PREDICTION OF ENERGY CONSUMPTION OF RESIDENTIAL BUILDINGS BY ARTIFICIAL NEURAL NETWORKS AND FUZZY LOGIC

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ABSTRACT

PREDICTION OF ENERGY CONSUMPTION OF RESIDENTIAL BUILDINGS BY ARTIFICIAL NEURAL NETWORKS AND FUZZY LOGIC

There are several ways to attempt to forecast building energy consumption. Different techniques, varying from simple regression to dynamic models that are based on physical principles, can be used for simulation. A frequent hypothesis for all these models is that the input variables should be based on realistic data when they are available, otherwise the evaluation of energy consumption might be under or over estimated. The aim of this thesis is to create simple models based on artificial intelligence methods (artificial neural networks and fuzzy logic) as predicting tools and to compare these methods with a building energy performance software (KEP-IYTE ESS). Architectural projects and heat load calculation reports of 148 apartment buildings (5-13 storey) from three municipalities in İzmir provide the input data for the models and software. Building energy consumption is modeled as a function of zoning status, heating system type, number of floors, wall overall heat transfer coefficient, glass type, area/volume ratio, existence of insulation, total external surface area, orientation, number of flats, total external surface area/total useful area, total windows area/total external surface area, width/length, total wall area/total useful floor area, total lighting requirement/total useful floor area and total wall area. Four different artificial neural network models and one fuzzy logic model were constructed, trained, tested and the results were compared with the software outcomes. The lowest mean absolute percentage error (MAPE) and mean absolute deviation (MAD) of ANN models appeared to be 4.1% and 6.57, respectively, which shows that ANN can make accurate predictions. On the other hand, fuzzy model gave an 4.86% and 7.59 of MAPE and MAD, respectively, which can be considered as sufficient accuracy.

ÖZET

YAPAY SİNİR AĞLARI VE BULANIK MANTIK İLE KONUTLARIN ENERJİ TÜKETİMİNİN TAHMİN EDİLMESİ

Binalarda enerji tüketimini tahmin etmek için bir çok yöntem vardır. Basit regresyonlardan fiziksel prensiplere dayanan dinamik modellere kadar bir çok method simülasyon için kullanılabilir. Tüm bu modeller için yaygın olan varsayım giriş değişkenlerinin gerçek verilere dayanması gerektiğidir, aksi takdirde enerji tüketiminin değerlendirilmesi tahmin edilenin altında veya üstünde olabilir. Bu tezin amacı binalarda enerji tüketimini tahminlemek amacıyla yapay zeka kullanılarak (yapay sinir ağları ve bulanık mantık) basit modeler oluşturmak ve bina enerji performans yazılımı olan KEP-IYTE ESS'i karşılaştırmaktır. İzmir'de bulunan 3 farklı ilçeden elde edilen 148 binanın(5-13 katlı) mimari projeleri ve ısı hesap raporlarından elde edilen veriler hem modellerin hem yazılımın giriş parametrelerini oluşturmaktadır.Binaların enerji tüketimi imar düzeni, ısıtma sisteminin tipi, kat sayısı, duvar toplam ısı transfer katsayısı, cam tipi, alan/hacim oranı, izolasyon varlığı, toplam dış yüzey alanı, bina yönü, daire sayısı, toplam dış yüzey alanı/ toplam faydalı alan, toplam pencere alanı/toplam dış yüzey alanı, genişlik/uzunluk, toplam duvar alanı/toplam faydalı alan, toplam aydınlatma ihtiyacı/toplam faydalı alan ve toplam duvar alanının bir fonksiyonu olarak modellenebilir. Dört değişik yapay sinir ağı modeli ve bir bulanık mantık modeli oluşturuldu, eğitildi, test edildi ve yazılım çıktılarıyla karşılaştırıldı. En düşük ortalama mutlak yüzde hata (MAPE) %4.1 ve ortalama mutlak sapma (MAD) 6.57 olarak tesbit edilmiştir. Bu sonuçlar yapay sinir ağlarının doğru tahminler yapabildiğini göstermektedir. Diğer taraftan, bulanık mantık modelinin ortalama mutlak yüzde hatası %4.86 ve ortalama mutlak sapması 7.59 bulunmuştur. Bulanık mantık modelinin de yeterli sonuç verdiği düşünülebilir.

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ANN	Artificial neural networks
BOA	Bisector of area
BP	Back- propagation algorithm
CDA	Conditional demand analysis
CO_2	Carbon dioxide
COG	Centre of gravity
CV	Coefficient of variance
E	Error function
EC	Energy consumption
GA	Genetic algorithm
GRNN	General regression neural network
HST	Heating system type
LM	Leftmost maximum
L-M	Levenberg-Marquardt
MAE	Mean absolute error
MAD	Mean absolute deviation
MAPE	Mean absolute percentage error
MF	Membership function
MOM	Mean of maxima
OR	Orientation

PURELIN	Linear transfer function
R^2	Coefficient of multiple determination
RBF	Radial basis function
RM	Rightmost maximum
SIG	Sigmoid function
TESA	Total external surface area (m^2)
TRAP	Trapezoid
TRI	Triangular
WOHTC	Wall overall heat transfer coefficient

Greek symbols

(w_{ij})	Weight
(u_i)	Net function
($f(u)$)	Transfer function
(a_i)	Activation value
u_i	Summation of the weight

CHAPTER 1

INTRODUCTION

Turkey energy consumption is low while energy intensity is high compared with Western European countries. However, young and increasing urban population together with industrial development potential, energy consumption of the country is expected to grow significantly. Currently, Turkey is a major energy importer, as the increase in its energy consumption has outpaced domestic production. Substantial investment in the energy sector will be required in near future in order to meet the increasing demand. Energy consumption has reached a level of 109.3 million tons of oil equivalent, or 1.521 kg of oil equivalent per person in 2010 (which is still below the level of developed countries) with an increasing trend between 2004 and 2010 (BP, 2011). Given the slowdown in the economy since mid-2008, the increase in energy consumption slowed down from 5.3% in 2007 to 1.4% in 2008. The decline continued in 2009 with a fall of 5.3% due to the global recession; however a 2.5% annual increase is expected between 2010 and 2013 (DEK-TMK, 2010). On the other hand, Turkey's energy dependency is gradually increasing from 70.5% in 2009 to 72.4% in 2011 (TMMOB, 2012). In accordance with the predicted results, energy dependency is expected to increase from 72% to 84% within 14 years (Sözen, 2009).

Along with the increase in population, Turkey's urbanization rate increased from 52.9% (1990) to 74% (2010) and urbanization rate is expected to reach to 80% in 2020 (Deliktaş, 2008). As a result, the number of residential and commercial buildings in highly populated cities has risen rapidly. In terms of final energy consumption, the building sector represents the second-largest energy consumer accounting for 37% of the total final energy consumption (18% for residential buildings, 19% for non-residential buildings) in 2010. As a consequence buildings were responsible from 32% of the total national energy-related CO_2 emissions (MENR, 2012). On the other hand, the building sector holds significant opportunity for cost-effective energy and CO_2 savings which as high as 30-50% of the current energy consumption (DEK-TMK, 2010).

In residential building, 80% of the total energy consumption is used for heating purposes (Ekici et al., 2009). This amount of energy is luxury for a country like Turkey which imports almost all of the energy it is consuming. With the decrease of fossil resources, taking into account technological and expensive energy costs, the best solution energy saving in buildings (Dombayci, 2010). On the other hand, according to the estimation for 2020, total energy demand in buildings can be decreased by 47% (Şevki, 2012). Considering energy efficiency on the basis of building sector, residential buildings have high energy saving potential.

There are several ways to model a building' energy consumption from statistical methods to artificial intelligence methods. Statistical methods generally based on semi pragmatic relations among measurements and sample data. Relations between cause and effects are not shown in statistical methods (Abdul-Wahab et al., 1996). Traditionally, regression analysis has been the most popular modeling technique in predicting energy consumption (Tso, 2003; Egelioğlu, 2001). However, some complex and inter-related problems can make statistical models inexpert.

The fundamental parameters affect the building energy consumption are space heating and cooling, domestic hot water heating, lighting, fan and pump consumption, internal gains, solar gains, ventilation systems and infiltration. The degree to which these parameters affect the overall energy consumption is highly dependent on climate, physical characteristics of the building, ownership and occupant behavior. It can be easily concluded that energy consumption characteristics of buildings are complex and inter-related. Comprehensive models are needed to understand relationships among these parameters that can handle non-linearities among the parameters (Dodier et al., 1996).

In this regard, artificial neural networks (ANN) or fuzzy logic methods can be an effective method to fulfill this need with much better accuracy. The advantages of artificial intelligence methods with respect to others model is their ability of modeling a multivariable problem given by the complex relationships between variables.

This thesis is based on a TUBITAK project titled as "Determination of significant relations between energy performance of multi-floor residential buildings and their design efficiency indicators- "Çok katlı konut yapılarının enerji performansları ile tasarım verimlilik göstergeleri arasındaki ilişkinin belirlenmesi" (Kazanasmaz, 2012). In this project, 148 residential buildings (5-13 storey) in 3 municipalities (Konak, Karabağlar and Balçova) of İzmir were selected as case study. The project was aimed to determine energy performance of residential buildings in Izmir, to analyze significant relationships between their performance and architectural configuration through statistical analyses (analysis of variance (ANOVA), regression, t-Test, scatter charts).

The purpose of this study is to investigate the ability of ANN and fuzzy logic models on estimating the residential building energy consumption in İzmir and to determine the most significant input parameters on the high accuracy models. The ANN and fuzzy logic model were compared with the results of a building energy performance software (KEP-IYTE ESS). In this thesis, zoning status, type of heating system, number of floors, wall overall heat transfer coefficient, glass type, area/volume ratio, existence of insulation, total external surface area, orientation, number of flats, total external surface area/total useful floor area, total wall area/total useful floor area, total lighting requirement/total useful floor area, total wall area and energy consumption of building were used as parameters. The project was the first one including both evaluation of energy performance of residential buildings and the impact of building design parameters of these buildings on their energy performance.

The thesis is composed of six chapters. The second chapter discusses the previous ANN and fuzzy logic modeling studies related to the building energy consumption. In chapter three, the details of ANN and fuzzy logic methods were presented. The forth chapter presents ANN and Fuzzy logic model construction works. The model results were discussed in the fifth chapter. The final chapter presents the conclusions.

CHAPTER 2

LITERATURE SURVEY

Energy consumption of buildings is affected by a wide range of parameters which have been investigated by various techniques such as analytic techniques, statistical techniques like regression analysis and artificial intelligence techniques like fuzzy logic, artificial neural networks (ANN) and genetic algorithm (GA). Artificial intelligence techniques have become more popular for the last two decades due to the limitation of statistical techniques against the energy consumption model's complexity.

ANN have been widely used for prediction of a range of building energy cosumption (Gonzales et al., 2005; Santamouris et al., 2006; Neto et al., 2008; Ekici et al., 2009; Dombayci, 2010). Ansett and Kreider (1993) studied ANNs to predict daily energy use in a complex building. Building utility measurement data from a university campus building, including electricity, natural gas, water and steam consumptions were modeled using back-propagation algorithm. Independent variables were selected as weather data (relative humidity, wet-bulb temperature and dry-bulb temperature) building occupancy and activity. The aim of that study was to test various training methods and data input order. The study also presented encouraging potential for the application of ANNs in building energy modeling. Cohen and Krarti (1995) developed an ANN model with generated inputs from DOE 2.1E software. The authors applied multi-layered feed forward networks aiming to predict potential energy savings in the building. Nevertheless, the authors have recommended that real building measurement data should be used for the future ANN modeling studies. Kalogirou et al. (2000) used ANN to predict energy consumption of a solar building. The input parameters were selected as season, insulation (characterizing whether thermal insulation was used on all walls or not), masonry thickness, function (characterizing whether the heat transfer coefficient was constant or not) and time of the day. A standard back-propagation learning algorithm with 46 neurons in the hidden layer was applied. The model results fit the experimental data with a coefficient of multiple determination (R^2 value) of 0.9991 which can be considered as a very good fitting. According to the author, the ANN model proved to be much faster than the dynamic simulation programs.

Additionally, Breekweg et al. (2000) evaluated various ANN techniques to develop a generalized model for building energy related fault detection. Data from four different buildings and simulation data from one building were modeled. Radial basis function (RBF) and general regression neural network (GRNN) was used. The coefficient of variation was obtained in the range of 20-40%. However, two buildings were in the range of 4-8%. The reasons for these large deviations were the building operation consistency, minimization of the noise elements and the quality of the data measurements. Also, the authors indicated that there is a requirement to examine this generalized model with energy data of different buildings.

Yik et al. (2001) modelled 23 commercial buildings and 16 hotels by ANN for forecasting the energy consumption of the buildings. The model including several input parameters such as hotel grade, air conditioning type, floor area and construction year was compared with the detailed simulation programs. The result showed an average deviation of 2% between detailed simulation programs and the model. The authors also suggested that the variations in the outdoor weather conditions and seawater temperatures that affect efficiency of air-conditioning plants can be included in the model.

Additionally, Ben-Nakhi et al. (2004) proposed the use of ANN models in order to predict building cooling load. The cooling load profiles investigated utilizing a model based on physical principle that provides the data for training and validation phase of the model. The aim of the study was to optimize thermal storage in public buildings as well as office buildings. The model was successful with an average coefficient of multiple determination (R^2 value) of 0.95.

In another study, Gonzales et al. (2005) has described a new approach for short-time load prediction in buildings. The method was based on a particular ANN that feeds back a part of its output. ANN was trained by a hybrid algorithm that uses actual and forecasted values of temperature, the current load and the hour and the day as input. The mean absolute percentage error (MAPE) value was found as 1.945.

Most of the surveyed literature focuses on using static ANN models at time *t* and all the independent parameters are known at the same time *t*. However, Yang et al. (2005) evaluated the performance of adaptive ANN models to predict cooling demand of the building. The authors applied a model that can be used for the real-time online energy consumption predictions. Input parameters were selected as outdoor dry-bulb temperature, outdoor wet-bulb temperature, temperature of water leaving the chiller.

The static models applied to real measurements lead to lower accuracy (Coefficient of variance (CV = 0.23) than in the case of synthetic data (CV = 0.07). Additionally, though the study has used one hidden layer, it suggested adding more layers or neurons can improve the prediction accuracy while adding complexity to the ANN training time. In a study by Yalcintaş et al. (2005), an ANN model based on back-propagation algorithm was developed to predict Honolulu high rise building's chiller plant power consumption. The model coefficient was 0.88 which was a good indication of the predictive power of the ANN. Another significance of the study was to do with the tropical climate content of the building data used in the model.

Ekici et al. (2009) implemented an ANN model for prediction of building energy consumption and compared the model with a computer program which calculates building energy consumption written in FORTRAN. The input parameters were orientation, insulation thickness and transparency ratio in using artificial neural networks. As a conclusion; when the calculated values compared with the outputs of the network, it is proved that ANN gives satisfactory results with average deviation of 3.43% and successful prediction rate of 94.8–98.5%.

Neural networks seem to be appropriate for forecasting energy consumption of buildings. In a study by Pao et al. (2009), several linear and non-linear models including ANN models were compared. The main focus was to predict energy consumption of buildings in Taiwan by utilizing linear and non-linear models. Back-propagation model was selected for the ANN model. The authors concluded that ANNs are more suitable to catch complicated non-linear integrating effects through a learning process.

Similarly, Köksal et al. (2008) investigated residential energy consumption modeling. The study compared ANNs and conditional demand analysis (CDA) to forecast energy consumption using actual data collected from 247 household. The selected input parameters were appliances, lighting and space cooling energy consumption of residential buildings. The result presented that R^2 of ANN model is better than CDA model, 0.909 and 0,795, respectively. The comparison of the models indicated that both models were capable of accurate prediction of energy consumption of residential buildings.

Neto et al. (2008) compared a dynamic energy simulation software (EnergyPlus) with a simple ANN for forecasting building energy consumption. The administration building of the University of Sao Paulo was selected for the case study and the model inputs were chosen as dry-bulb temperature, relative humidity and global solar radiation. The results indicated that EnergyPlus and ANN model were predicted the energy consumption of the building by average error of 13% and 10%, respectively.

Yeziero et al. (2008) recommended to use ANN models if the study has many variables or is a complex problem. The authors evaluated ANNs approach towards assessing building performance simulation tools such as Energy_10, eQuest, EnergyPlus and Green Building Studio. The input parameters were chosen as outdoor temperature, relative humidity, set point temperature and occupancy schedule. The heating/cooling energy consumption of the case building was predicted by feed-forward training algorithm and 16 hidden-neurons were selected to reach more accurate results. Therefore, mean absolute error (MAE) was obtained only 0.9%. However, the tools covered a range of 3-15.4% MAE.

Swan et al. (2009) searched end-use energy consumption in the residential sector by ANN models. They provided an up-to date review of the various modeling techniques used for modeling of residential sector energy consumption. Four major residential energy modeling approaches (top-down and bottom-up, statistical and engineering approaches) were used. The authors indicated that bottom-up models have the capability of determining the impact of new technologies.

Dombayci (2010) studied the prediction of heating energy consumption in a model house by using ANN. The model inputs were chosen as month of the year, day of the month, hour of the day and energy consumption of the previous hour. R^2 was obtained as 0.9907 for training stage and, 0.9880 for testing stage, respectively. However, the study showed that ANN can predict energy consumption values with given limited input parameters but more data is required (for example; solar radiation, relative humidity, wind speed and direction) in order to reach more accurate results.

Succeeding in modeling of energy consumption of buildings is a complex problem. The fuzzy logic aims to point out the input and output variables directly by defining them with fuzzy sets that can be expressed in linguistic terms (e.g. cold, warm and hot) (Tsoukalas, 1997). A limited number of studies on fuzzy logic applications on the building energy consumption exist in the literature.

