are appeared in Figure 6. Wind information were measured at three-hour interims at an elevation of 10 m. Appropriately, the most noteworthy average month to month wind speed in April is 5 meters per second and the average wind speed in all months of the year is between 3 to 5 meters per second [27].

5. 1. 4. Wind Turbine In this research, a NEW SKY MAX800W home wind turbine has been used to supply wind energy. This turbine is operated with a minimum wind speed of 1.5 meters per second, suitable for Tehran. The roof of the buildings 4, 6, and 8 units, a wind turbine the specifications of Figure 6, is installed in the direction of the prevailing wind in Tehran, from southwest-northeast, which has the highest efficiency of the year. Using MATLAB software, a Datarand function is defined. Random values of wind energy production are based on wind speed at diverse time of the day and diverse months of the year (Figure 5) in Tehran and turbine production capacity and its characteristics (Figure 6). It is provided. The available data are presented in three Excel files (for each building) that represent the values of wind energy production of each building. 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 wind energy production values in Wh.

TABLE 1. Tehran's monthly solar radiation for different slope angles [33]

Season	Month	Monthly solar radiation for θ = 0 ($kWh.m^{-2}$)	Monthly solar radiation for θ = 30 ($kWh.m^{-2}$)	Monthly solar radiation for θ = 60 ($kWh.m^{-2}$)	Monthly solar radiation for θ = 90 ($kWh.m^{-2}$)
	December	68.49	115.88	132.22	113.13
Winter	January	75.75	123.83	138.73	116.46
	February	100.83	145.95	151.97	117.26
	March	128.58	161.78	151.62	100.84
Spring	April	162.00	180.28	150.26	79.97
	May	189.57	192.97	144.66	57.59
	June	219.39	214.16	151.54	48.32
Summer	July	214.89	212.92	153.89	53.64
	August	200.16	212.28	167.53	77.88
	September	170.16	201.09	178.13	107.45
Fall	October	125.73	169.96	168.64	122.14
	November	87.24	135.28	147.08	119.46

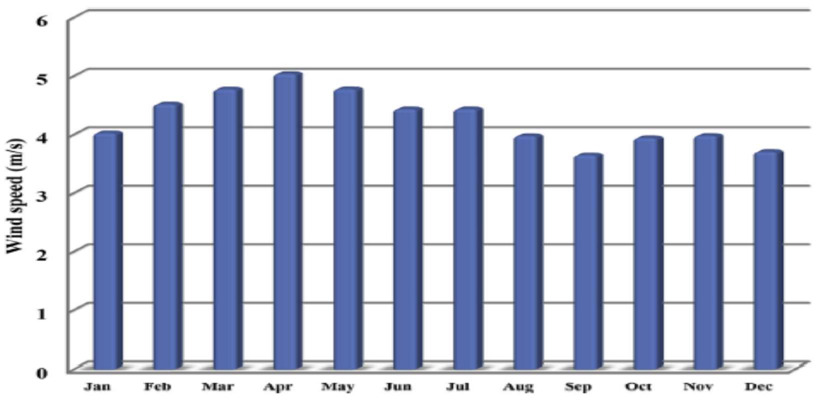


Figure 5. Monthly specifications of daily wind speed data for Tehran, Iran [29]

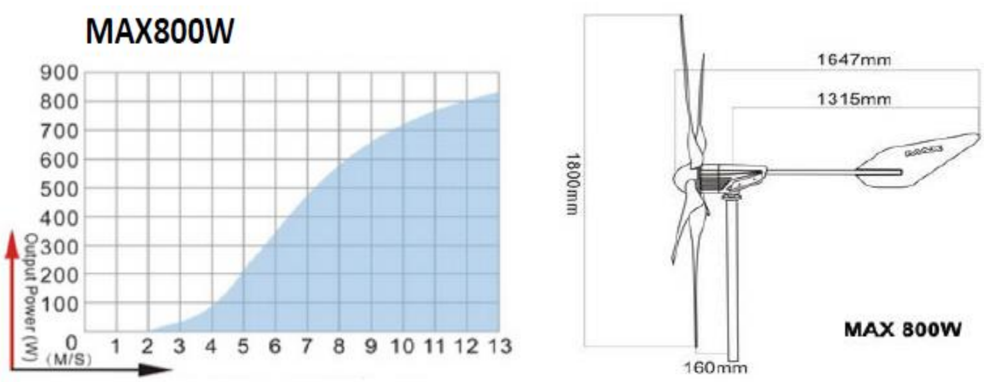


Figure 6. Physical characteristics and power curve of MAX800W turbine

The prepared database contains the consumption and production of wind and solar turbine energies during a period (8760 hours per year) separate for all three buildings.

5. 2. Mackey-Glass Equation The Mackey Glass equation could be a nonlinear time-delay differential condition concurring to Equation (3).

$$\frac{dx}{dt} = \beta \frac{x_\tau}{1+{x_\tau}^n} - \gamma x, \quad \gamma, \beta, n > 0. \tag{3}$$

That β, γ, τ, and n are real numbers, and x_τ indicating the variable x at time t−τ. Depending on the values of the parameters, this condition appears a range of occasional and chaotic elements (Figure 7). From a biological point of view and its mathematical properties, this equation is used to predict time series and some other problems.

The ANFIS adaptive fuzzy-neural inference system is utilized to get ready a time arrangement forecast demonstrate created by the McKee-Glass time-delay differential condition. In time series prediction, known values of time series t are used to predict the value at a future point t + p. When predicting, it is assumed that the behavior of this system is constant at different times, and not much change in the behavior of the system should be observed. Furthermore, 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 8.

X(t) = f(x(t-1), x(t-2), …, x(t-d)

Nonlinear Differential Equation (4)

In the time series prediction structure, using an estimated function f (.) 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.

5. 3. 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

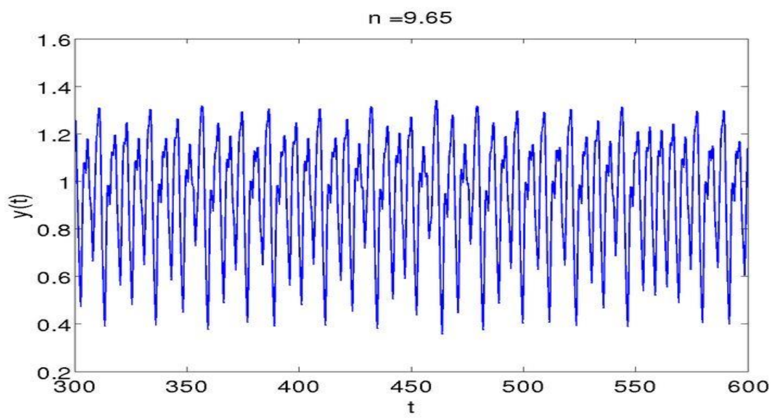


Figure 7. Dynamics in the Mackey-Glass equation, Equation (3), for $\gamma = 1. \beta = 2. \tau = 2. and\ n = 9.65$