In a study by Kajl et al. (1997), a neural-fuzzy logic model was created to perform a quick and easy prediction of building energy consumption. Nevertheless, the model did not include many variables since it has been based on the simulations performed on DOE-2 software. The fuzzy model was chosen with eleven variables as length of building, width of building, number of floors, R-value of exterior wall, fenestration, windows solar protection, U-value of window, lighting power density, exterior air rate, occupancy density and boiler efficiency at full load. Firstly, ANN was modeled and then, the corrections of the ANN results were introduced by utilizing fuzzy logic. The authors suggested that to make the corrections using fuzzy logic is useful for the accuracy of the ANN results, especially for the energy consumption prediction of existing buildings.

Both fuzzy logic and neural network were used to forecast building energy consumption in a study by Li et al. (2011). According to the authors, fuzzy logic is an alternative approach to predict building energy consumption. More accurate results were obtained in the fuzzy model than ANN model.

The aim of this thesis is to create simple models based on artificial intelligence methods (artificial neural networks and fuzzy logic) as predicting tools and to compare these methods with a building energy performance software (KEP-IYTE ESS).

CHAPTER 3

NEURAL NETWORK AND FUZZY LOGIC

Artificial intelligence encompasses a number of technologies that includes expert systems, neural networks, genetic algorithms, fuzzy logic systems, cellular automata, chaotic systems and anticipatory systems. In this thesis we have placed emphasis on artificial neural networks and fuzzy logic.

3.1. Artificial Neural Networks (ANN)

Artificial neural networks (ANNs) which are inspired from the biological nervous system are parallel-interconnected networks of simple computational elements which aim to interact with the objects of the real world.

A neuron is the fundamental cellular unit of the nervous system. It is a very simple processing element which receives and combines signals from the other neurons through input paths called dendrites. If the combined input signal is strong enough, the neuron fires producing an output signal along the axon that connects to the dendrites of many other neurons. Figure 3.1 shows the basic architecture of the network which consists of dendrites, axon and synapse (Soucek, 1989).

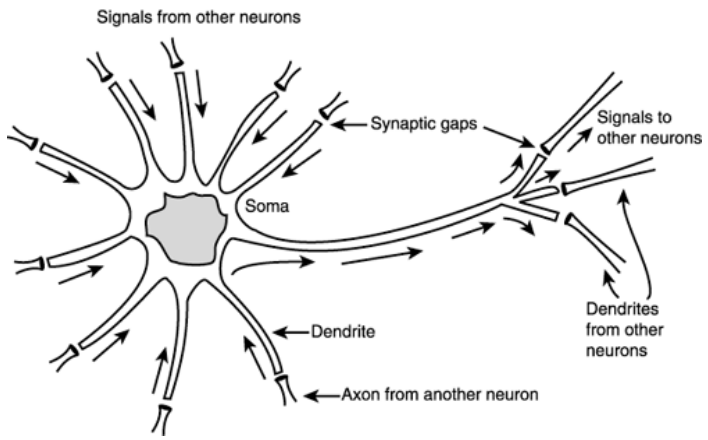

Figure 3.1. Sketch of a biologic neuron showing components
(Source: Soucek, 1989)

The fundamental actions of the neuron are chemical, in nature, and the neurotransmitter fluid produces electrical signals. They reached to the nucleus or the soma of the neuron. The adjustment of the impedance or conductance of the synaptic gap is a critically important process. Indeed, these adjustments lead to memory and learning. As the synaptic strengths of the neurons are adjusted, the brain learns and stores information.

An artificial neuron is a model whose components have directly analogs to the components of an actual neuron. Figure 3.2 shows the schematic representation of an artificial neuron (Luger, 2009).

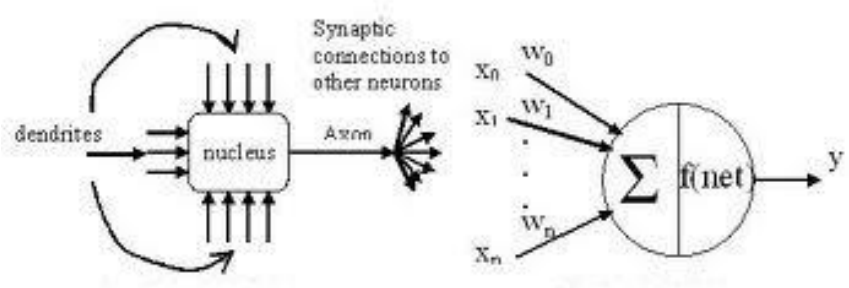

Figure 3.2. Representation of a neuron versus biologic neuron
(Source: Luger, 2009).

The input signals are represented by x_1, x_2, x_3, ….x_n . These signals are continuous variables, not the discrete electrical pulses that occur in the brain. Each of these inputs is modified by a weight. These weights can be positive or negative. Depending on the weights, the computation of the neuron can be different. By arranging the weights of an artificial neuron, the output can be obtained from specific inputs.

An artificial neural network can be defined as;

A data processing system consisting of a large number of simple, highly interconnected processing elements (artificial neurons) in an architecture inspired by the structure of the cerebral cortex of the brain (Tsoulukas, 1997).

An example of a neural network is shown in Figure.3.3 (Antognetti, 1991);

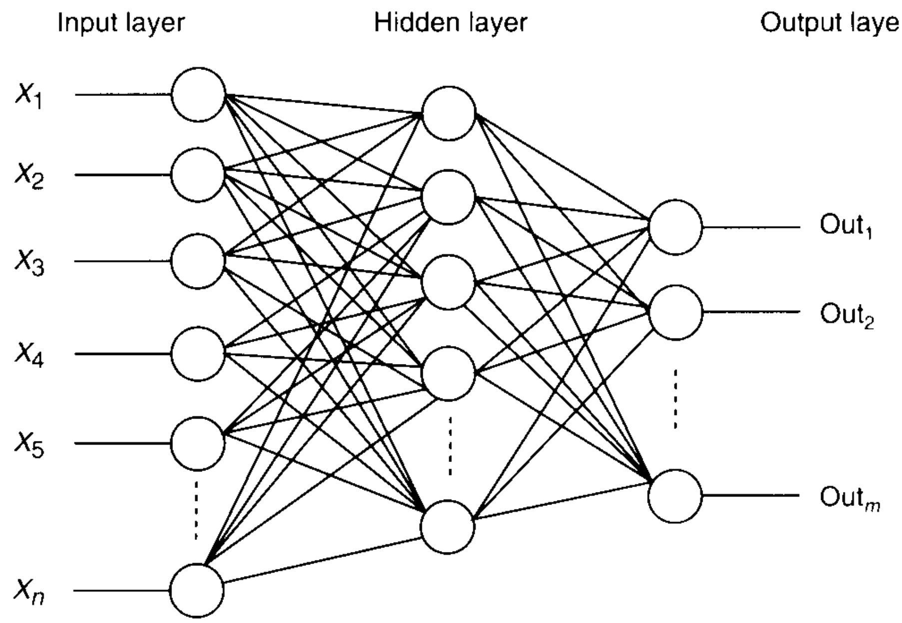

Figure 3.3. Example of neural network architecture
(Source: Antognetti, 1991)

Processing elements in the architecture of the model are usually organized into an order of layers with full or random connections between the layers. Input layer presents data to the network. This layer is not a neural computing layer since the nodes have no weights or activation functions. Output layer presents the output response to a given input. The other layer (or layers) is called hidden layer (or intermediate layer) since it has no connections to the outside world.

The information that is contained in each neuron is first weighted (w_{ij}), and summed up as a net function (u_i). Then the value from that net function is transferred, by a transfer function ($f(u)$) with activation value (a_i), to the next neuron. Thus, each input has relative weights that show the impact of that input.

Scalar input $x_1, x_2, \ldots, x_n$ are multiplied by weights $w_{1j}, w_{2j}, \ldots w_{nj}$ and the weighted values are fed to the summing confluence. The neuron has a bias bi which is summed with the weighted inputs in order to form the net input net_j given in Equation (3.1). Net input is the argument of the transfer function f. Therefore, the output value obtained is given in Equation (3.2).

$$(net_j) = x_1 w_{1j} + x_2 w_{2j} + \ldots\ldots + x_n w_{nj} + b_i \quad (3.1)$$

$$o_j = f(\text{net}_j) \tag{3.2}$$

Two net functions are used in the literature: Linear-basis and radial-basis net functions. In linear-basis function (Equation 3.3) u_i is summation of the weight (w_{ij}) from the ij_{th} neuron multiplied with the j_{th} input (x_j). Radial-basis function can be seen in Equation (3.4).

$$u_i(w,x) = \sum_{j=1}^{n} w_{ij} x_j \qquad \text{Linear-basis function} \tag{3.3}$$

$$u_i(w,x) = \sqrt{\sum_{j=1}^{n} (x_j - w_{ij})^2} \qquad \text{Radial-basis function} \tag{3.4}$$

The sum of the weighted inputs becomes the input for an activation (transfer) function, which processes that input to a new output. There are chiefly six transfer functions. Figure 3.4 shows commonly used transfer functions. These are the sigmoid function, the linear function, the step function, the step function with threshold, the ramp function, and the hyperbolic tangent function.

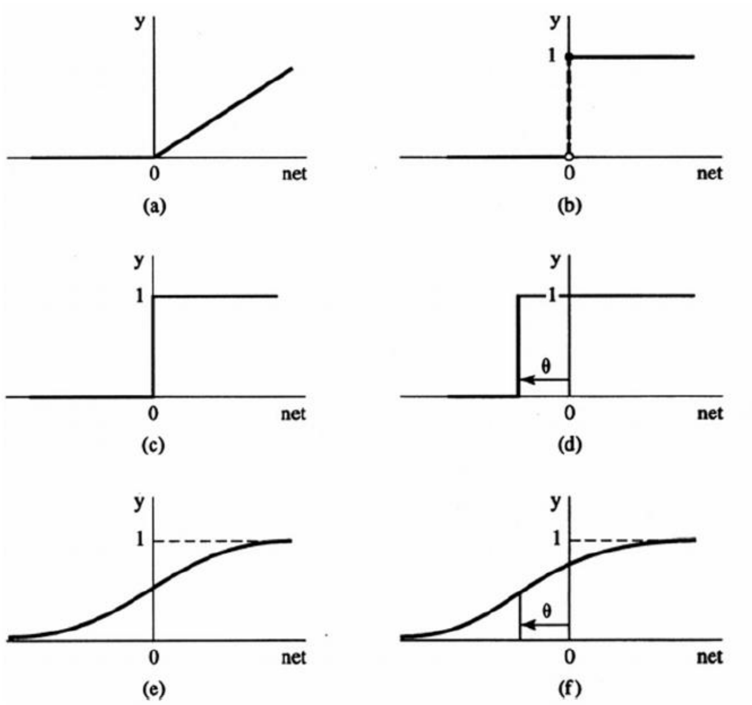

Fig. 3.4. (a) A piecewise linear function (b) A step function (c) A conventional approximation graph for the step function defined in (b) (d) A step function with threshold θ (e) A sigmoid function (f) A sigmoid function with threshold θ (Source: Munakata, 1998).

Equation 3.5 shows the commonly used one being the sigmoid transfer function. It produces outputs in the interval of (0 to 1), and is continuous like its derivative. Its function is non-decreasing and monotonous (Kauffmann, 1991). Another widely used function, that is, the Gauss function is shown in Eq. (3.6). Linear function calculates the output by the equation f(x) = αx where α is constant. Neurons with this type of transfer function result in linear approximations (Zurada, 1992).

$$f(u_i) = \frac{1}{1+e^{-ui/\sigma}} \quad \text{Sigmoid transfer function} \qquad (3.5)$$

$$f(u_i) = ce^{-ui^2/\sigma^2} \quad \text{Gauss function} \qquad (3.6)$$

Neural networks could be single-layer or multi-layer networks. Single-layer neural network type has one layer of connection weights. Multi-layer neural network contains more than one layer of the nodes between the input and output neurons. Artificial neural networks activate two major functions; first, they learn and second they recall. A neural network model learns the patterns by adjusting its weights. Weights are adjusted in order to produce required outputs with respect to given inputs (Dombayci, 2010). Later, the adapted weights give an output with new and independent from those of training, input data. This is a recall process which is employed for the testing of the model or for the sensitivity analysis.

Sensitivity analysis explores the rate of the impact of input parameters on the model output (Kazanasmaz et al., 2009). Therefore, it provides the irrelevant inputs which may be eliminated from the model for the sake of simplicity and to improve the prediction power of the model. By doing this, the performance of the model results in a lower rate of prediction error, relatively.

3.1.1. Learning Algorithms

There are various learning algorithms like Kohonen self-organizing maps, The Widrow-Hoff rule, feed forward back propagation, The Hopfield rule, Elman back-propagation, Cascade-forward back-propagation (Munakata, 1998). However, back-propagation (BP) is the most commonly used learning algorithm (Rumelhart and McClelland, 1986, Base et al., 1996)

The back-propagation algorithm (Rumelhart and McClelland 1986) is used in layered feed-forward ANN. This means that the artificial neurons are systemized in layers, and send their signals “forward”, and then the errors are generated backwards. The network receives inputs by neurons in the *input layer*, and the output of the network is given by the neurons on an *output layer*. One or more intermediate *hidden layers* may be used. Supervised learning is used by the back-propagation algorithm. This means that the algorithm is supplied with the examples of the inputs and outputs which were applied to be computed by the network. Then, the error (difference between actual and predicted results) is calculated. BP algorithms are separated into two concepts; forward pass and backward pass. In forward pass; inputs are fed, transferred with weights, processed in the neurons and finally an output value is found. That value is compared with the actual value and finally the error is calculated. In backward pass, the same way as the forward pass is followed, by this way the error from the first pass is distributed through the weights (Base et al., 1996). The idea of the back-propagation algorithm is to reduce this error, until the ANN learns the training data. The training starts with random weights, and the aim is to adjust weights so that the error will decreased. The error of the network will simply be the sum of the errors of all the neurons in the output layer as shown in Equation 3.7;

$$E(\overline{x}, \overline{w}) = \sum_{j} (O_j(\overline{x}, \overline{w}) - d_j)^2 \tag{3.7}$$

Where E is the error, O_j is observed value and d_j is predicted value.

The modification of the weights throughout the network is shown in Equation 3.8.

$$w_{ij}^{new} = w_{ij}^{old} - \partial \frac{\delta E}{\delta w_{ij}} \tag{3.8}$$

E is the error function and ∂ is a positive term called learning rate (Tsoukalas, 1997).

3.2. Fuzzy Logic

Fuzzy logic is a logical system that aims at a formulation of approximate reasoning. First, it was proposed by Loutfi A. Zadeh in 1965 with the work “Fuzzy Set Theory” (Zadeh, 1965). Zadeh defined the concept of Fuzzy Sets as a class of objects with a continuum of grades of membership. Such a set is characterized by a membership function which assigns to each object a grade of membership ranging between zero and one. After 1974, this technique was applied in many areas such as controlling of physical or chemical parameters like temperature, electric current, flow of fluid, motion of machines etc. (Munakata, 1998). The general structure of the fuzzy logic modeling is presented in Figure 3.5.

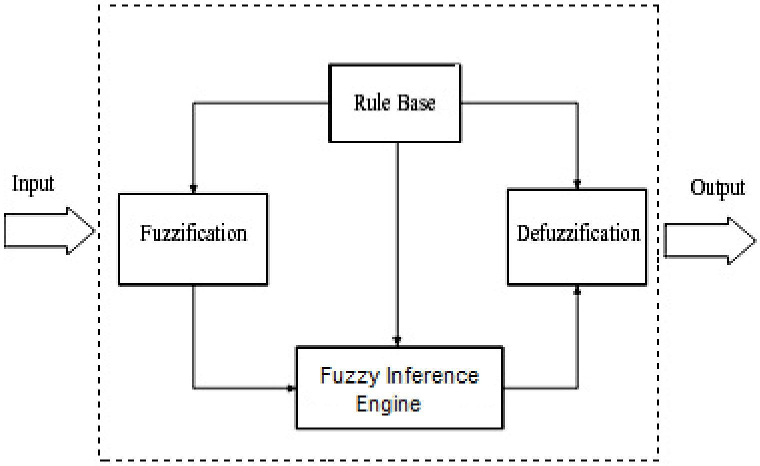

Figure 3.5. The structure of Fuzzy logic modeling
(Source: Tayfur, 2012)

3.2.1. Foundations of Fuzzy Sets

A fuzzy set is a generalization of an ordinary set by allowing a degree (or grade) of membership for each element. Many degrees of membership are allowed in fuzzy sets. The degree of membership is indicated by a number between 0 and 1. In extreme cases, if the degree is 0, the element does not belong to the set, and if 1, the element belongs 100% to the set.

In a set, every element is associated with a degree of membership. This means that the membership function (MF) of a set represents each element to its degree. The membership function assists the partial belongings mathematically which have values between 0 and 1. It is formally written as Equation 3.9.

$$\mu_A(x) : X \rightarrow [0,1] \tag{3.9}$$

3.2.2. Fuzzy Set Operations

Basic relations for fuzzy sets are specified like in the ordinary sets. Fuzzy operations include union, intersection, complement, binary relations and composition of relations as classical operations. Table 3.1 shows three operations for fuzzy and classical sets. α indicates the membership of subsets *A* and *B*.