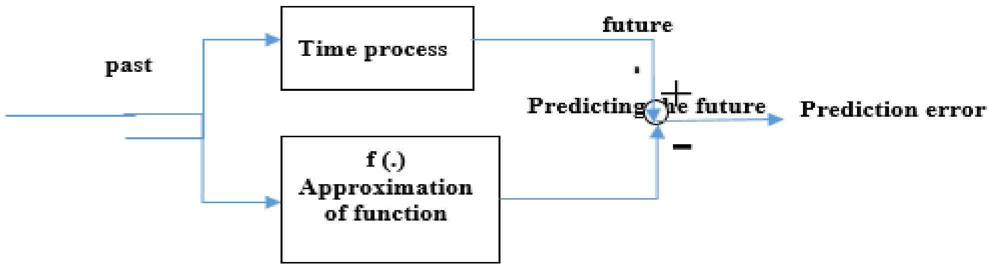


Figure 8. Time series prediction structure and prediction error determination

the input data for network training and 30% for test data. Here, three types of genes are used to design ANFIS, which include:

GENFIS 1 Grid Partition: The data generates a single-output fuzzy inference system of the SUGENO type using a network partition on the data. The type of Gaussian input function is GAUSSMF (Gaussian membership function), and the type of membership function is linear output.

GENFIS 2 (Sub Clustering): A SUGENO FIS structure. It was made utilizing subtraction clustering. Besides, it requires partitioned sets of input and output information as input contentions, which have a infiltration span.

GENFIS 3 (FCM): Utilizing fuzzy c-means clustering, FCM produces a FIS by extricating a set of rules that models information behavior. Given that there's as it were one output, GENFIS 3 has made an starting FIS for ANFIS preparing. The number of clusters is break even with to 10, the number of segments of frameworks is break even with to 2, the greatest number of cycles is rise to to 100, and the least sum of framework advancement is break even with to 1e-5 (Figure 9).

The number of repetitions of Epochs training here is 100, the target for error rate is zero, the starting step measure is 0.01, the step estimate decrease rate is 0.9, and the step measure increment rate is 1.1. This method usually gives better results than genfis1 and GENFIS2. In this research, this method has been used to predict the amount of energy consumption and production.

5. 3. 1. Output Membership Function Type This method is suitable for multi-input and multi-output calculations with any level of complexity. The error can be reduced by determining the number of clusters in a targeted way. In the following figure, we can see the relationship between software applications based on the choice of each of the GENFIS methods (Figure 9). (The following is the choice for the FCM method).

5. 4. Steps of Conducting Research 1. Extractable energy values are introduced from solar boards and wind turbines, and the energy utilization of each building gotten by Datarand functions is used as input parameters of the ANFIS fuzzy-neural network. Each file has three columns, each representing the amount of energy produced or consumed for one year in terms of Wh.

2. ANFIS fuzzy-neural network using the data of the first and second columns of the Datarand record in terms of prepared time and predicts the sum of energy generation from renewable sources and energy utilization in each building utilizing the method (FCM) GENFIS3 (CONP, SUNP, WINDP).

3. The values of the third column of each Datarand file are also considered as actual values of solar energy production and wind and energy consumption (RAE). Therefore, maximum renewable energy production (solar and wind) is also available (REM).

4. Predicted amounts of renewable energy from solar panels and wind turbines in each residential building are available separately every year in Wh. (RE).

5. The necessary calculations and outputs have been prepared for each of the buildings of four, six, and eight units separately using MATLAB software.

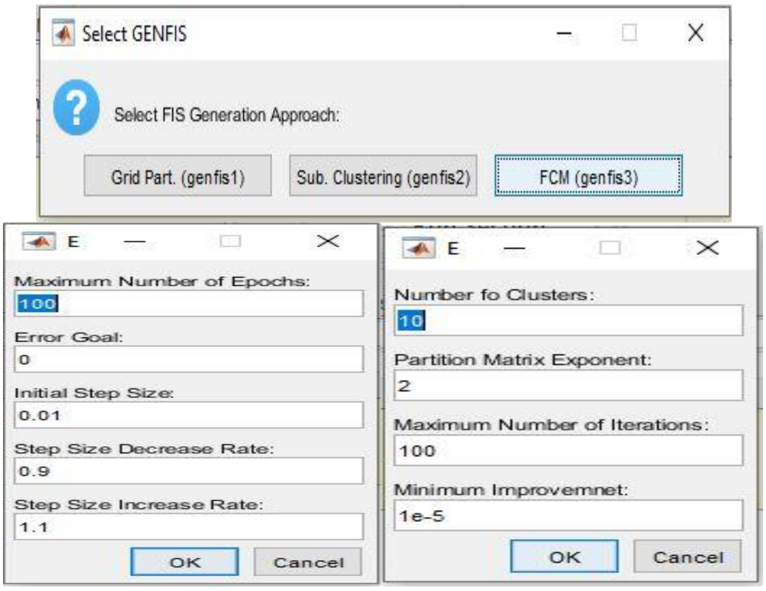


Figure 9. Applied relationship for selecting FCM design method in ANFIS in all three buildings

6. Energy Harvest Management (RAC) algorithm is such that the higher the amount of energy extracted from renewable sources (solar and wind), the lower the amount of harvest from the sources of the municipal electricity network. The ideal model is to supply all the electricity consumption of buildings from renewable energy sources. The worst-case scenario is to supply all the energy consumption of the building from the municipal electricity supply networks. In this study, the sum of energy extracted from renewable sources usually cannot exceed 2200 Wh, while the amount of consumption can be around 12000 Wh, even in an 8-unit building. According to the declared limits of fuzzy logic and ANFIS for the predicted values of production and consumption, in this system, the amount of energy allowed for withdrawal from the city network is determined by subtracting the total energy production from the maximum energy consumption (RAC) and increasing the actual value. The projected consumption values are considered a system error (CE).

7. Considering that the range of energy extractable from wind for all three buildings is between 0 to 200 Wh and sunlight between 0 to 2000 Wh (the existence of a home wind turbine and between 12 to 24 solar panels). The maximum energy extracted from renewable sources for buildings of 4, 6, and 8 units is about 1000, 1500, and 2000 Wh, respectively (REM).

8. The contrast between the entire and genuine generation of renewable energy (solar and wind) (RAE) and the total projected renewable energy production (RE) is considered as the amount of forecast error and the actual renewable energy production, i.e. (GE).

9. Finally, a statistical comparison between the values of CE, RE, RAE, and GE has been made.

6. FINDINGS AND RESEARCH RESULTS

In this investigate, the ANFIS versatile fuzzy-neural induction framework has been utilized to calculate the estimate of energy utilization and generation within the building. One of the foremost vital discoveries of this investigate is to plan a demonstrate for foreseeing vitality generation and utilization in private buildings utilizing the over apparatuses. The comes about appear that the network error is worthy, and their speed and capacity to memorize and effectiveness in assessing the generation and energy utilization of private buildings are exceptionally exact. First, we can examine the results obtained from the energy consumption in 4-unit building and examine its graphs.

The energy utilization of a four-unit building in Figure 10 is exceptionally comparative to the Mackey-Glass chart. Of course, the energy consumption of six- and eight-unit buildings are similar.

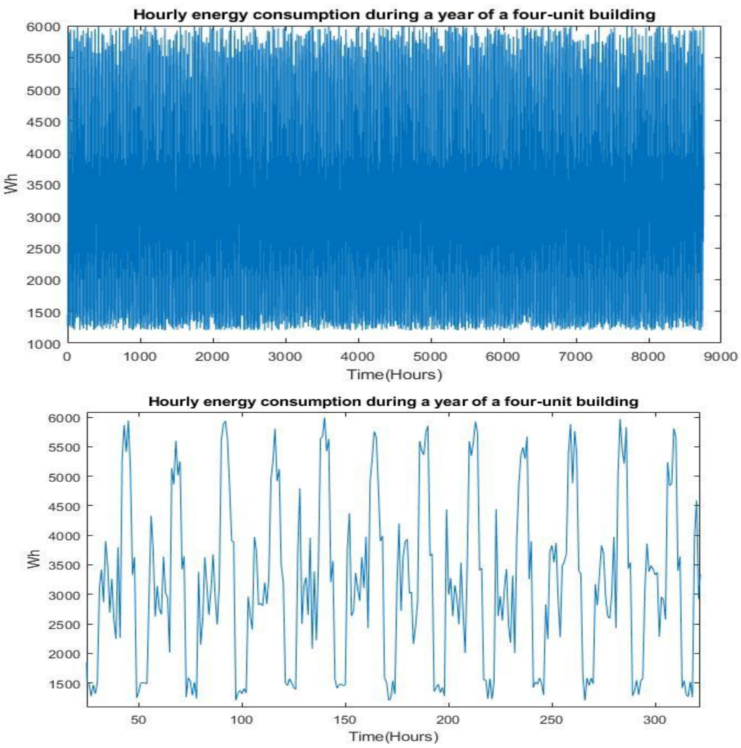


Figure 10. Energy consumption per year and over some time in a 4-unit building

By performing training and testing processes of the ANFIS adaptive fuzzy-neural inference system in all three 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, R, mean, std is calculated. These statistical indicators are very suitable. In Figure 11, actual and projected of solar and wind energy production, MSE, RMSE, std and estimated regression equation for 8 unit building are shown in order as can be seen, the calculated dispersion statistics of MSE=3324.47, RMSE=57.65, Std=57.66 and the value of R^2 is equal to 0.99, which shows a very good fit of this model.

Due to the large number of results obtained, the results obtained from different stages and the outputs of the ANFIS fuzzy-neural inference system related to all three buildings are presented in Table 2. The forecast accuracy in buildings is more than 99%, which is a sign of the proper performance of the designed model.

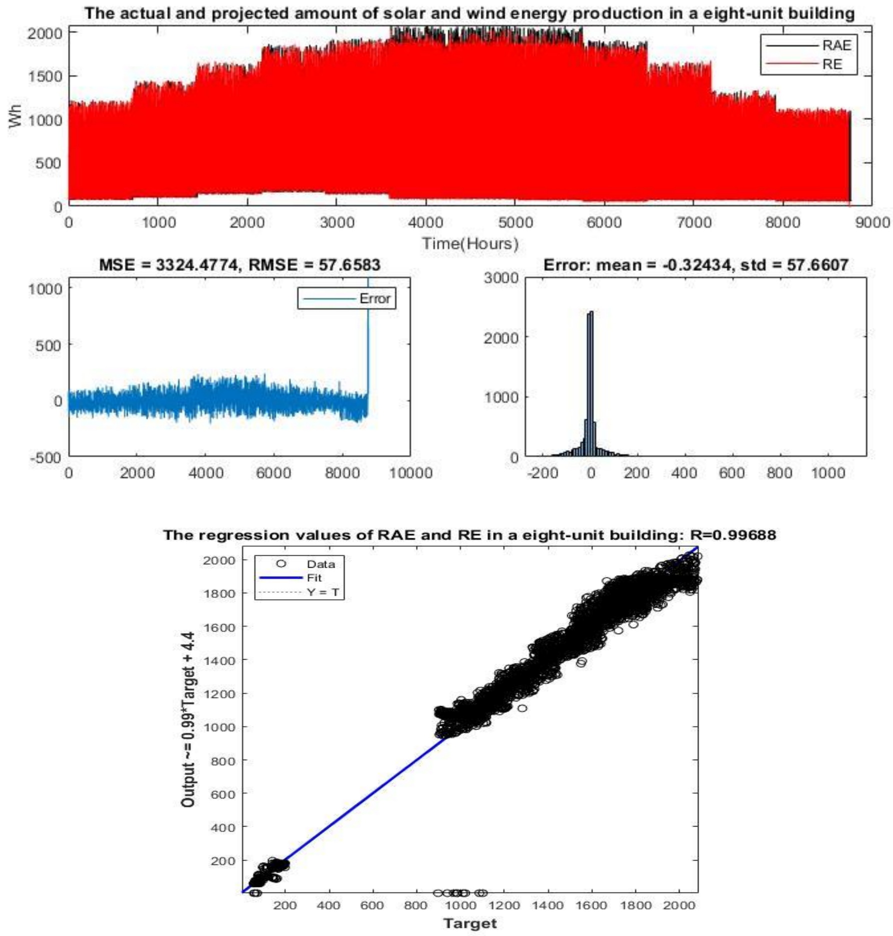


Figure 11. Actual values (RAE) and forecast (RE) of energy production of an 8-unit building using ANFIS

TABLE 2. Statistical indicators of MSE, RMSE, R, MEAN, and STD in ANFIS system in all three residential buildings

Statistical index	4-unit building	6-unit building	8-unit building
MSE	857.37	1864	3324
RMSE	29.28	43.17	57.66
R	0.9968	0.9970	0.9968
μ(mean)	0.67	1.31	0.32
σ(std)	29.28	43.17	57.66

Figures 12, 13, and 14 show the production, forecast, and average absolute error of solar and wind energy. Figures 15, 16, and 17 compare the actual and predicted production of solar and wind energy.

Here we can see the result obtianed form the ANIFS system in Table 3. It can be seen that according to Table 3, the average value of energy production forecast error for a four-unit residential building (GE) is about 16 Wh. Also, according to Table 7, the average renewable energy production is equal to (3480402/8760) 397 Wh. It means that the percentage of forecast error is equal to 4%. Therefore, the forecast accuracy is about 96%. The forecast accuracy in buildings of six and eight units is 96.5% and 96.3%, respectively, which is a sign of proper performance of the designed model. Figure 18 shows the absolute average error of energy consumption prediction during one year in an eight-unit building.