Table 3.1. Comparison between Fuzzy and classical operations
(Source: Larsen, 2003)

Intersection	*Union*	*Complement*
$\alpha_{A\cap B}(x) =$	$\alpha_{A\cap B}(x) =$	$\alpha_{\bar{A}}(x) =$
classical $\begin{cases} 1 & x \in A \cap B \\ 0 & x \notin A \cap B \end{cases}$	$\begin{cases} 1 & x \in A \cup B \\ 0 & x \notin A \cup B \end{cases}$	$\begin{cases} 1 & x \notin A \\ 0 & x \in A \end{cases}$
fuzzy $\min(\alpha_A(x), \alpha_B(x))$	$\max(\alpha_A(x), \alpha_B(x))$	$1 - \alpha_A(x)$
AND	**OR**	**NOT**

A graphical explanation of two fuzzy sets and fuzzy operations is indicated in Fig.3.6 (Munakata, 1998).

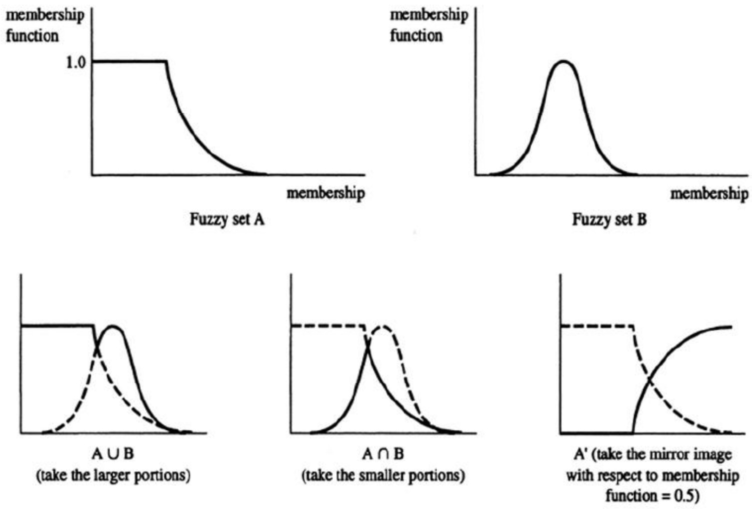

Figure 3.6. A graphical explanation of two fuzzy sets and their union, intersection, and complement (Source: Munakata, 1998)

3.2.3. Fundamental of Fuzzy logic

Fuzzy logic is similar with fuzzy set theory. Table 3.2 indicates correspondences between fuzzy logic and fuzzy set theory.

Table 3.2. Representing the Correspondences between Fuzzy Set and Fuzzy Logic (Source: Munataka, 1998)

Fuzzy Set	Fuzzy Logic
Degree of membership	Truth value of proposition
∩	AND
U	OR
complement	NOT

Fuzzy logic rules are called as contingent statements that describe the dependence of one or more linguistic variable on another. The simple form of the basic lingual If-Then rule is shown as;

If "α" is A and "β" is B, then "λ" is C

Here, the corresponding linguistic values are A, B and C while α, β and λ are the inputs. For example "if temperature is HIGH the humidity is ZERO" is a fuzzy implication.

3.2.4. Fuzzy Systems

The model basically includes four components: fuzzification, fuzzy rule base, fuzzy output engine, and fuzzification (Tayfur, 2012).

3.2.4.1. Fuzzification

For each input and output variable selected is converted to degrees of membership by fuzzificiation. It includes definition of fuzzy sets, determination of the degree of membership of crisp inputs in appropriate fuzzy sets. All fuzzy variables are theoretically represented as a number between 0 and 1 (Tayfur, 2012).

3.2.4.2. Fuzzy Rule Base

In order to obtain the fuzzy output, Fuzzy rule base form the basis for the fuzzy logic. It contains rules that cover all suitable fuzzy relations between inputs and outputs. The fuzzy rule-based system uses IF-THEN rule based system given by IF ascendant, THEN consequent (Sivananam, 2007). Following rules are constituted for the example (Kulkarni, 2001).

R1 : If x_1 is LOW and x_2 is SHORT then y is VILLAGE
R2 : If x_1 is LOW and x_2 is LONG then y is TOWN
R3 : If x_1 is HIGH and x_2 is SHORT then y is TOWN
R4 : If x_1 is HIGH and x_2 is LONG then y is TOWN

For the fourth rule; it is assumed as if the population of the settlement (x_1) is high and the distance to the furthest municipality (x_2) is high then the rate of being municipality (y) is high.

3.2.4.3. Fuzzy Inference Engine

Each fuzzy rule gives a single number that represents the truth value of that rule. All fuzzy rules are taken into account by fuzzy inference engine in the fuzzy rule base. The fuzzy inference system is a framework based on concepts of fuzzy set theorem, fuzzy if-then rules, and fuzzy reasoning. Conventional fuzzy inference systems are typically built by domain experts and have been used in automatic control, decision analysis, and expert systems. Optimization and adaptive techniques expand the applications of fuzzy inference systems to fields such as adaptive control, adaptive signal processing, nonlinear regression, and pattern recognition. Fuzzy inference system can take either fuzzy inputs or crisp inputs, but the outputs it produces are almost always fuzzy sets. Sometimes it is necessary to have a crisp output, especially in a situation where a fuzzy inference system is used as a controller. Therefore, a method of defuzzification is required to extract a crisp value that best represents the fuzzy set. With crisp inputs and outputs, a fuzzy inference system implements a nonlinear mapping from its input space to output space. This mapping is accomplished by a number of fuzzy if-then rules, each of which describes the local behavior of the mapping (Hirota, 1991). There are two methods widely used; the minimum and the product operation methods. If “°” is the operator that indicates rule of inference, Equation 3.10 can be written in terms of membership function for minimum operator;

$$^{\circ}B(y) = MAX[MIN(^{\circ}A(X), ^{\circ}R(x, y))]x \in E1 \tag{3.10}$$

Similarly, Equation 3.11 can be written in terms of membership function for prod operator;

$$^{\circ}B(y) = MAX[(^{\circ}A(X), ^{\circ}R(x, y))]x \in E1 \tag{3.11}$$

3.2.4.4. Defuzzification

Defuzzification converts fuzzy output set to crisp. It is necessary to convert the fuzzy quantities into crisp quantities because generated fuzzy results cannot be used as such to the applications. Defuzzification can also be called as “rounding off” method (Sivanandam, 2007). There are many defuzzification methods named as (COG)(centroid), bisector of area (BOA), mean of maxima (MOM), leftmost maximum (LM), rightmost maximum (RM),centre of sums and weighted average method.(Jantzen,1999; Tayfur, 2012). Centroid method is the most widely used method as expressed in Equation 3.12;

$$K_x^* = \frac{\sum_i \mu(K_{xi})K_{xi}}{\sum_i \mu(K_{xi})} \tag{3.12}$$

K_x^* is the defuzzified output value, K_{xi} is the output value in the ith subset, and $\mu(K_{xi})$ is the membership value of the output value in the ith subset. Figure 3.7 represents centroid method graphically (Tayfur, 2012).

CHAPTER 4

MODEL CONSTRUCTION

A hundred forty six residential buildings (5-13 storey) in 3 municipalities that are located in İzmir were selected as case study for artificial neural network and fuzzy logic building energy consumption predictions to compare with KEP-IYTE ESS results.

4.1. Data Collection

Selection criteria for residential buildings to be examined are listed below;

- Zoning status (attached, detached and corner)
- Orientation (north, south, east, west)
- Floor numbers (5-13)
- Heating system type (individual and central)
- Construction year (TS 825 (2000) before and after).

Architectural and mechanical drawings were obtained from archives of Konak, Karabağlar and Balçova Municipalities by permits from the departments of Zoning and Urban Development. The input data for the models were determined by utilizing of architectural and mechanical projects obtained from related municipalities.

Addresses (avenue, street names and apartment number) and 3D models of majority of buildings in İzmir were accessed by using “3D City Guide of İzmir” which was prepared by department of Geographical Information Systems. Figure 4.1 indicates example image that includes 3D model and the address information of an apartment building.

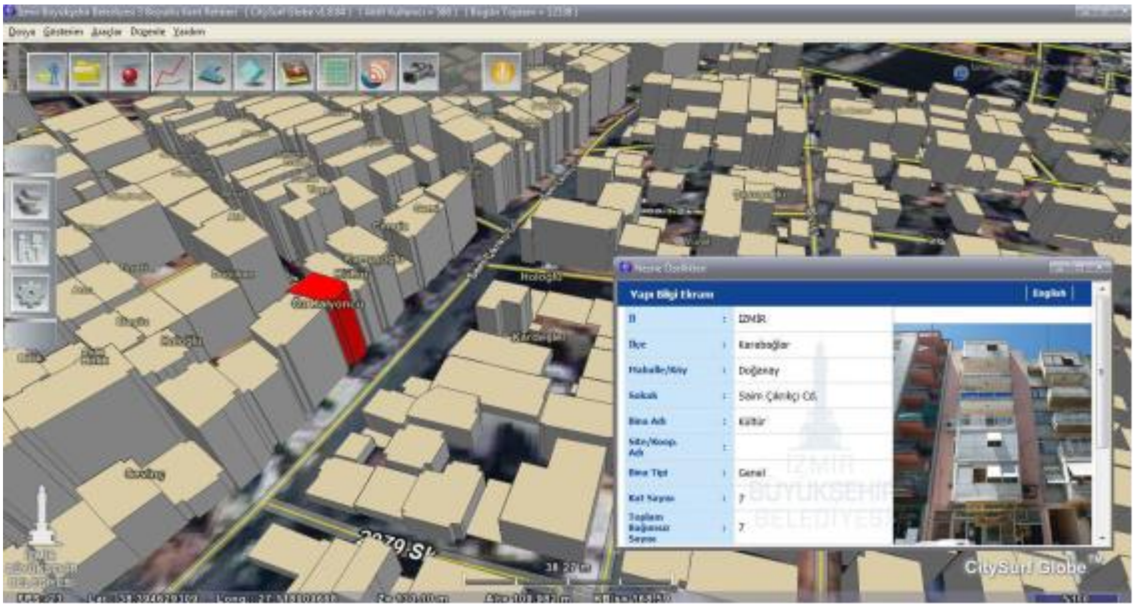

Figure 4.1. Building selection from 3 municipalities by using “3D City Guide” of İzmir

After analyzing architectural and mechanical projects obtained from municipalities by address, island and plot numbers, a total of 148 multi story residential buildings have selected for case study. Among these, 50 out of 148 were in Konak, the other 50 were in Balçova and the rest in Karabağlar. Case buildings had a total of 2136 apartments. 674 out of 2136 were in Konak, 790 in Karabağlar and the rest of 672 were in Balçova.

4.2. Model Input Parameters

The 16 model parameters which were compiled from projects of residential buildings are listed in Table 4.1 are described below;

***Zoning status*:** Zoning status (attached, detached and corner) which determines the relationship of the selected building with buildings in neighboring parcels affect design phase. Attached zoning status is desirable to minimize heat losses (Soysal, 2008).

Architectural projects obtained from municipalities were investigated in three groups based on zoning status. So, the zoning status of the case buildings were defined as corner (attached to a building on one side and situated at the corner), attached (attached to a building on two opposite sides) and detached (not attached to a building). Zoning status of the building was considered with the orientation. Figure 4.2 illustrates this case by an example of a sketch. As the figure shows, Building A that has three façades of open to the outdoor is a corner building. Furthermore , its orientation is North/South/West. Zoning status of building B is attached and its orientation is North/South because of that it has two façades facing to North and South. Building C is detached building that has four façades facing outside. None of the buildings is adjacent to Building C.

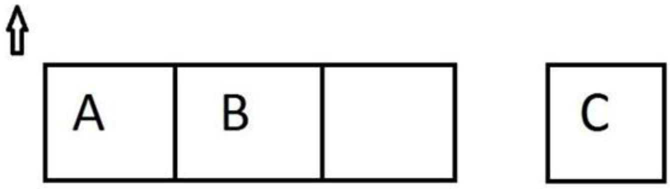

Figure 4.2. Zoning status of buildings

Type of heating system: Types of heating system of residential buildings can be divided into two groups; individual and central heating system. Residential heating systems present a unique and high impact opportunity to influence existing homes' energy performance and carbon emissions, because they are replaced on a regular interval and represent the largest energy end-use in the home in much of the country. The heating systems assessed include mainstream system types such as furnaces, boilers, and air-source heat pumps, as well as less common options including dual fuel systems and ground-source heat pumps. The energy sources are electricity, fuel oil, and propane, and most of the systems are evaluated at a high efficiency and a standard efficiency level. (Audenaert et al., 2012).

Number of floors: The number of floors and building setback are the two main physical variables influencing energy consumption. The parcel with a longer setback will attract more sun exposure so the energy consumption is expected to be lower. (Capeluto et al., 2003).

Wall overall heat transfer coefficient (W/m^2K): It is the heat transfer coefficient of external surfaces which is calculated in accordance with rules and standards of engineering. The wall overall heat transfer coefficient can be used to calculate the total heat transfer through a wall. The overall heat transfer coefficient depends on the thermo-physical properties of air on both sides of the wall, and the properties of the wall and the transparent surfaces. Decreasing wall overall heat transfer coefficient minimizes the total energy consumption of the building (Soysal, 2008).

Glass type: The glass is the transparent surfaces which is necessary to benefit from sunlight. To keep the energy consumption low, the lowest U–Value glasses are required (OTB, 2004). Energy consumption increases from opaque glazed windows, low-e glasses, and triple glazed to double glazed windows, respectively (Wall, 2006).

Area/Volume ratio: Surface area to volume ratio of a building is an important factor determining heat loss and gain. The greater the surface area the more the heat gain/ loss through it. So small A/V ratios imply minimum heat gain and minimum heat loss (Basham, 2002).

Insulation existence**:** It is considered that insulation which is implemented to building shell is a dominant and effective factor in energy consumption. Insulated walls reduce conductive heat loss through the wall (Taylor et al., 1998).

Total external surface area: It is calculated from external perimeter and the floor to ceiling height of residential building. The greater the surface area, the more the energy consumption (Basham, 2002).

Orientation: Direction of the residential unit is important to benefit from natural climate conditions, solar light and heat. Since energy performance calculations include solar gain attained from window area and coefficients, to calculate solar gain changes according to orientation (Tavil et al., 1997). Main façade of the building should face south, and large windows should be located on this façade to benefit from solar light and heat extensively (Smeds and Wall, 2007).

Number of flats: Floor area of flats must be considered while investigating energy consumption of a building.

Total external surface area/Total useful area : Total useful areas are known as living space, circulation area, bedrooms, wet spaces, kitchen and bin. This is an indicator that reflects form of the building by its volume in zoning status. Therefore, it is highly related in exterior surface design and in cost efficiency of energy consumption by concerning surfaces.

Total windows area/Total external surface area: This is viewed as the indicator for the equilibrium of solid-void, describing effects of void surfaces to hold minimum heat load. The relatively low insulation levels afforded by windows will have an impact on the internal thermal performance of a home during the winter, while larger windows will increase internal solar heat gains (Wang et al., 2009).

Width/Length: This is an indicator of plan configuration. The objective is to determine maximum utility spaces and building surfaces in suggested zoning plan. Width/Length ratio is one of the main factors that determines the relationship between solar gain and energy consumption (Lam et al., 1994). The studies on Width/Length ratio have showed that, maximum elongation in east-west axis (1:2) is preferable in hot climates (Diyarbakir, Izmir, Antalya). For cold cli-mates, building having a compact form with Width/Length ratio of 1:1.2 turns out to be the optimum case (İnanıcı et al., 2000).

Total wall area/Total useful area: This ratio was used to define design efficiency indicator related flexibility, utility and cost efficiency of designed spaces. It is one of the general design principle, creating minimum wall area and minimum fragment plan scheme.

Total lighting requirement/Total useful area: To illuminate interior volumes, total lighting load of building is calculated. This ratio is an indicator of the efficiency power of the net-usable floor area in determining the lighting load of the building.

Total wall area: Total wall area affects the heat gain or loss that is passing through the wall. When the total energy consumption (cooling + heating) is considered, it is calculated that the east and west sides have the largest total effect and the northern wall has the smallest total effect (Çomaklı et al., 2003).

4.3. KEP-SDM (KEP-IYTE-ESS Software)

The Standard Assessment Method for Energy Performance of Dwellings (KEP-SDM) was developed to obtain energy certificate of buildings by utilizing a calculation procedure including heating, domestic hot water production and lighting energy consumptions and CO_2 emissions of dwellings by the Chamber of Mechanical Engineers, Izmir Institute of Technology and Istanbul Technical University in 2008 (KEP-SDM, 2008). The method is referred to TS 825 (TS 825, 1999; Ministry of Public Works (Ministry of Environment and Urban Planning), 2008) which provides a framework for the calculation of heating energy demand in buildings and European standard EN ISO 13790 (2008) (Manioğlu, 2008).

According to EN ISO 13790 (2008), there are three classifications of energy performance evaluation methods: seasonal or monthly static method, simple hourly dynamic method (simple dynamic) and detailed hourly dynamic method (full dynamic).

KEP-SDM is a monthly method including degree-day correction. The calculation is based on the energy balance considering a range of factors which contribute to energy efficiency, as mentioned below;

- Materials used for construction of the dwelling
- Thermal insulation of the building fabric
- Ventilation characteristics of the dwelling and ventilation equipment
- Efficiency and control of the heating system(s)
- Solar gains through openings of the dwelling
- The fuel used to provide space and water heating, ventilation and lighting
- Renewable energy technologies

The calculation ignores some of the factors, as mentioned below;

- Household size and composition
- Ownership and efficiency of particular domestic electrical appliances
- Individual heating patterns and temperatures.