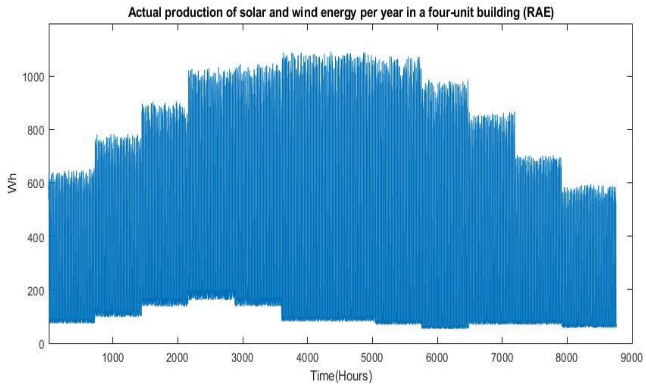


Figure 12. Real solar and wind energy production of a 4-unit building per year

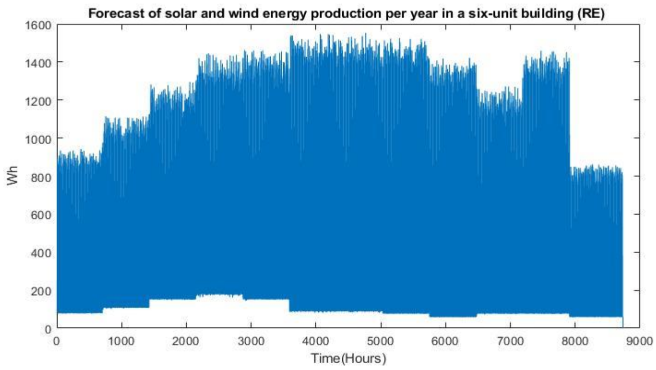


Figure 13. Forecast of solar energy and wind production of a six-unit building per year

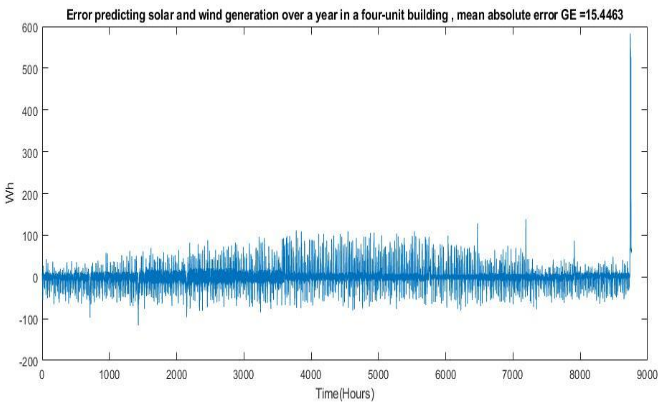


Figure 14. Absolute mean forecast error of solar and wind energy production during a year in a four-unit building

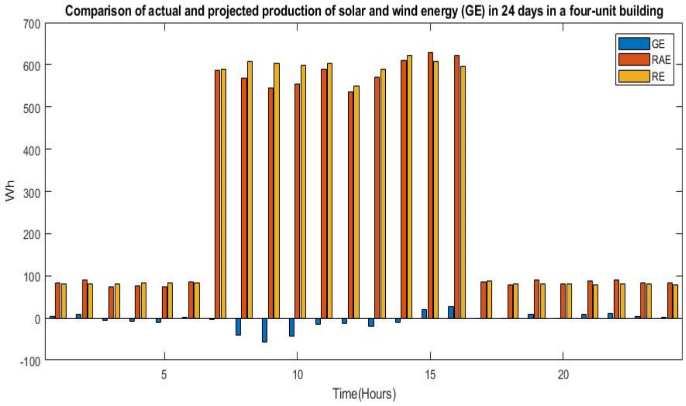


Figure 15. Comparison of actual and projected production of solar and wind energy (GE) in 24 hours in a four-unit building

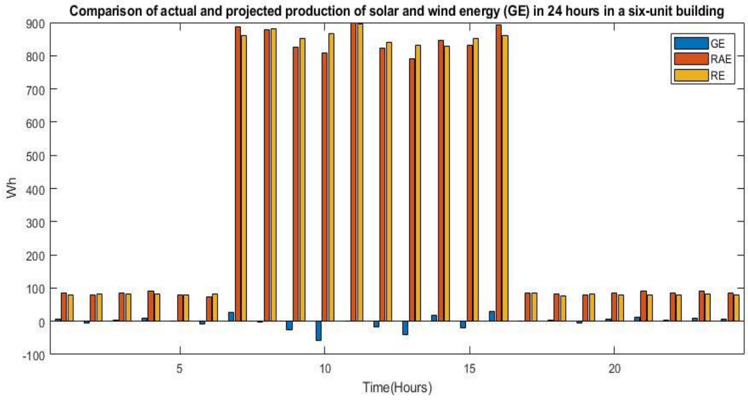


Figure 16. Comparison of actual and projected production of solar and wind energy (GE) in 24 hours in a six-unit building

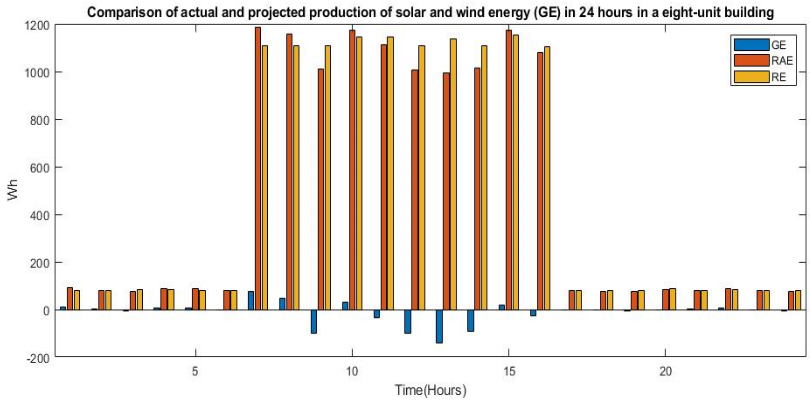


Figure 17. Comparison of actual and projected production of solar and wind energy (GE) in 24 hours in an eight-unit building

TABLE 3. Values of GE, CE, SM, and WM indices in ANFIS system in all three residential buildings

Index	4-unit building (Wh)	6-unit building (Wh)	8-unit building (Wh)
Average energy production forecast error (GE)	15.45	21.72	27.57
Average energy consumption forecast error (CE)	359	510	659
Maximum energy production from the sun (SM)	993	1490	1987
Maximum energy production from the wind (WM)	200	200	200

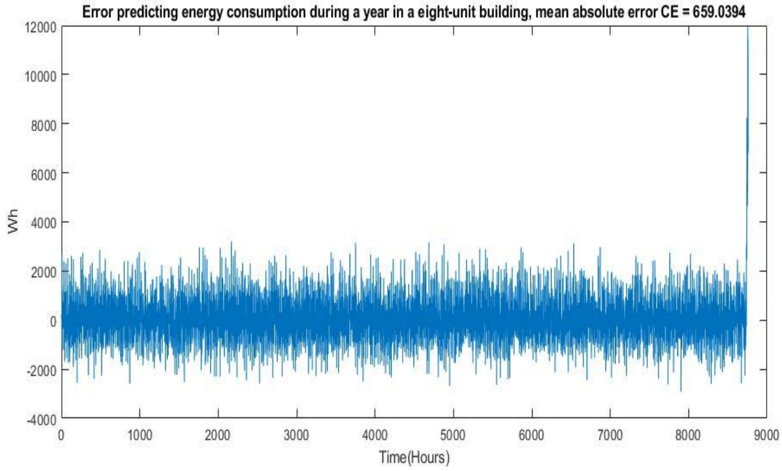


Figure 18. Absolute average of energy consumption forecast error during a year in an eight-unit building

According to Table 3, the average value of energy consumption forecast error for a four-unit residential building (CE) is 359 Wh. Also, according to reported data, the average energy utilization of the building is break even with to (28237406/8760) 3223 Wh. That is means that the percentage of forecast error is equal to 11%. Therefore, the forecast accuracy is about 89%. Prediction accuracy in six- and eight-unit buildings is 89.5% and 90%, respectively, and this is a sign of acceptable performance of the model. Figures 19, 20 and 21 show the results of training, testing, and predicting energy consumption in buildings.

By use the general prediction processes of the ANFIS system and the obtained results, it was observed that the statistical distribution of energy production and consumption in all three buildings is entirely consistent with the normal distribution. The system error rate that calculated based on MSE, RMSE, μ, σ, and R statistical

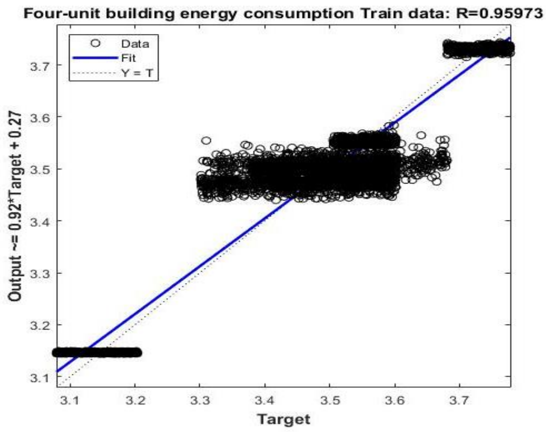
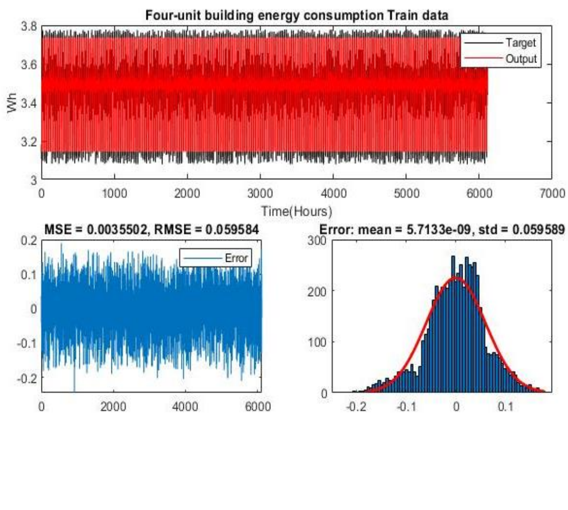
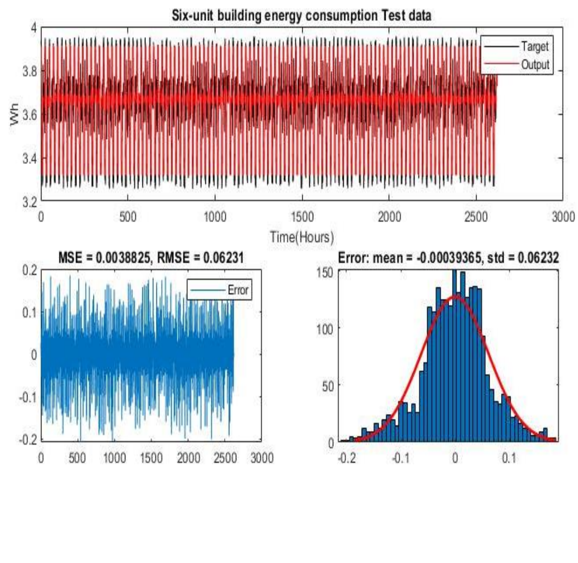


Figure 19. Results of energy consumption training in ANFIS four-unit building





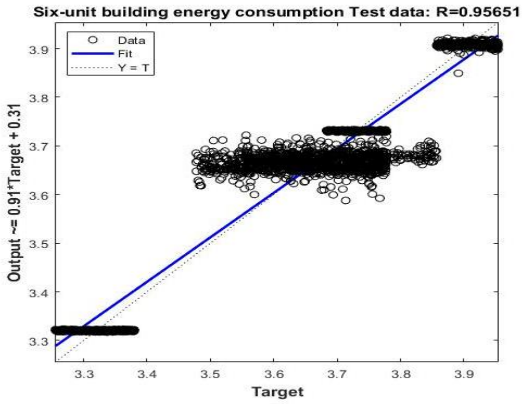


Figure 20. Energy consumption test results in ANFIS six-unit building

indices are very little. The values of R in the outputs for energy consumption and production of solar energy and wind are 95%, 99%, and 97%, respectively, which is a sign of the proper performance of the designed model.
Due to the large number of results obtained, the results of different stages of energy consumption forecasting from the output of the ANFIS fuzzy-neural induction framework related to all three buildings are displayed in Table 4. As can be seen, the value of MSE, RMSE, std are very small and are close to zero.therefore the fitted model has very little error, which shows its suitability. R square measure shows how well a regression model matches the data. So we can conclude that the bigger the R^2 measure, the better the model matches the data under investigation. As can be seen, this criterion is greater than 0.95 for all three building types. It provides a good and high explanation of the model The std dispersion index also shows the dispersion (changes) of each data value around the average, and as can be seen, it has a small value in all three types of buildings, and shows the appropriateness of the model. Figures 22, 23 and 24 show the results of training, testing and forecasting solar energy production in buildings using a neural network and fuzzy inference system.

Due to the large number of results obtained, the results of different stages of predicting solar energy production from the outputs of the ANFIS fuzzy-neural inference system for all three buildings are presented in Table 5.

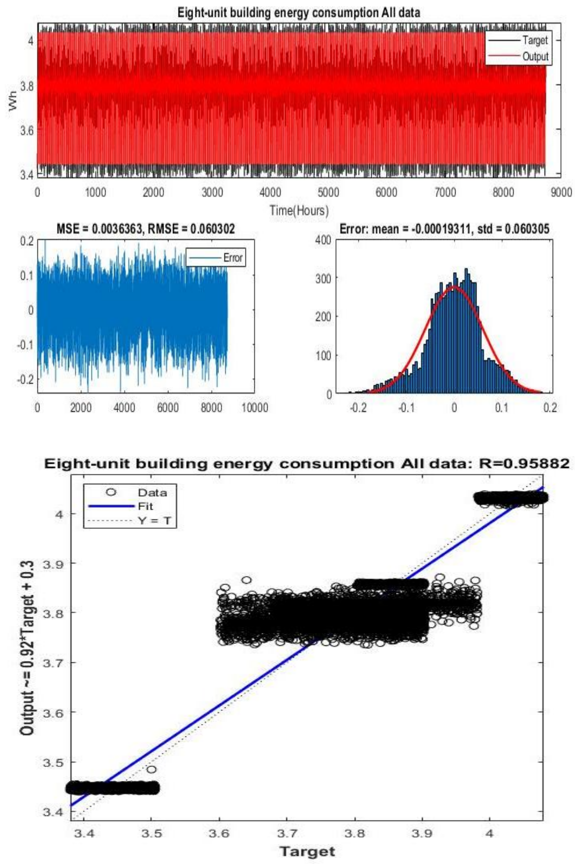


Figure 21. Energy consumption forecast results in ANFIS eight-unit building

Here also, all three important criteria MSE, RMSE and R^2 in solar energy production show the appropriateness of the model. As can be seen, the values of MSE and RMSE are very small and close to zero, and the value of R^2 is greater than 0.99 in all three types of buildings and is almost equal to one, which shows the very accurate fit of our model.