KEP-IYTE-ESS is a software developed based on the KEP-SDM methodology. It describes the buildings as a single-zone but internal temperature is separated according to the living area and the rest. Furthermore, the calculation allows thermal bridges in the building unlike thermal mass of the building and weather data is taken from National Meteorological Institution for each city. The software gives the users two outputs; annual energy consumption per unit floor area (kWh/m^{2}year) and annual CO_2 emissions per unit floor area (kgCO_2/m^{2}year) (MMO, 2008).

In order to obtain the energy consumption of case buildings, KEP-IYTE-ESS Software was used. The software calculates the energy performance of buildings including 17 calculation modules, as listed below;

- Dwelling dimensions and internal parameters
- Ventilation rate
- Heat losses
- Specific heat loss and heat loss parameter
- Domestic hot water
- Internal gains
- Solar gains and gain utilization factors
- Mean internal temperature
- Degree-days

- Space heating requirements
- Lighting energy requirements
- Total and primary energy consumption
- CO^2 emissions
- Energy and CO^2 certificates

The methodologies are reliable if they are validated. KEP-IYTE-ESS was tested using a well-known validation and diagnostic procedure, Building Energy Simulation Test (BESTEST) (Judkoff, 1995). BESTEST is a procedure, which was developed by International Energy Agency (IEA) in 1995, to test and diagnose the building energy simulation programs. The procedure contains several tests assessing the effect of physical properties on the results of building energy simulations. The purpose of this procedure is to create obvious, well-defined test series for software-to-software comparisons and program diagnostics. KEP-IYTE-ESS was validated by the BESTEST procedure and the outputs were in the range of acceptable values of BESTEST.

4.4. ANN Models

Five different modeling studies were performed in this thesis by using the same data.

1) The ANN model with 16 input parameters (Model A)
2) The ANN model with 8 input parameters (By applying input parameters reduction according to the sensitivity analysis results) (Model B)
3) The same ANN model in Model B with orientation parameter (Model C)
4) The ANN model with 4 input parameters (Model D)
5) The fuzzy logic model

The model was developed with the assistance of MatLAB® (MatLAB 2008b, 2008) then subjected to a sensitivity analysis to determine the relationship between input and output variables using NeuroSolutions Software (NeuroDimensions Inc, 2002).

Table 4.1 shows all the parameters and their ranges used in this study. Some of the parameters are verbal like zoning status, glass type, orientation and existence of insulation. In order to model these parameters, numerical values were given.

Table 4.1. The parameters and their ranges used in this study

Code	Input parameter	Range	
		Minimum	Maximum
x_1	Zoning status	1	3
x_2	Heating system type	1	2
x_3	Number of floors	5	11
x_4	Wall overall heat transfer coefficient (W/m^2K)	0.43	1.83
x_5	Glass type	1	2
x_6	Area/Volume ratio (1/m)	0.579	0.640
x_7	Insulation existence	1	2
x_8	Total external surface area (m^2)	208.44	2655.82
x_9	Orientation	1	8
x_{10}	Number of flats	3	38
x_{11}	Total external surface area/Total useful area	0.0230	1.0856
x_{12}	Total windows area/Total external surface area	0.1048	0.6348
x_{13}	Width/Length	0.2125	1.000
x_{14}	Total walls area/Total useful area	0.0138	1.2131
x_{15}	Total lighting requirement/Total useful area	0.1456	187.8945
x_{16}	Total walls area (m^2)	110.02	2141.21
y_1	Total energy consumption of the building (kWh/year)(output)	88.74	367.01

Data Reduction: 148 data points of 16 inputs and one output parameter data needed to be reduced into 3 inputs and one output data points. For fuzzy logic model, only 3 input parameters appeared to be reasonable in this study since the fuzzy logic model required rule sets that contain all possible combinations of parameter levels. Three important parameters (Type of heating system, total external surface area and wall overall heat transfer area) were selected for fuzzy logic model.. Considering that each input parameter had 2 or 3 subsets in the membership function, a total number of combinations was 18. If the original data with 16 parameters had been used, this number would have been 3^{16} ~ 43 millions combinations. This number, obviously, is impractical to write fuzzy sets. Therefore, sensitivity analysis was applied to reduce 16 input parameters in ANN Model A.

The collected data were separated into two groups; training (first 118 data) and testing (last 30 data). Several trials have been done with these sets and different topologies. Levenberg-Marquardt (LM) learning algorithm that is variant of feed-forward back-propagation and sigmoid (SIG) and linear (PURELIN) transfer functions were used in the hidden layer and output layer, respectively. The purpose of these trails is to obtain the highest R^2 values. Learning rate was constant and equal to the 0.02 for all ANN models and to predict energy consumption, MATLAB 2008b's neural network toolbox was selected as a software. The sensitivity analysis has been done by utilizing a software called Neuro Solutions 5. All the models have been run for 10000 iterations. The main procedure of all ANN model simulation is shown in Figure 4.3.

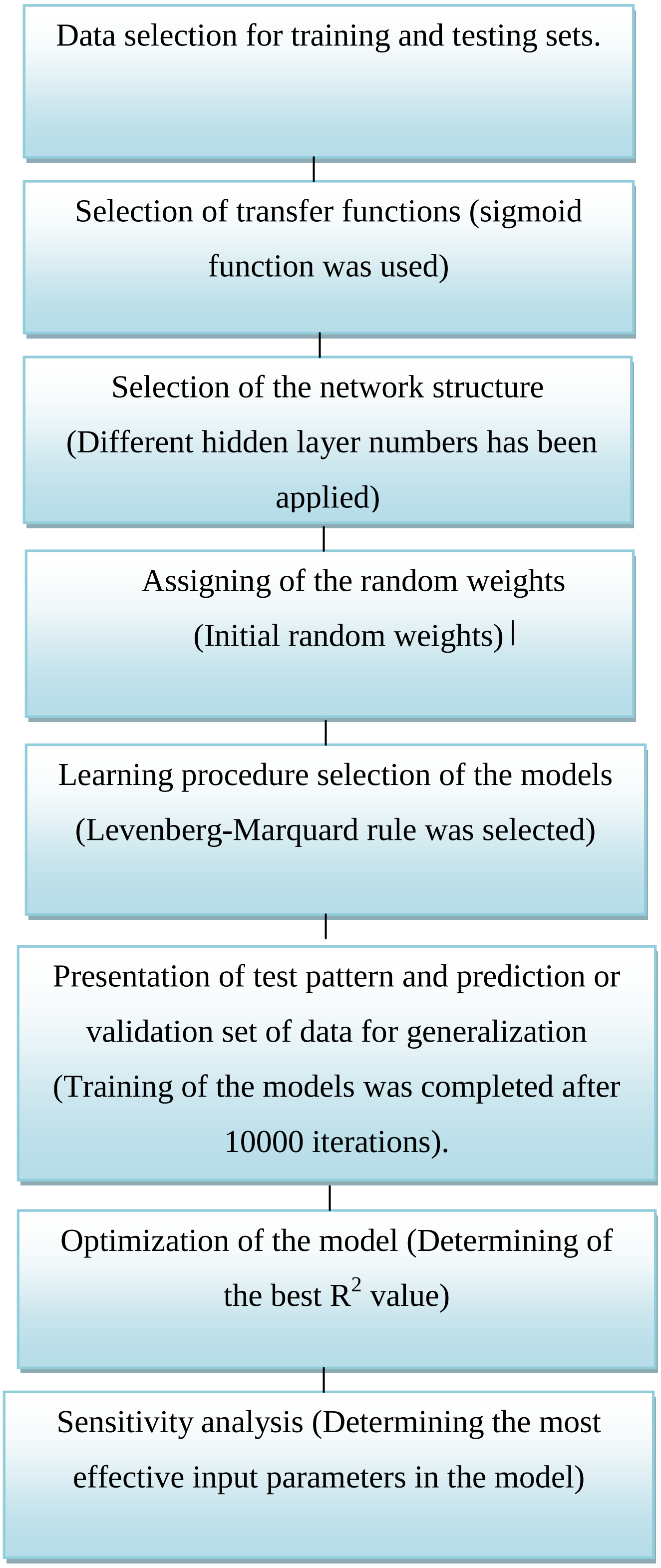

Figure 4.3. Flow diagram of the main procedure of all ANN models

4.4.1. The Model A

The ANN architecture was of feed-forward type of composed input layer, hidden layer and output layer. In the input layer, 16 neurons were used for 16 input variables while one neuron was used for the output variable of the total energy consumption of the building among various hidden layer numbers attempt. The best result was obtained with 10 hidden layer numbers. The variables and their ranges are listed in Table 4.1. No bias term was used while there were 148 data points each with 17 components (x_1, x_2, $x_{3\ldots}x_{16}$, y). 16 of which were the input variables whereas the 17th one was the output variable.

Data standardization was applied using the following formula (Tayfur, 2012);

$$x_i = 0.1 + 0.8\,(x_i - x_{min\ i}) / (x_{max\ i} - x_{min\ i}) \tag{4.1}$$

where $x_{max\ i}$ and $x_{max\ i}$ are the minimum and maximum values of ith node in the input layer for all feed data vectors, respectively. Before the application of the model, the network was trained to minimize the differences between the target output and predicted output (model output). During this training, different learning algorithms and hidden layer numbers were analyzed.

The model was introduced to run 10000 iterations in order to determine optimal weights while the mean absolute percentage error and mean absolute deviation were calculated.

Sensitivity Analysis: Sensitivity analysis was performed to explore the rate of the impact of input parameters on the model output. Therefore, it provided the irrelevant inputs which may be eliminated from the model for the sake of simplicity and to improve the prediction power of the model. By doing this, the performance of the model resulted in a lower rate of prediction error, relatively.

4.4.2. The Model B

In order to obtain the best mean absolute percentage error (MAPE), a new ANN model was created following the same procedures explained in Model A. The only exception was that the new ANN model had 8 input parameters which were selected based on the sensitivity analysis of Model A (Table 4.2).

Table 4.2. The parameters whose ranges used in Model B

Code	**Input parameters**	**Data used in ANNs model**	
		Minimum	**Maximum**
x_1	Zoning status	1	3
x_2	Heating system type	1	2
x_3	Number of floors	5	11
x_4	Wall overall heat transfer coefficient(W/m^{2}K)	0.43	1.83
x_5	Glass type	1	2
x_6	Area/Volume ratio (1/m)	0.579	0.640
x_7	Insulation existence	1	2
x_8	Total external surface area (m^2)	208.44	2655.82
y_1	Total energy consumption of the building (kWh/year)(output)	88.74	367.01

As shown in Figure 4.4, the Model B had three layers: input, hidden, and output. The input layer had 8 neurons, while the hidden layer only four neurons. The output variable was the total energy consumption of building. Bias term was not used in training phase while learning rate was 0.02 and the model was trained 10000 iterations. A slight increase in mean absolute percentage error (MAPE) was expected after the reduction in the number of input parameters from 16 to 8.

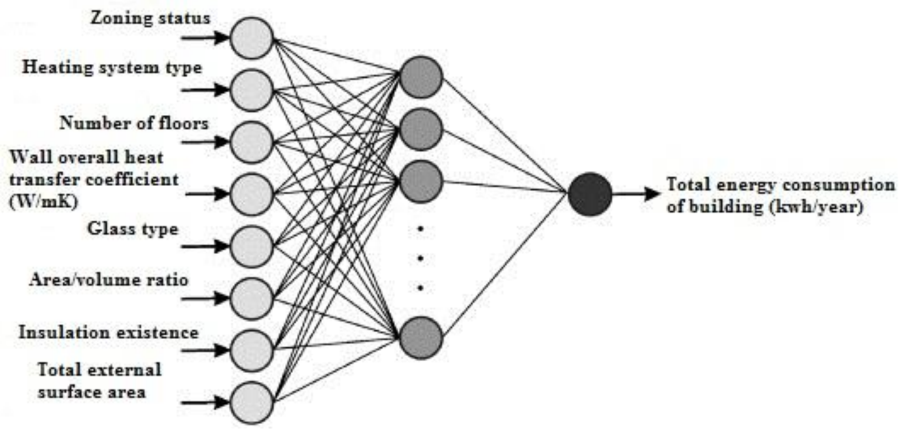

Figure 4.4. The ANN architecture of the Model B

4.4.3. The Model C

The orientation was added to Model B in order to observe the effects of various combinations of parameters. The new model was also constructed by using MATLAB® NN Toolbox. Nine input parameters were investigated in the Model C. They had one hidden layer containing 5 hidden neurons. One output layer was used for the output variable of the total energy consumption of buildings. Different learning algorithms like Elman BP, Time-delay BP and Cascade-forward were also tested. The best results were obtained with Levenberg-Marquard algorithm while sigmoid transfer function was used.

4.4.4. The Model D

A new ANN model was created only with numerical input parameters used in Model C. Four input parameters (floors number, total external surface area, the wall overall heat transfer coefficient and area/volume ratio) were included in to the Model D. The data for 4 inputs and one output parameters used in Model D are given in Appendix A. In the model, the input layer had 4 neurons, while the hidden layer only two neurons. The new model was constructed by using MATLAB® NN Toolbox and sensitivity analysis was applied via Nero Solutions 5. 10000 iterations were run to optimize the mean absolute percentage errors and mean absolute deviations.

The errors for all the ANN models are given in Chapter 5.

Sensitivity Analysis: Sensitivity analysis investigates the model feedbacks, evaluates the accuracy of model and tests the cogency of the assumption made in engineering design stage (Song, et al. 2008). The mapping Y= f (X) between an output Y of a computational model and a set of uncertain input factors X= (X_1; . . . ; X_k) is analyzed in order to quantify the relative contribution of each input factor to the uncertainty of Y (Ratto et al. 2008). Song et al. (2008) indicate that sensitivity is used to find the rate of change in a model output due to changes in the model inputs in deterministic design, which is usually performed by partial derivative analytically or numerically. By employing sensitivity analysis on a trained network, some irrelevant inputs can be found and then eliminated. Therefore, such an elimination of irrelevant inputs can sometimes improve a network's performance. This batch starts by varying the first input between its mean +/- a user defined number of standard deviations while all other inputs are fixed at their respective means. The network output is computed for a user defined number of steps above and below the mean. This process is then repeated for each input. Finally, a sensitivity analysis report is generated which summarizes the variation of each output with respect to the variation of each input. (NeuroSolutions 5, 2002).

The models were subjected to sensitivity analysis to determine the effect of each input variable on the model output. The analysis was applied by utilizing NeuroSolutions Software (NeuroDimensions Inc). The inputs and output were brought under the control of NeuroSolutions, but the network learning is disabled. As a result of this, the effect of network weights was avoided in the model. Then, corresponding effect on the output is reported as a percentage in a figure.

4.5. The Fuzzy Logic Model

ANN models are reliable but they are also “black-box” models. The user cannot interrupt and change the model easily during the operations. All that the model offers is a weight matrix that defines the weights of interlayer connections, which are optimized after thousands of iterations. In order to create simpler model for the prediction of the total energy consumption of buildings, fuzzy logic techniques were used (Fa-Liang, 1997). The fuzzy logic is more user friendly due to the selection of its own set rules to test fuzzy model.

The fuzzy logic toolbox of MATLAB® was used to construct the fuzzy logic. The prod and centre of gravity (COG) methods were employed as the inference operator and defuzzification methods, respectively.

For the model of this study, 3 inputs (Type of heating system, total external surface area and wall overall heat transfer coefficient) and one output (Total energy consumption of building) parameters were used. The aim of fuzzy logic models was to create rules that affect output parameter. Table 4.4 lists a total of 18 fuzzy logic rules.

Table 4.3. The whole 18 fuzzy rule sets used in this study

	THS	**TESA**	**WOHTC**	**EC**
R1	INDIVIDUAL	H	H	VH
R2	INDIVIDUAL	M	H	VH
R3	INDIVIDUAL	L	H	H
R4	INDIVIDUAL	H	M	H
R5	INDIVIDUAL	H	L	M
R6	CENTRAL	H	H	M
R7	CENTRAL	M	H	M
R8	CENTRAL	L	H	M
R9	CENTRAL	H	M	M
R10	CENTRAL	H	L	L
R11	CENTRAL	M	M	L
R12	CENTRAL	M	L	L
R13	CENTRAL	L	L	L
R14	CENTRAL	L	M	L
R15	INDIVIDUAL	L	L	L
R16	INDIVIDUAL	M	M	M
R17	INDIVIDUAL	M	L	M
R18	INDIVIDUAL	L	M	M

In the rules, THS refers type of heating system, TESA shows total external surface area, WOHTC is wall overall heat transfer and finally EC is energy consumption of building.

4.5.1. Membership Functions

In this study six membership functions were created for 5 inputs and one output. Each membership function was created in the fuzzy logic toolbox of MATLAB®. Mamdani rules and Prod method were chosen for the fuzzy inference engine. The membership functions that used in this study were shown in Chapter 5.

CHAPTER 5

RESULTS AND DISCUSSION

Developed ANN and one Fuzzy Logic models were tested to predict the total building energy consumption in this thesis. The input data were taken from 148 buildings from 3 municipalities in Izmir and output data is calculated by KEP-SDM software. The input data were separated into two sets while the first set was used to train the ANN models and the second set was used to test the models.

An initial ANN model (Model A) contains a large number of input parameters which is 16 to determine the level of influence of each parameter on total energy consumption of buildings. Then the most influencing parameters were chosen to construct the Model B, C and D. Another model with three parameters was created using Fuzzy Logic techniques.