TABLE 4. Results of statistical indicators of energy consumption forecast with ANFIS in all three residential buildings

Statistical index	4-unit building			6-unit building			8-unit building		
	All Data	**Train**	**Test**	**All Data**	**Train**	**Test**	**All Data**	**Train**	**Test**
MSE	0.0036	0.0036	0.0037	0.0037	0.0036	0.0038	0.0036	0.0036	0.0036
RMSE	0.06	0.059	0.061	0.061	0.06	0.062	0.06	0.06	0.06
R	0.9589	0.9595	0.9574	0.9581	0.9586	0.9568	0.9587	0.9587	0.9587
μ (mean)	0.0004	0.0006	0.0013	0.0007	0.0006	0.0002	0.0002	0.0006	0.0007
σ (std)	0.06	0.059	0.061	0.061	0.06	0.062	0.06	0.06	0.06

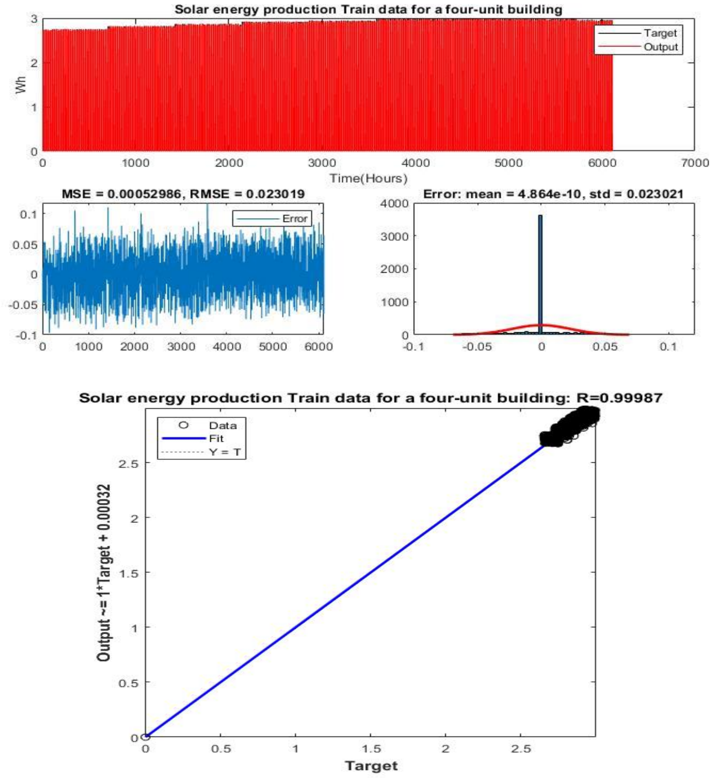


Figure 22. Results of solar energy production training in ANFIS four-unit building

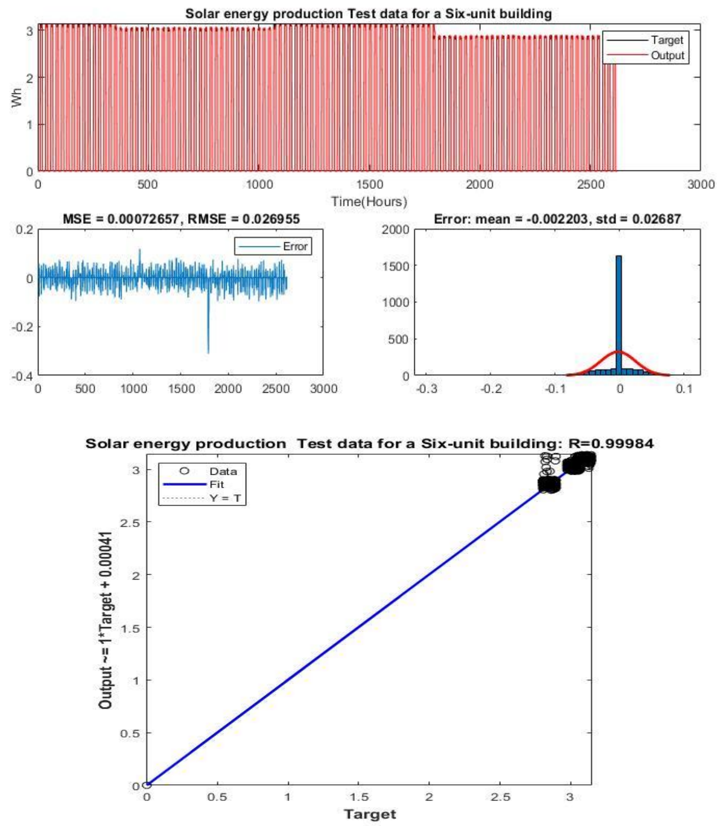


Figure 23. Results of a solar energy production test in ANFIS six-unit building

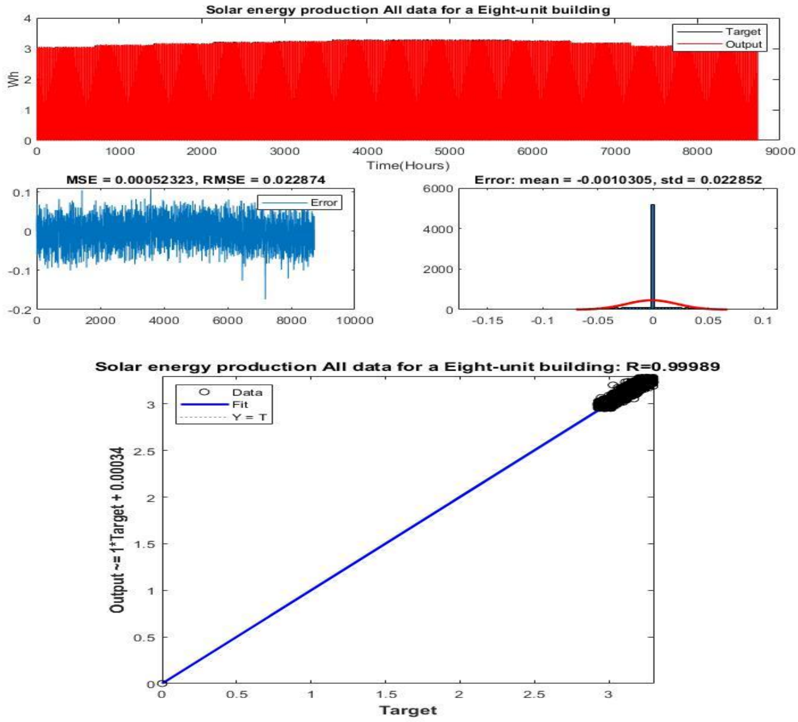


Figure 24. Results of solar energy production forecast in ANFIS eight-unit building