Table 5.1 shows a summary of absolute fractions of each ANN models to make a comparison between tested models. The errors (mean absolute percentage error (MAPE) and mean absolute deviation(MAD)) of the models A, B, C and D and Fuzzy Logic-based model were calculated by Equation 5.1 and 5.2.;

$$MAPE = 1/N * \sum |\text{observed values} - \text{predicted values}| / \text{observed values}) * 100\% \quad (5.1)$$

$$MAD = 1/N/ * \sum |\text{observed values} - \text{predicted values}|) \quad (5.2)$$

Table 5.1. Testing results of constructed models

Model name	MAPE	MAD	R^2
Model A	12.99%	19.10	83.01%
Model B	4.10%	6.57	96.85%
Model C	13.73%	21.88	87.29%
Model D	21.61%	29.49	66.91%
The fuzzy logic model	4.86%	7.59	93.95%

Finally, sensitivity analysis was performed on the models to determine the effect of each input variable on the model output by Neuro Solutions (NeuroDimensions Inc, 2002).

5.1. Artificial Neural Network Models

Model A

Model A which had 16 inputs and one output was created by ANN tools of MATLAB® (MatLAb 2008b, 2008).

As shown in Figure 5.1 and 5.2, the predicted output of Model A 16 are close to predicted values of the software which can be considered as satisfactory.

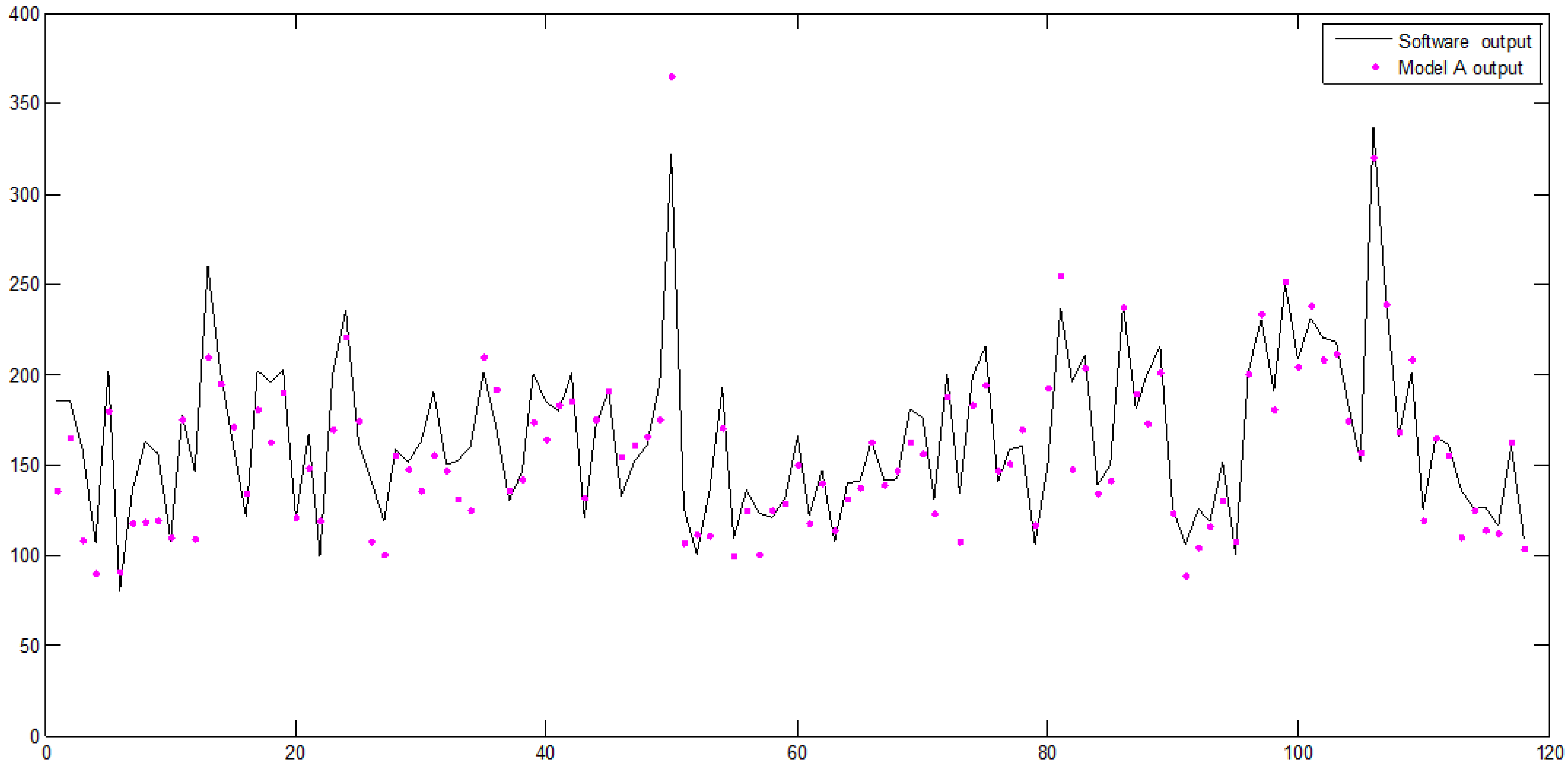

Figure 5.1. The training results of Model A (R^2=0.86)

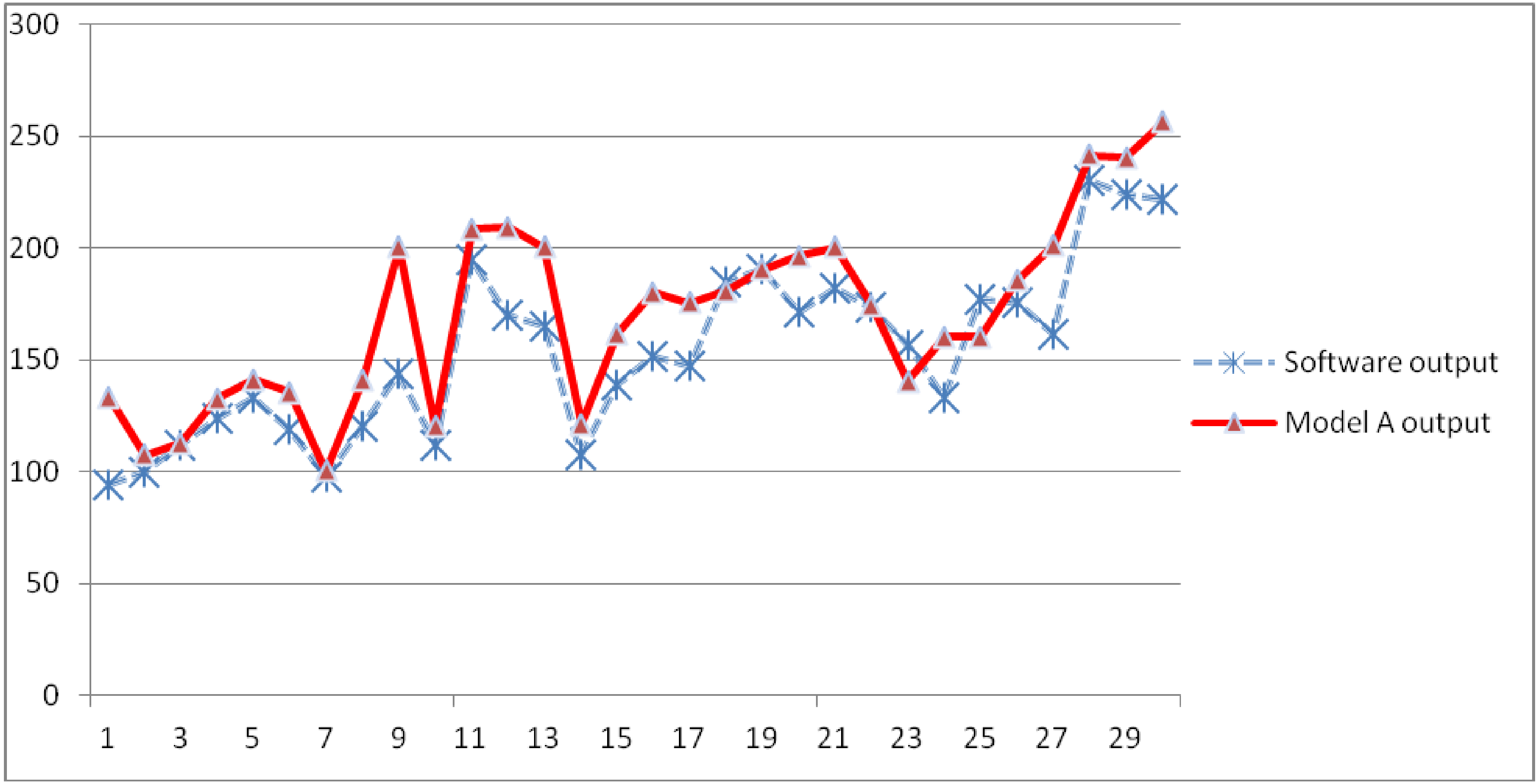

Figure 5.2. The testing results of Model A (R^2=0.83)

The mean absolute percentage error for the testing data was 12.9% while the mean absolute deviation was 19.10, which was quite high for a prediction model (Table 5.2).

Table 5.2. The R^{2}'s of Model A

	Number of data	**R^2**
Training	118	0.8605
Testing	30	0.8301
Total	148	0.8487

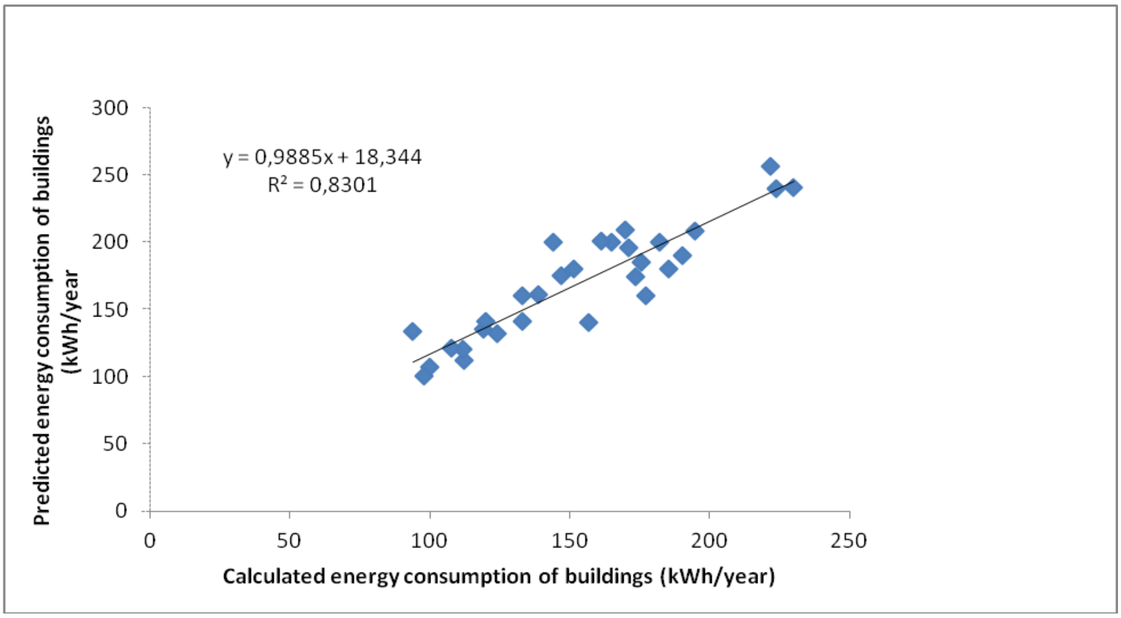

Figure 5.3. Comparison of the calculated energy consumption of buildings& predicted values by the sixteen parameter ANN model.

Sensitivity analysis of the model is displaced in Figure 5.4. The figure indicates that heating system type heating system type, total wall area/total useful area, orientation and total windows area/total external area have the highest effect having around 10%, on the energy consumption. Number of flats and total lighting equipment/total useful were found to be the least influencing parameters for the model.

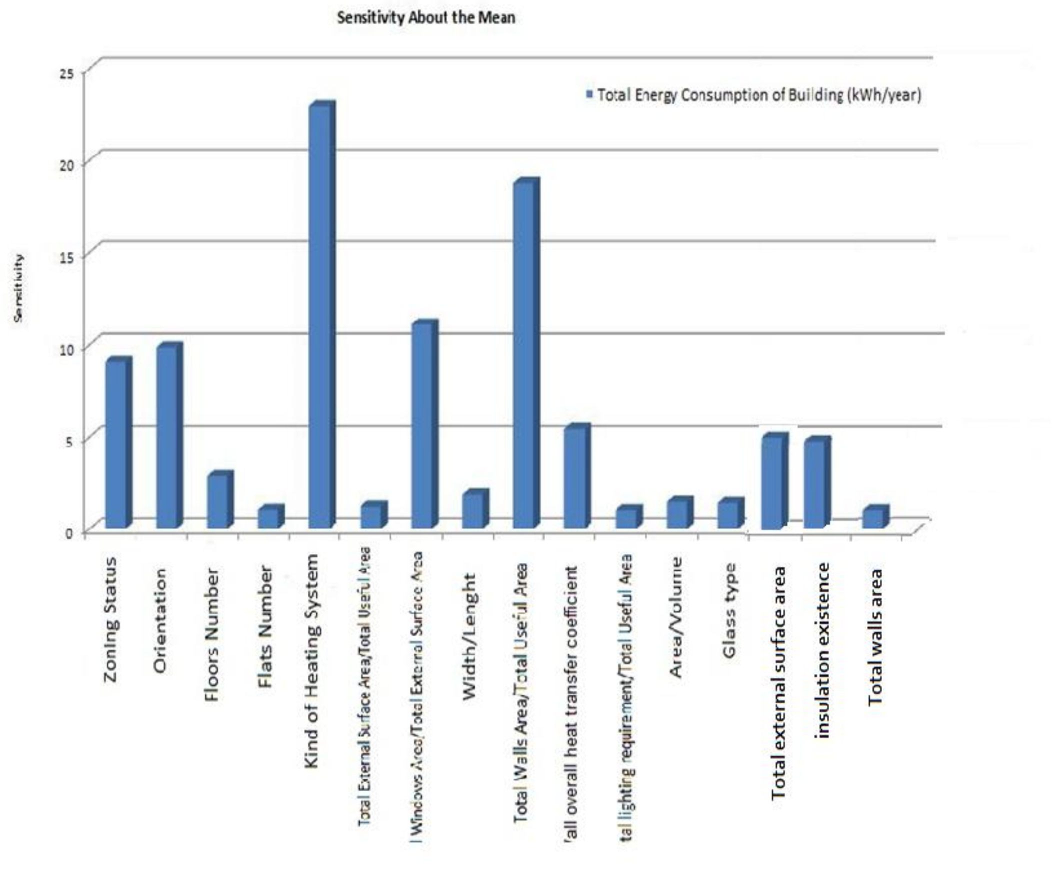

Figure 5.4. The sensitivity analysis of Model A

Model B

In order to reach the best mean absolute percentage error (MAPE) and mean absolute deviation (MAD), a new ANN model was created following the same procedure explained in Model A. The Model B was created with the same iteration numbers and learning algorithms as Model A including 8 effective input parameters chosen from sensitivity analysis of Model A. The input parameters were zoning status, heating system type, number of floors, wall overall heat transfer coefficient, glass type, area/volume ratio, existence of insulation and total external surface area. After applying various hidden layer numbers, the testing R^2 of the model was 96.85% as indicated in Figure 5.5 and 5.6. This value is set to be extremely higher compared to the previous model. The result of the decrease of the error eliminates insignificant parameters from the Model A and decrease the numbers of parameter from 16 to 8.