TABLE 5. Results of statistical indicators predicting solar energy production with ANFIS in all three residential buildings

Statistical index	4-unit building			6-unit building			8-unit building		
	All Data	Train	Test	All Data	Train	Test	All Data	Train	Test
MSE	0.0005	0.0005	0.0005	0.0005	0.0005	0.0007	0.0005	0.0005	0.0006
RMSE	0.023	0.023	0.024	0.023	0.022	0.027	0.022	0.022	0.024
R	0.9998	0.9998	0.9998	0.9998	0.9998	0.9998	0.9998	0.9999	0.9998
μ(mean)	0.0011	0.0004	0.0036	0.0011	0.0006	0.0037	0.0014	0.0004	0.0047
σ (std)	0.023	0.023	0.024	0.023	0.022	0.027	0.022	0.022	0.024

Due to the large number of results obtained, the results of different stages of predicting wind energy production from the outputs of the ANFIS fuzzy-neural deduction framework for all three buildings are displayed in Table 6. All three important criteria MSE, RMSE and R^2 in predicting wind energy production show the appropriateness of the model. As can be seen, the values of MSE RMSE,Std are very small and close to zero, and the value of R^2 is greater than 0.80 in all three types of buildings, which shows the very accurate fit of our model. Figures 25, 26, and 27 show the results of training, testing, and forecasting wind energy production in buildings using a neural network and fuzzy inference system.

TABLE 6. Results of statistical indicators predicting wind energy production with ANFIS in all three residential buildings

Statistical index	4-unit building			6-unit building			8-unit building		
	All Data	Train	Test	All Data	Train	Test	All Data	Train	Test
MSE	0.0011	0.0010	0.0014	0.0011	0.0010	0.0013	0.0011	0.0010	0.0013
RMSE	0.0338	0.0322	0.0375	0.0332	0.0318	0.0362	0.0336	0.0321	0.0366
R	0.9759	0.9764	0.7986	0.9767	0.9770	0.8073	0.9764	0.9765	0.8077
μ(mean)	0.0018	0.0003	0.0060	0.0013	0.0003	0.0045	0.0001	0.0005	0.0006
σ (std)	0.0338	0.0322	0.0370	0.0332	0.0318	0.0360	0.0336	0.0321	0.0361

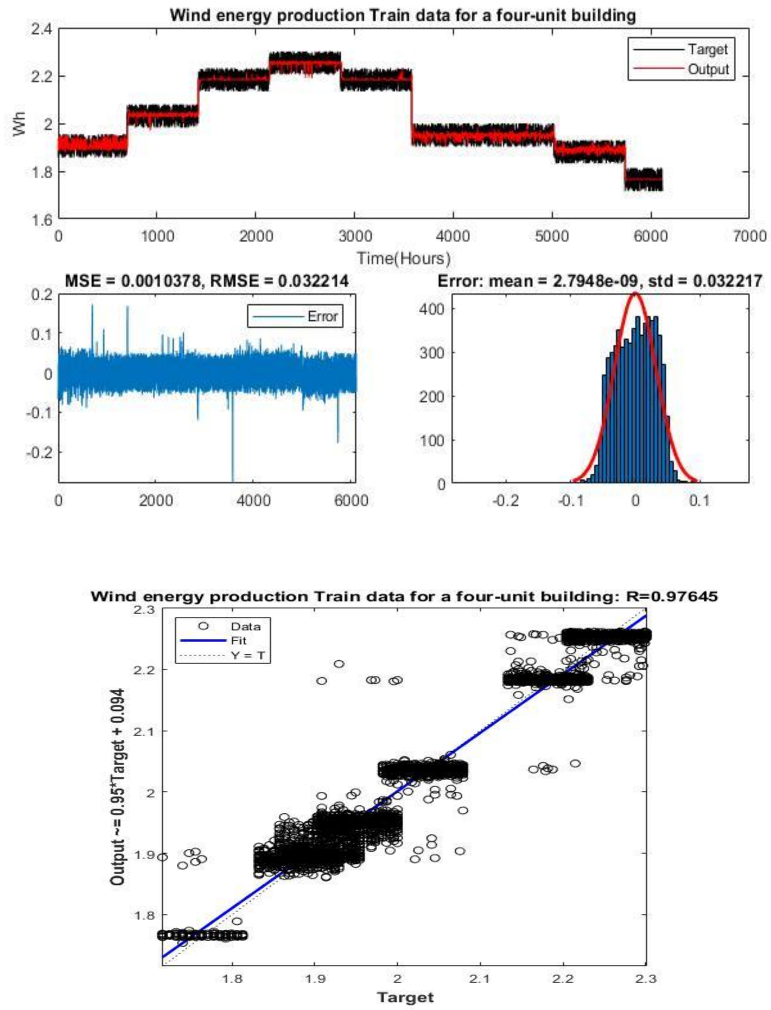
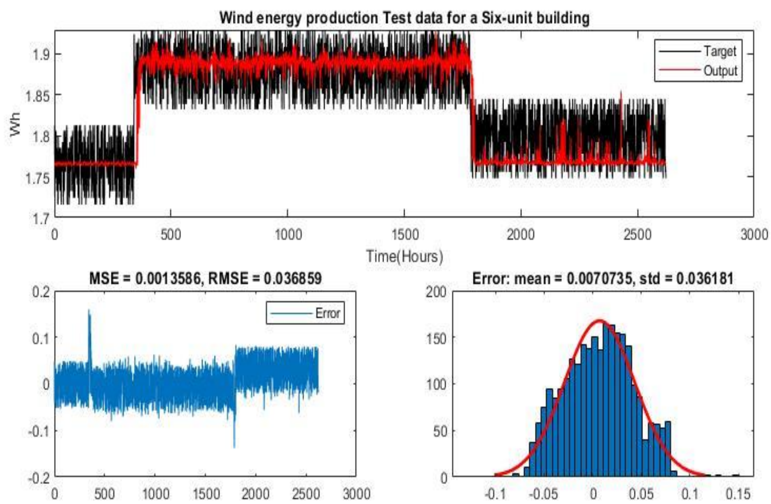


Figure 25. Results of wind energy generation training in ANFIS four-unit building