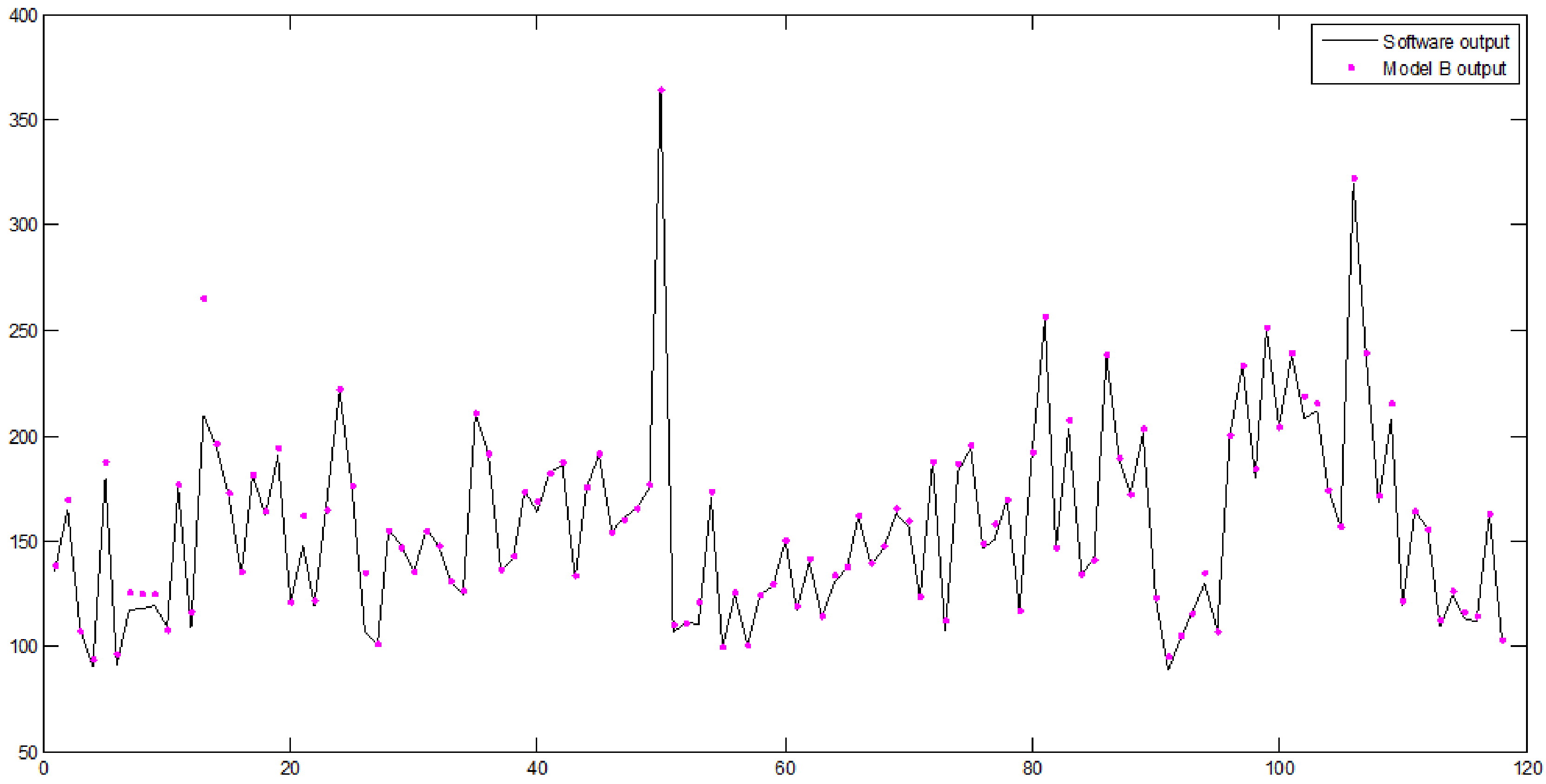

Figure 5.5. The training results of Model B (R^2=0.98)

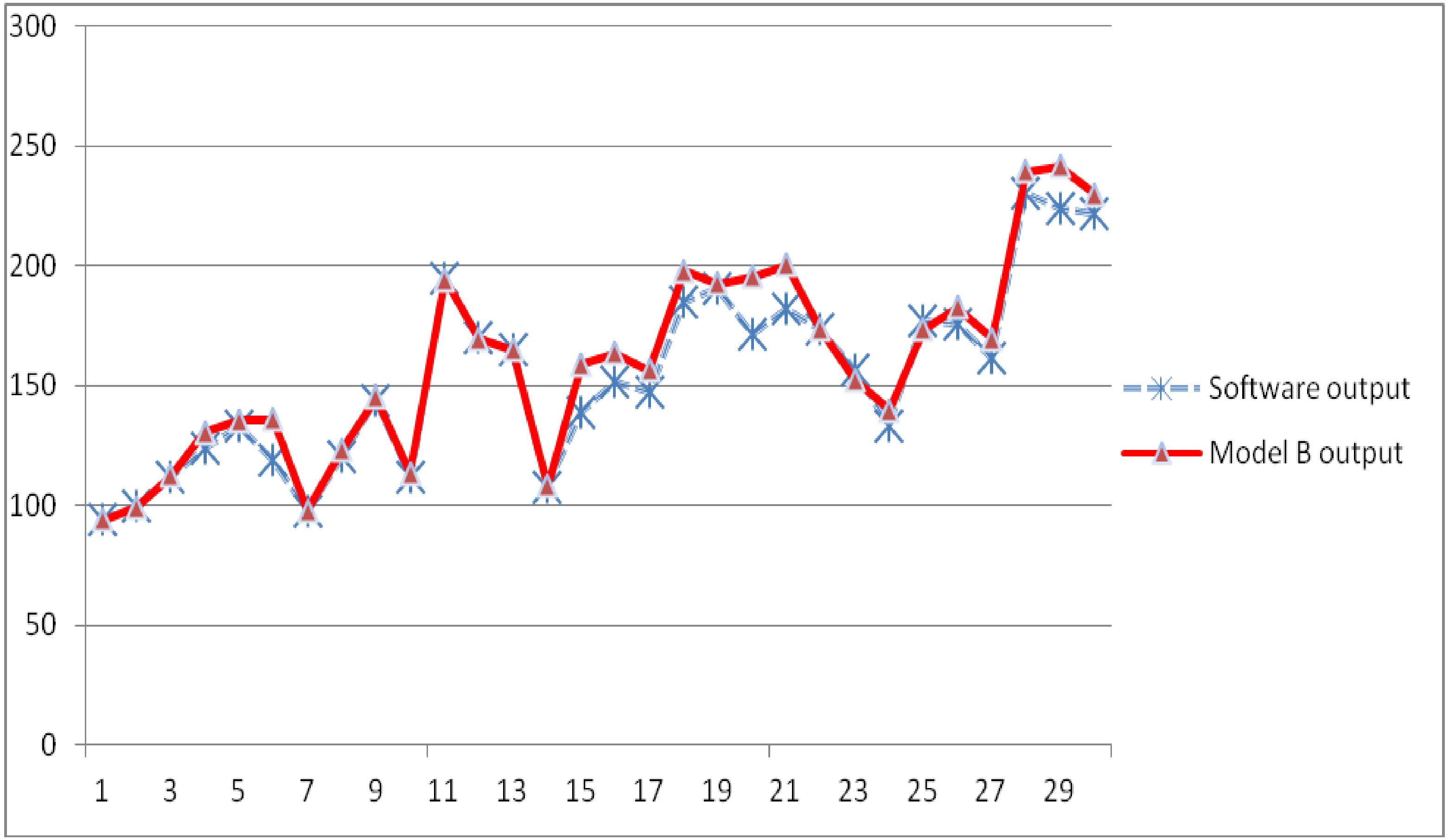

Figure 5.6. The testing results of Model B (R^2=0.96)

80% of the total number of input data was selected for training stage. By following the outcomes of calculations, the model reached the optimum solution with an R^2 of 0.9821. Thus, training of the model was successfully accomplished since the model fits with actual data (Figure 5.7). Following the optimization, the training data were tested with 30 data that are separated from 148 data aforementioned. The performance of the model was considered as successful with a MAPE of 4.1%. Thus, the total prediction power of the model was 97.8% as it can be seen in Table 5.3.

Table 5.3. Comparison of training and testing performance of the Model B

	Number of data	**R^2**
Training	118	0.9821
Testing	30	0.9685
Total	148	0.9787

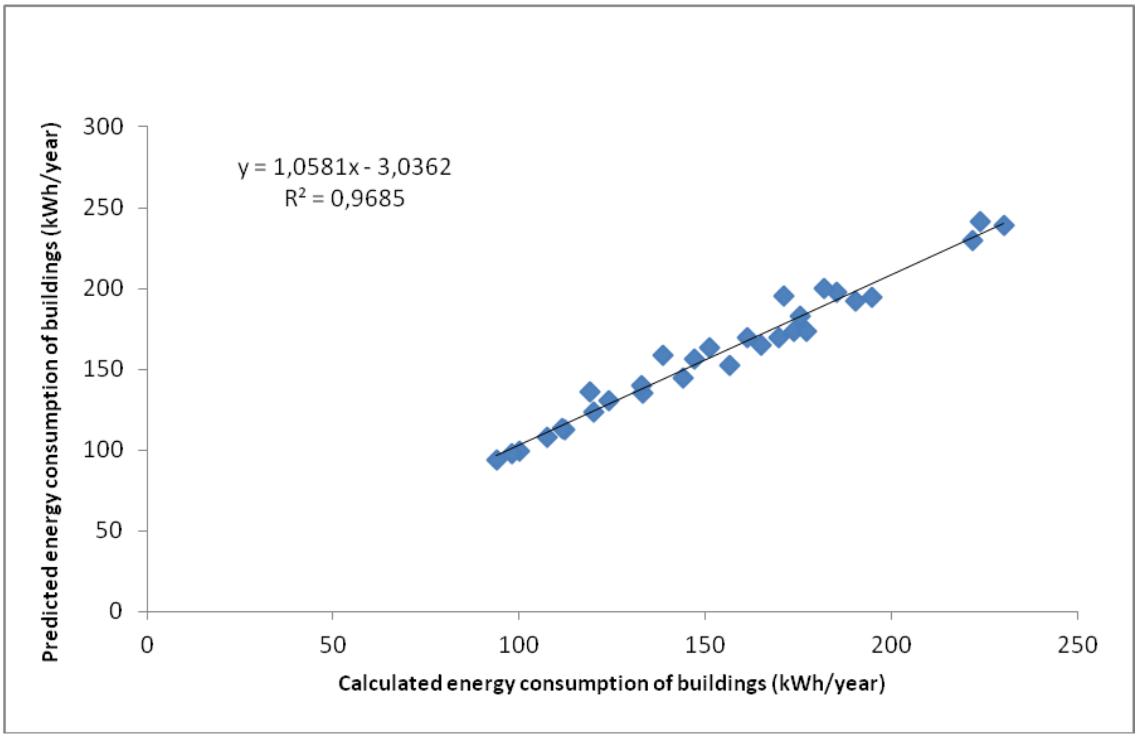

Figure 5.7. Comparison of the calculated energy consumption of buildings& predicted values by the eight parameter ANN model.

The model was tested for various numbers of hidden neurons (2-10) to be able to obtain the best R^2 values as indicated in Table 5.4.

Table 5.4. Comparison of final R^2 values according to the number of hidden neurons

Number of Hidden Neurons	**Final R^2 values**
2	76.35%
4	97.87%
5	94.75%
7	92.81%
10	95.45%

The sensitivity analysis was re-applied to the Model B in order to determine the most influencing parameters (Figure 5.8). In this model, sensitivity values of 3 input parameters were higher than 10% which were found to be the most influencing parameters namely types of heating system, wall overall heat transfer coefficient, total external surface area on energy consumption.

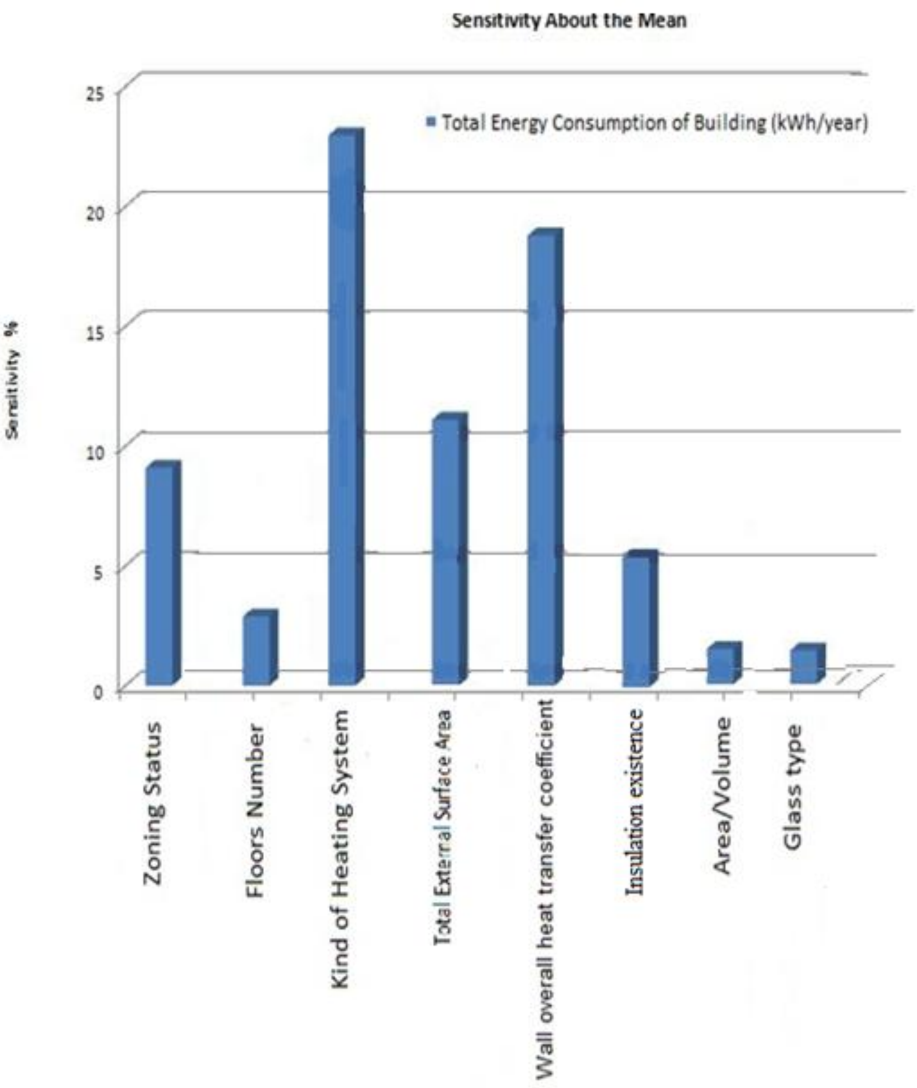

Figure 5.8. The sensitivity analysis result of the Model B

Types of heating system representing 22% of sensitivity and wall overall heat transfer coefficient representing 17% of sensitivity were found to be the most significant parameters that affect energy consumption of the building. Area/volume ratio and glass type were found to be the least influencing variables.

Model C

The Model C was constructed with the same input parameters of Model B adding one more parameter which is orientation. In this model, the effect of orientation parameter to the model prediction power was analyzed.

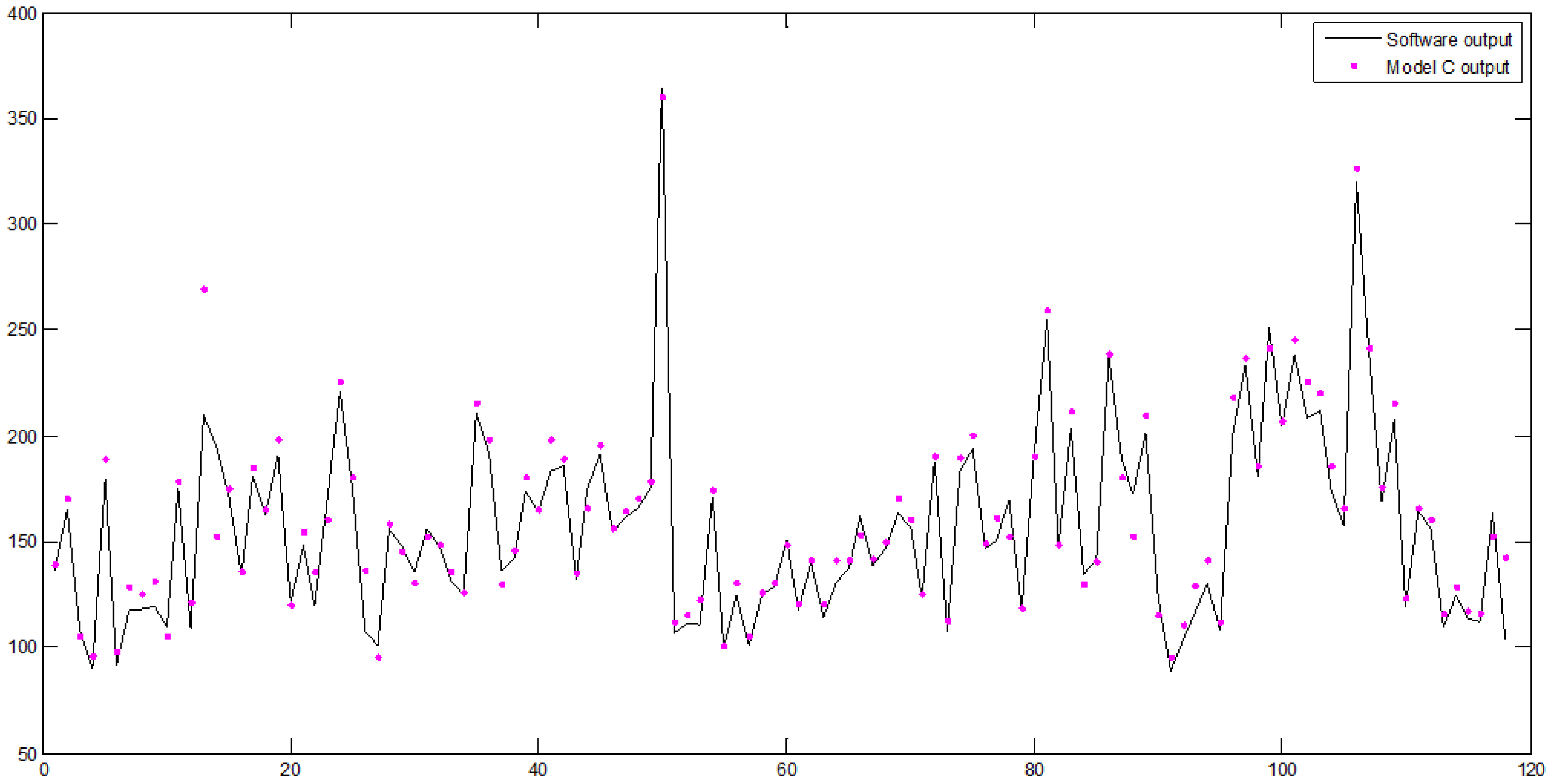

Figure 5.9. The training results of Model C (R^2=0.95)

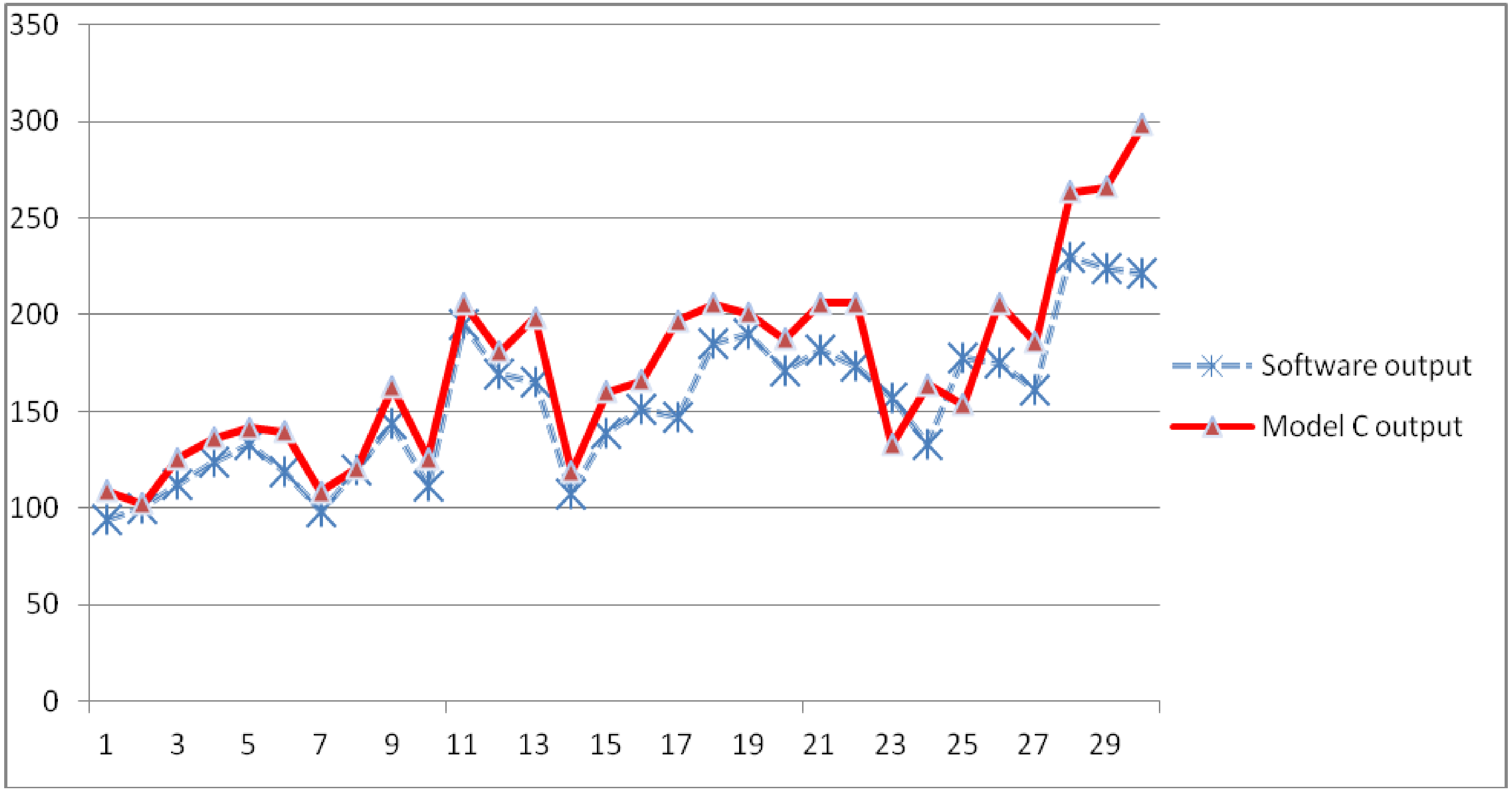

Figure 5.10. The testing results of Model C (R^2=0.87)

Figure 5.9 and 5.10 reveals that the predicted values in the model had close matches with the software outputs within the R^2 of 87.2% .This value was not higher than Model B. It should be stated that adding orientation to the input parameters affects the prediction power of the model.

Table 5.5. Comparison of training and testing performance of the Model C

	Number of data	$\mathbf{R^2}$
Training	118	0.9529
Testing	30	0.8729
Total	148	0.9142

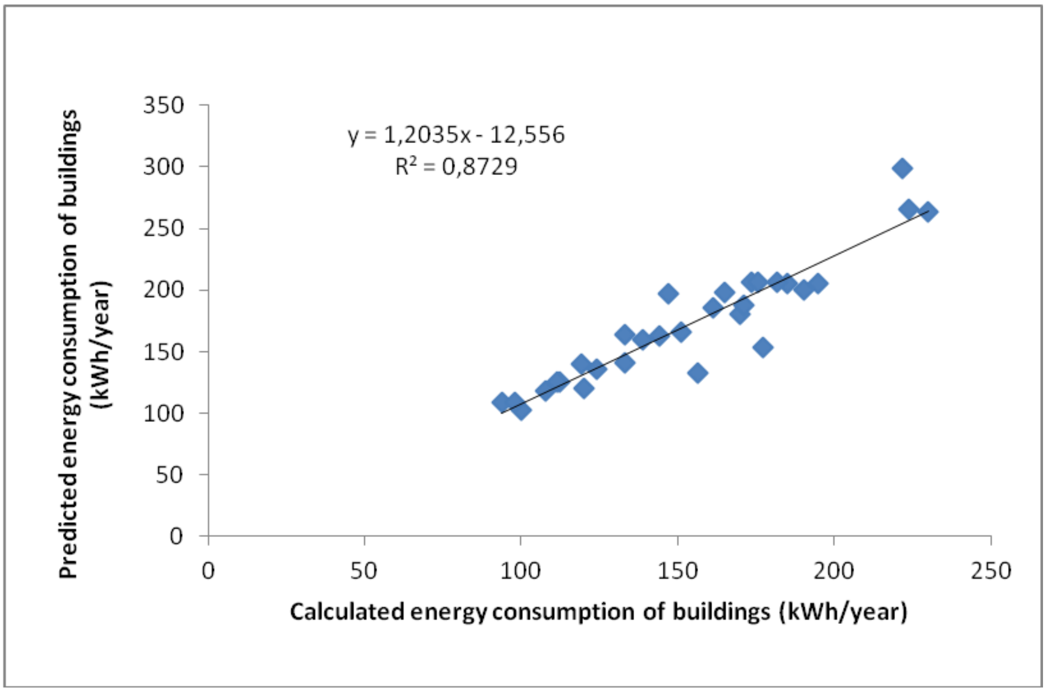

Figure 5.11. Comparison of the calculated energy consumption of buildings& predicted values by the nine parameter ANN model.

Model D

The number of parameters of Model B was decreased to 4 chosen the most significant parameters which are number of floors, the wall overall heat transfer coefficient, area/volume ratio and total external surface area, for the final ANN model. The model test results are given in Table 5.6. The table indicates that the R^2 for the testing data was 64.4%, which was considered to be high for a prediction model.

Table 5.6. Comparison of training and testing performance of the Model D

	Number of data	**R^2**
Training	118	0.7996
Testing	30	0.6691
Total	148	0.766

Figure 5.12 points out the trades of the calculated values and predicted values.

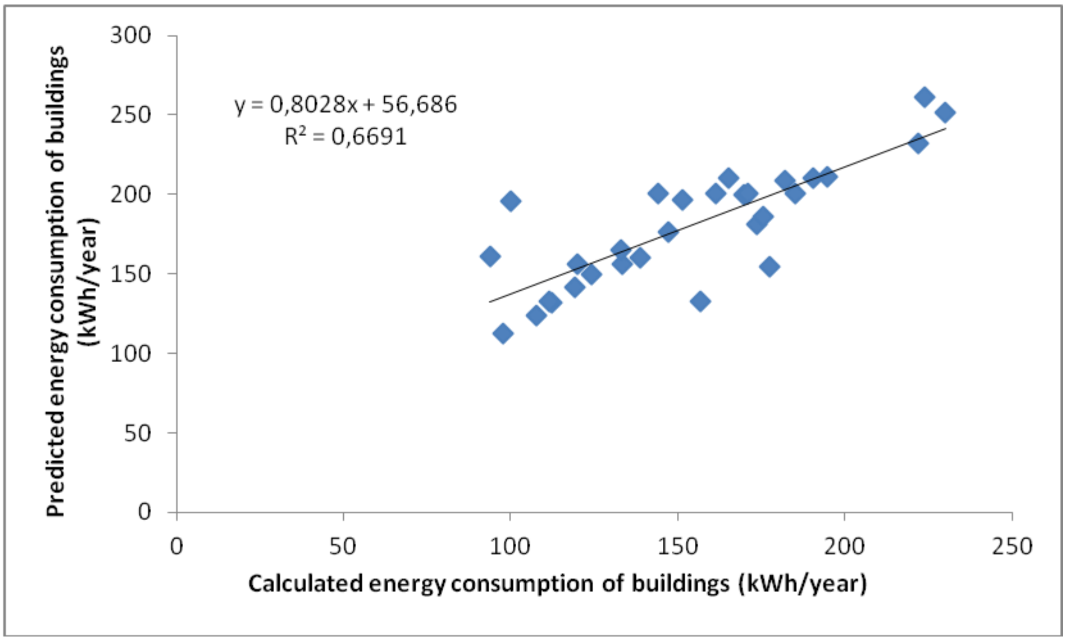

Figure 5.12. Comparison of the calculated energy consumption of buildings& predicted values by the four parameter ANN model.

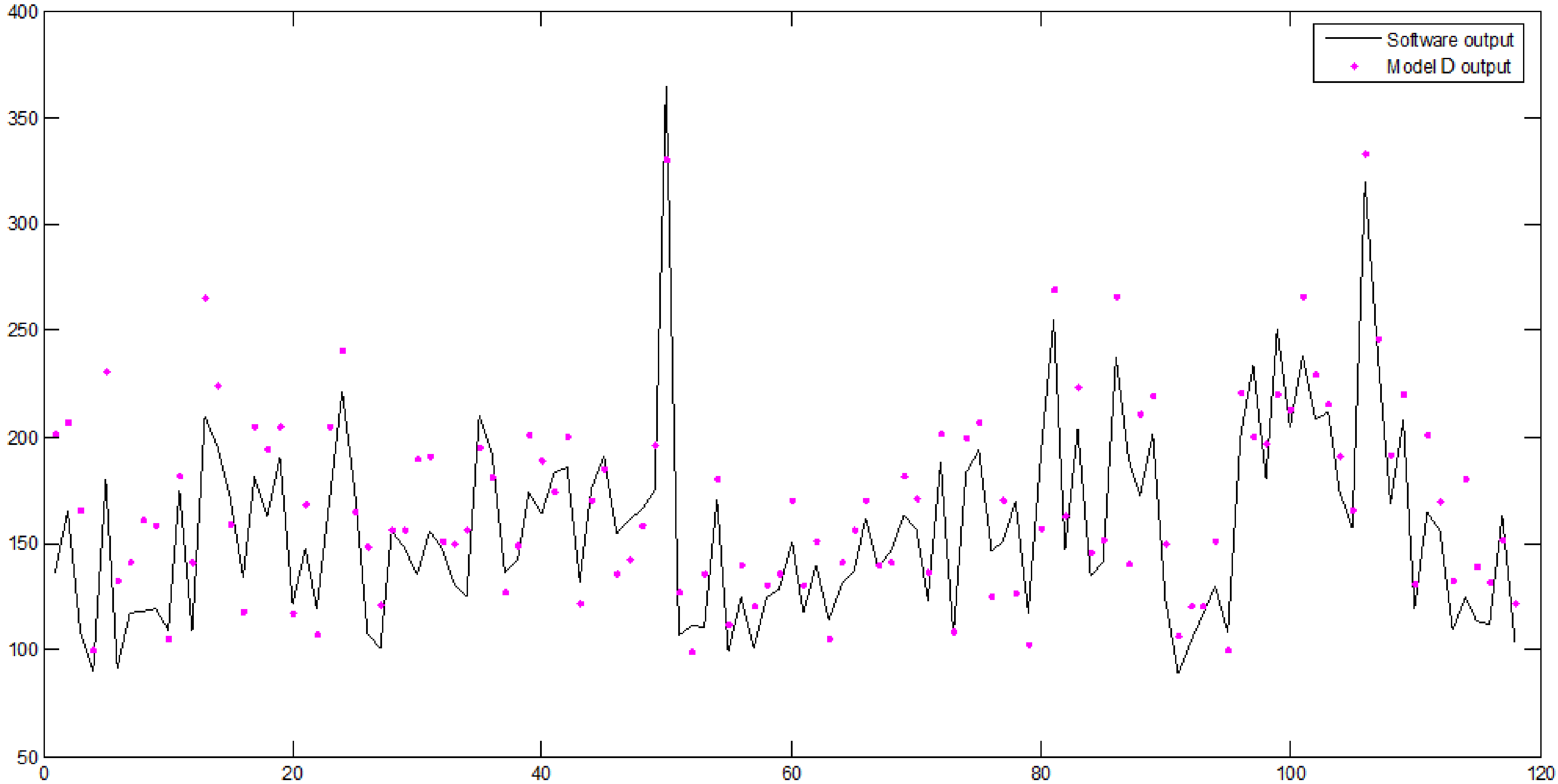

Figure 5.13. The training results of Model D (R^2=0.79)

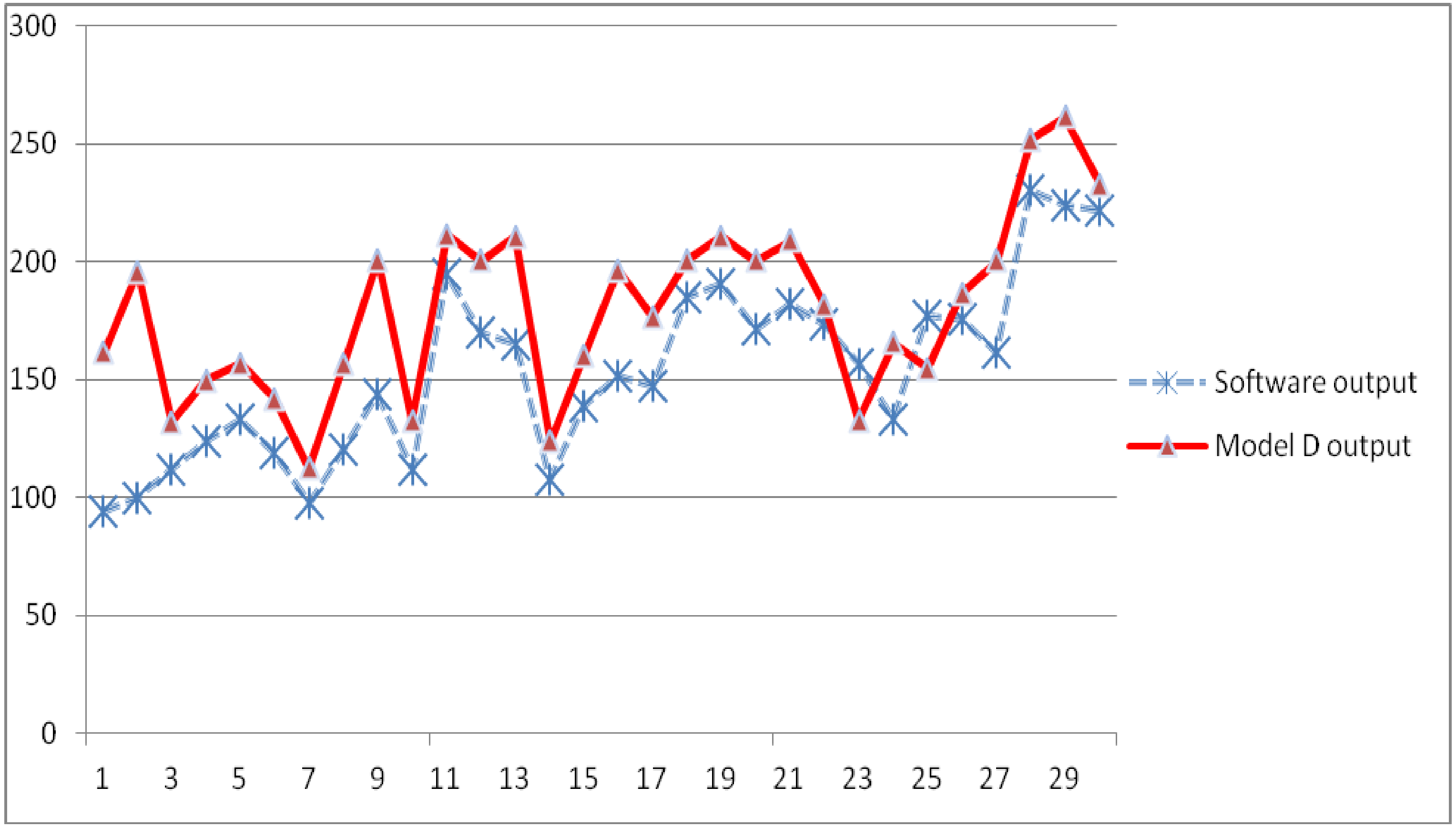

Figure 5.14. The testing results of Model D (R^2=0.66)

5.2. Fuzzy Logic Model

The Fuzzy-Logic based model which was created with the help of MATLAB® fuzzy logic toolbox was applied to verbal parameters which are zoning status, orientation, window type, insulation and types of heating system (Fig.5.15.) (MatLab 2008b, 2008). Mamdani fuzzy inference method was selected regarding optimum results (Luger, 2009). The prod and centroid methods were used as the operator and defuzzification methods, respectively. TRI (Triangular) and TRAP (Trapezoid) membership function geometries were applied as indicated in Figure 5.16.