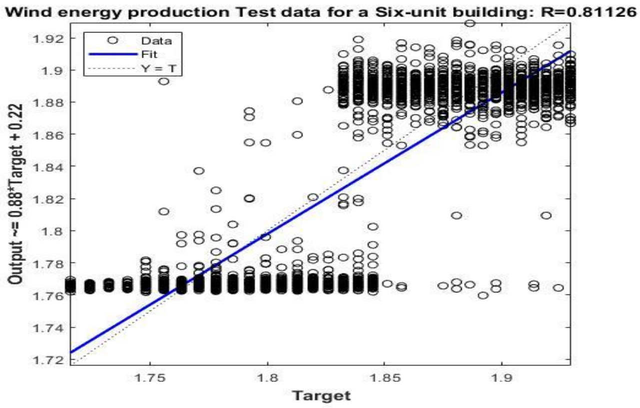


Figure 26. Results of wind energy production test in ANFIS six-unit building

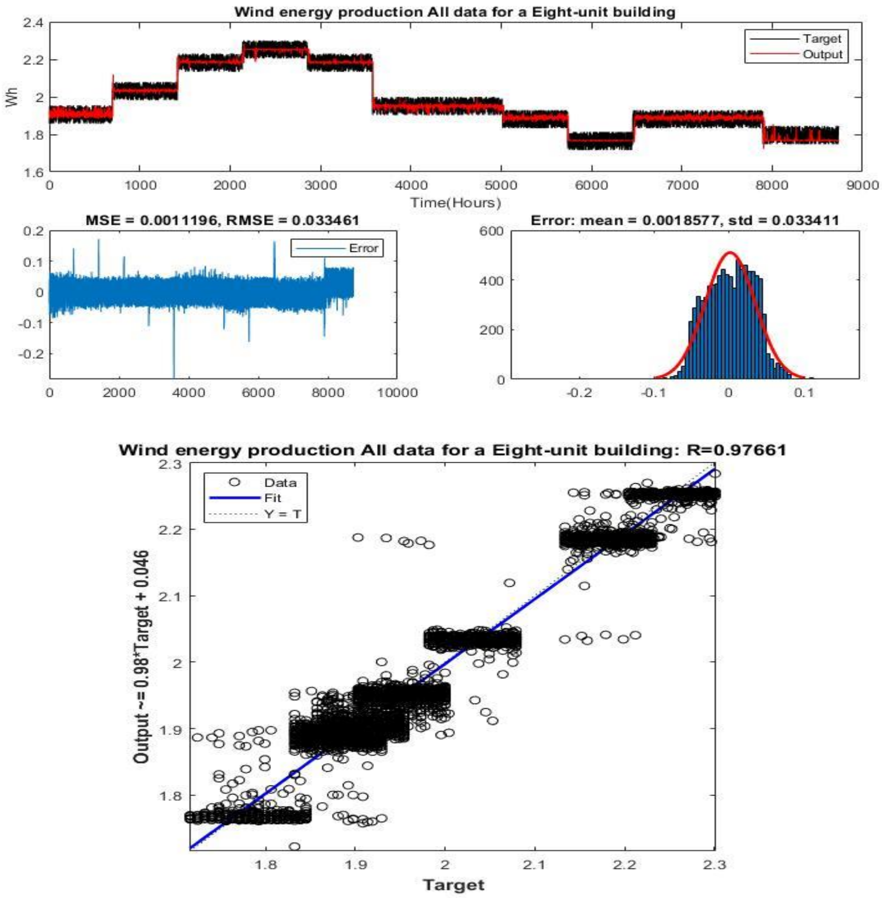


Figure 28. Results of wind energy production forecast in ANFIS eight-unit building

The statistical results presented in Table 7 generally show the performance of the ANFIS fuzzy-neural inference system in this study. In addition to high accuracy in forecasting energy consumption and production, management also determines the energy harvested from the city grid. Day and night, depending on the decisions of building managers. The results of this research compared to similar studies showed better and clearer results regarding the use of wind or solar energy in residential houses.

One of the most important findings of this research is its primary purpose: to design and present a model for predicting the production and consumption of electricity in conventional residential buildings in Tehran. It has

TABLE 7. Statistical results of actual values and forecast of energy consumption and production with ANFIS in all three residential buildings

Index	4-unit building (Wh)	6-unit building (Wh)	8-unit building (Wh)
Total energy consumption per year (CONR)	28,237,406	42,309,124	56,513,748
Total solar energy production per year (SUNR)	2,603,772	4,025,784	5,191,003
Total wind energy production per year (WINDR)	876,630	876,578	876,375
Total forecast of energy consumption per year (CONP)	27,922,366	41,798,817	55,873,986
Total forecast of solar energy production per year (SUNP)	2,603,916	4,021,003	5,199,955
Total forecast of wind energy production per year (WINDP)	870,600	869,831	870,263
production of solar and wind energy per year (RAE)	3,480,402	4,902,362	6,067,378
Forecast of solar and wind energy production per year (RE)	3,474,516	4,890,835	6,070,219
The maximum energy that can be produced from the sun and wind (REM)	1,193	1,690	2,187
The amount of energy harvested from the national grid per year (RAC)	24,447,849	36,907,981	49,803,767

been prepared using ANFIS adaptive fuzzy-neural inference system with high accuracy and appropriate validity. The output of this research is an intelligent ANFIS system.

7. DISCUSSION AND CONCLUSION

In this paper, the application of an ANFIS for modelling of electricity supply model of conventional residential buildings in Tehran with priority on renewable energy has been demonstrated. By performing training and testing processes of the ANFIS adaptive fuzzy-neural inference system in three 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, R, mean, std is calculated. The results of running the models showed that in all the models of actual and projected of solar and wind energy production and consumption. The criteria of dispersion and changes, MSE, RMSE, are very small, close to zero, and the coefficient of determination of the models (R) is also very high and shows the appropriateness of the estimated models. In addition, the values related to the determination of the total production of solar and wind energy per year (SUNR), the amount of energy harvested from the national grid per year (RAC), high accuracy in forecasting energy consumption and production, management also determines the energy harvested from the city grid. Therefore, It is shown that ANFIS with regard to clean and renewable energies, can predict electricity production and consumption pretty well.

8. DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Persian Abstract

چکیده

موضوع مصرف انرژی خانوارها در بعد ملی، مساله ای اساسی است. استفاده از انرژی های تجدیدپذیر باعث کاهش استفاده از شبکه ملی تامین برق و کاهش مصرف سوخت های فسیلی در نیروگاه ها می شود و در فرآیند توسعه پایدار شهری موثر است. از جمله منابع تولید انرژی تجدیدپذیر در یک ساختمان مسکونی، انرژی خورشیدی و انرژی باد است. مدارهای منبع تغذیه و ولتاژ متغیر تا ولتاژ ثابت در ساختمان ها معمولاً از سیستم های ذخیره انرژی (باتری) استفاده می کنند. ظرفیت این باتری ها نیز محدود است، بنابراین مدیریت تولید، ذخیره سازی و مصرف انرژی بازیافتی نیاز مبرمی به الگوریتم های پیش بینی تولید دارد. در این تحقیق از سیستم استنتاج فازی–عصبی تطبیقی (ANFIS) و نرم افزار MATLAB برای پیش بینی تامین انرژی الکتریکی ساختمان های مسکونی استفاده شده است. همچنین از داده های تصادفی جمع آوری شده بر اساس میزان مصرف برق ساعتی ساختمان های مسکونی متعارف شهر تهران استفاده شده است. تولید انرژی خورشیدی و بادی توسط پنل های خورشیدی و توربین های بادی انجام شده است. برای ارزیابی مدل از شاخص های آماری استفاده شد. مقادیر به‌دست‌آمده به خوبی توانایی این مدل را در پیش‌بینی تولید و مصرف انرژی در ساختمان‌های مسکونی با دقت بالای حدود ۹۶ درصد و ۹۰ درصد نشان می‌دهد.