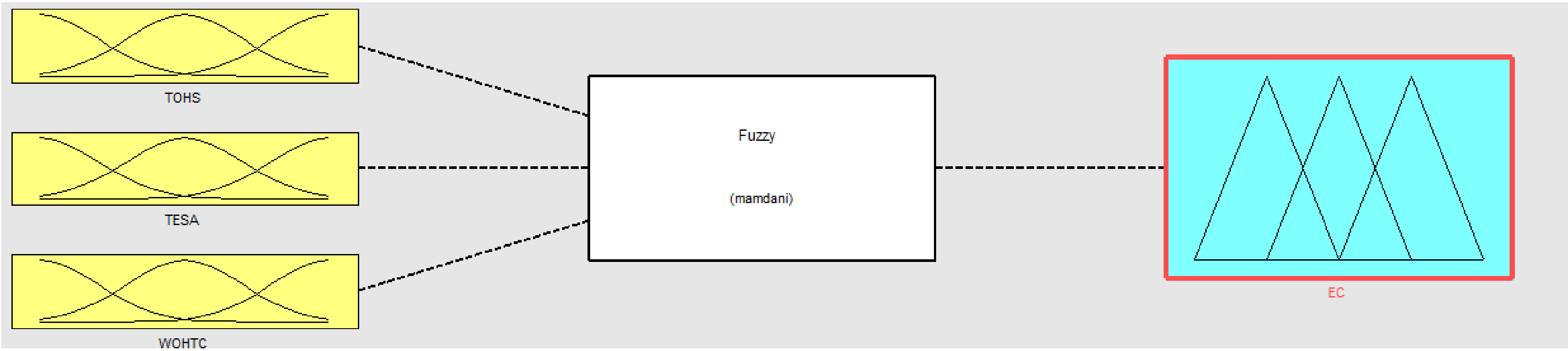

Figure 5.15. The schematic view of the fuzzy model used in this study

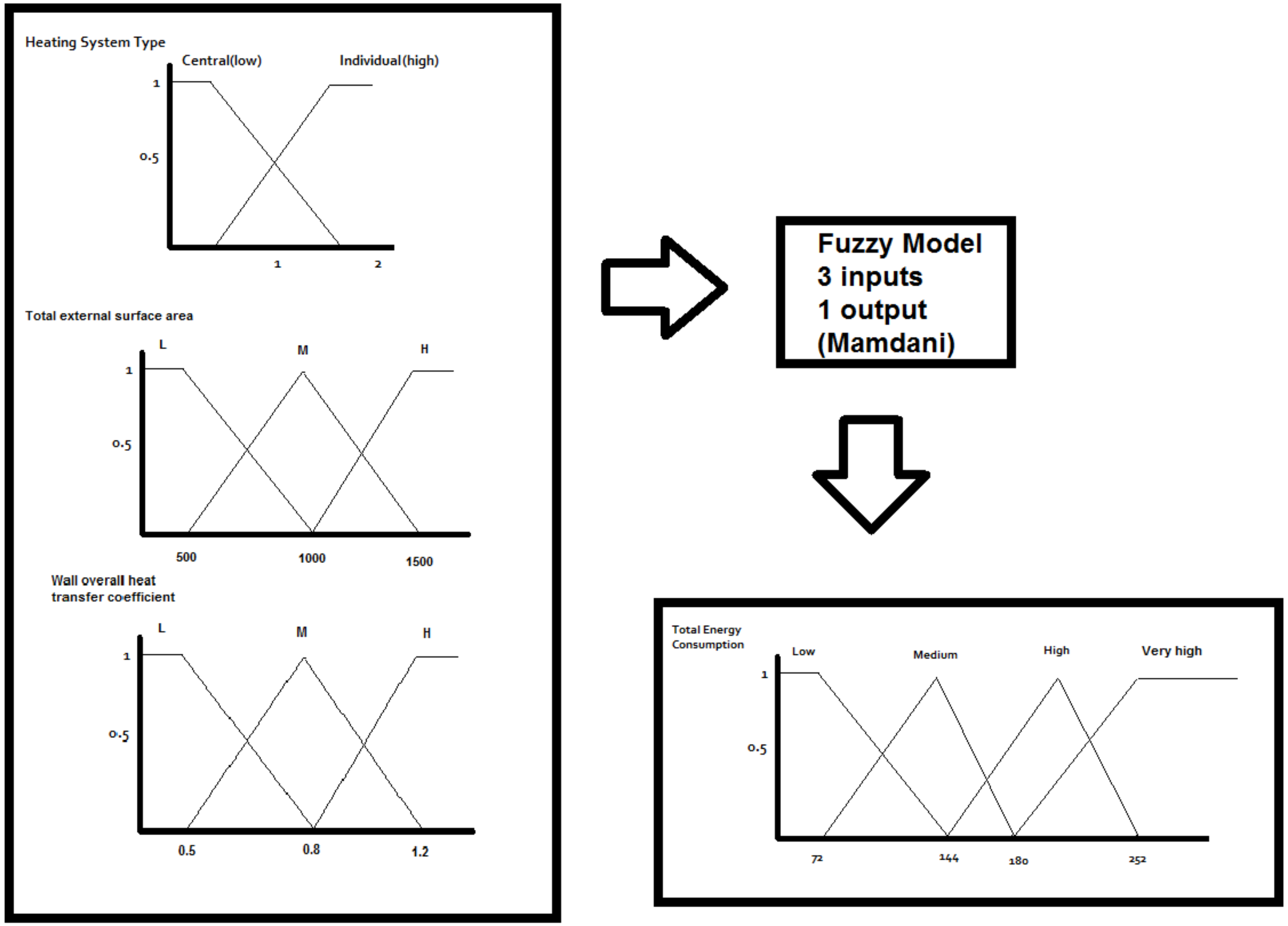

Figure 5.16. Membership functions for input and output parameters

The number of fuzzy rules for 3 input parameters was 18 while the MAPE and MAD of the fuzzy model was 4.86% and 7.59, respectively. If the number of parameters had been increased, the mean absolute percentage error could have decreased. Nevertheless, such an increase in the number of parameters can cause a complicated fuzzy model and the difficulty in creating fuzzy rules. Various defuzzification methods were also applied but it could be said that there were no significant differences of using these methods.

The fuzzy logic based model gave the same error compared to Model B as indicated in Figure 5.17 and 5.18. However, the advantage of the fuzzy logic is that all the rules are shown verbally similar to human thought. Furthermore, the rules can be changed and membership functions can be improved.

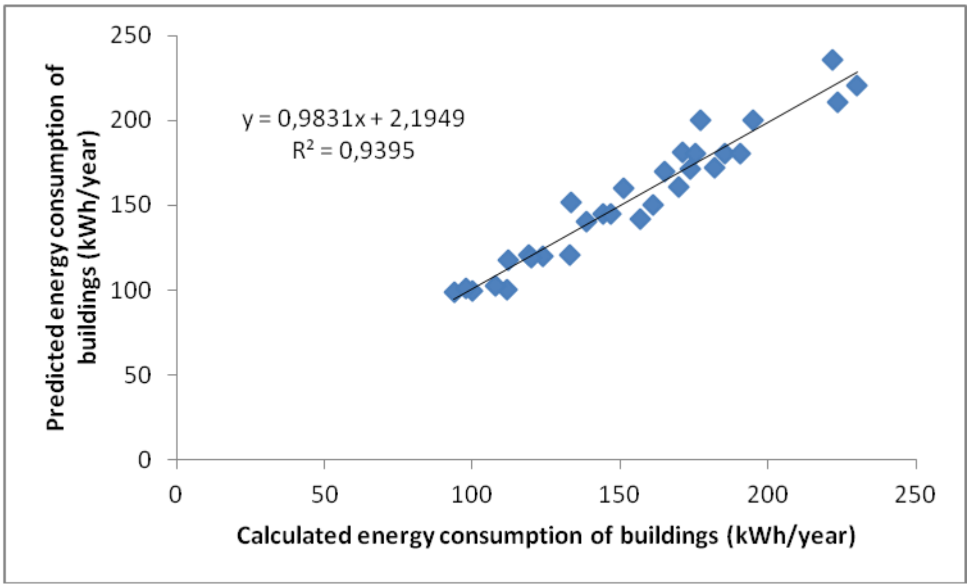

Figure 5.17. Comparison of the calculated energy consumption of buildings& predicted values by the three parameter Fuzzy model.

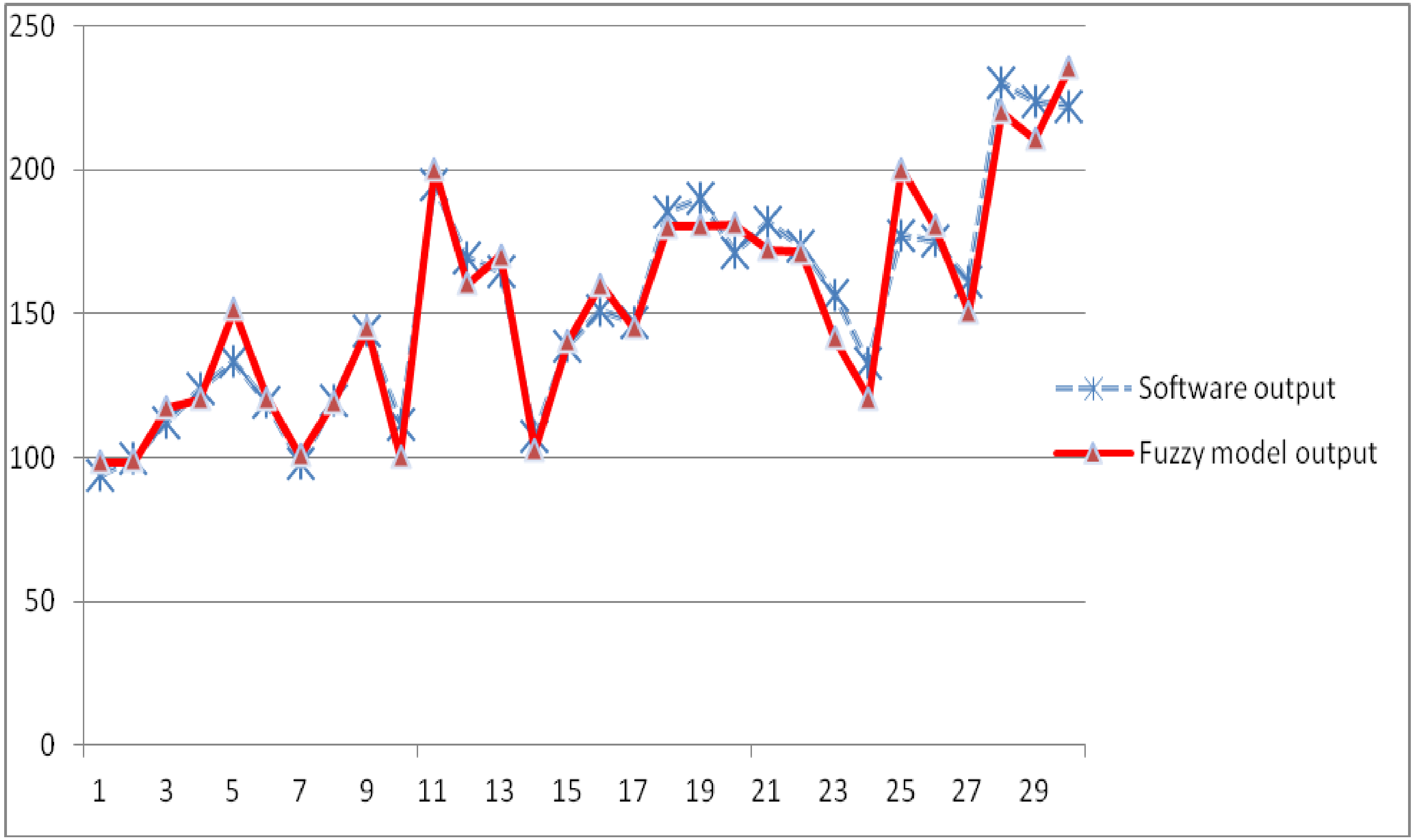

Figure 5.18. The testing results of Fuzzy model (R^2=0.93)

CHAPTER 6

CONCLUSIONS

In this study, neural networks and fuzzy logic model are used to predict the energy consumption of buildings and the results are compared with a Building Energy Performance software output. First, the input data were compiled from architectural projects of 148 buildings located at 3 different municipalities of Izmir-Turkey and fed to Building Energy Performance software called KEP-IYTE ESS obtaining total energy consumption of the buildings as output. Then, four different ANN models and a fuzzy logic model were created using MATLAB® toolboxes for neural network and fuzzy logic and sensitivity analysis were applied by NeuroSolutions Software. In this case, the input data were divided into three groups as 80% for training set and 20% for testing. Back-propagation algorithm was applied to all ANN models and number of hidden layers, number of input parameters and learning algorithms were tested. Finally average absolute percentage errors and R^2 were determined and compared with software outputs.

An ANN model (Model A) was created with all energy consumption parameters to evaluate influencing parameters with the help of the sensitivity analysis. The MAPE of Model A was high because of the existence of insignificant parameters in the model.

In the light of the results presented and the discussed in the previous chapter, it was concluded that eliminating the insignificant parameters from the main model predict energy consumption of buildings with a good degree of success (Model B).

The results also indicated that adding one more parameter (orientation) to the model did not provide any performance improvements, rather created a reduction in the performance (Model C). This increase of the error was a result of lack of the intermediate orientations. Thus, variation of the orientation parameter was added to total error variance.

Another interesting conclusion based on the results was that decreasing numbers of input parameters from 8 to 4 produced higher error (Model D). The reason for the excessive increase of the final weight error may refer the effects of the other parameters on energy consumption of buildings. The effect of eliminated input parameters was added to the variance of the error.

The Fuzzy logic model employing only the most influencing parameters and the fuzzy rules were created by using sensitivity analysis of Model B. Based on the results presented, energy consumptions of buildings were also predicted accurately.

On the other hand, dynamic building energy simulation software are time-consuming with a high number of inputs and not all the required input can be obtained, furthermore require experienced users. The ANN models with high accuracy can give similar results with software, would be useful guide for engineers and architects in designing phase of the buildings to decrease energy consumption prior to operation phase and at the same time evaluating the existing buildings as also concluded in the literature (Neto et al., 2008; Ben Nakdi et al., 2004; Dombayci, 2010)

Some parameters that affect energy consumption of buildings were neglected in this study such as occupancy, ownership and occupant behavior. By including these parameters, more accurate prediction of total energy consumption would be obtained. Furthermore, building samples on training stage should be increased in order to reduce model errors.

Fuzzy model is a preliminary study which should be developed in order to improve the accuracy.

Consequently, the results show that total energy consumption values can be predicted with great accuracy indicating that ANN and fuzzy logic are very useful and effective methods.

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APPENDIX A

THE DATA USED IN MODELING OF THE ANN MODEL D

Building Sample	Number of floors	The wall overall heat transfer coefficient (W/m^2K)	Area/ Volume ($1/m^2$)	Total external surface area (m^2)
KONAK 01	5	1.4300	0.4134	180.70
KONAK 02	11	1.3700	0.4006	1187.32
KONAK 03	8	1.4300	0.4139	295.69
KONAK 04	8	1.4300	0.3942	464.45
KONAK 05	10	1.3700	0.3432	1445.67
KONAK 06	10	1.4300	0.3866	185.43
KONAK 07	10	1.4800	0.3916	710.74
KONAK 08	9	1.4300	0.4325	190.89
KONAK 09	10	1.4300	0.4167	165.38
KONAK 10	8	1.3700	0.3907	267.58
KONAK 11	5	1.6400	0.3894	288.96
KONAK 12	10	1.4300	0.3985	464.35
KONAK 13	8	1.6400	0.4216	192.26
KONAK 14	7	1.6400	0.3795	218.65
KONAK 15	10	1.6400	0.3891	823.07
KONAK 16	7	1.4300	0.3879	1321.84
KONAK 17	6	1.6400	0.4086	158.84
KONAK 18	6	1.6400	0.4083	173.72
KONAK 19	6	1.6400	0.4117	408.20
KONAK 20	10	1.2400	0.4107	1110.24
KONAK 21	8	1.6400	0.3896	215.91
KONAK 22	9	1.6400	0.3942	700.34
KONAK 23	8	1.6400	0.3396	401.17
KONAK 24	6	1.6400	0.4201	209.73
KONAK 25	6	1.6400	0.3465	112.02
KONAK 26	6	1.6400	0.3574	580.27
KONAK 27	10	1.6400	0.3828	452.50
KONAK 28	10	1.6400	0.3921	738.67
KONAK 29	5	1.4800	0.4108	131.21
KONAK 30	8	1.3700	0.4089	343.63
KONAK 31	10	1.8100	0.3704	1445.67
KONAK 32	7	1.4300	0.4105	298.79
KONAK 33	8	1.6400	0.4456	493.27
KONAK 34	10	1.6400	0.5220	633.59
KONAK 35	5	1.6400	0.4420	439.70

KONAK 36	6	1.6400	0.5133	516.65
KONAK 37	7	1.6400	0.4166	207.12
KONAK 38	6	1.6400	0.3877	184.53
KONAK 39	6	1.6400	0.3895	469.79
KONAK 40	6	1.6400	0.3810	459.54
KONAK 41	7	1.6400	0.3857	508.58
KONAK 42	7	1.6400	0.3908	477.03
KONAK 43	6	1.6400	0.3834	200.55
KONAK 44	6	1.6400	0.3831	328.00
KONAK 45	9	1.6400	0.3949	551.20
KONAK 46	5	1.6400	0.3664	463.89
KONAK 47	6	1.6400	0.3622	184.41
KONAK 48	10	1.6400	0.3838	646.94
KONAK 49	5	1.6400	0.3870	740.77
KONAK 50	6	1.6400	0.3608	381.66
KA 01	8	0.4300	0.4661	365.36
KA 02	5	0.7870	0.3958	263.11
KA 03	8	0.5570	0.4202	417.93
KA 04	10	1.6400	0.3884	871.77
KA 05	10	0.8400	0.4240	298.77
KA 06	10	1.8000	0.4073	348.55
KA 07	10	1.6400	0.3857	260.40
KA 08	10	1.1300	0.3823	565.08
KA 09	10	1.6000	0.3784	1027.91
KA 10	7	1.3800	0.4202	373.06
KA 11	10	1.6400	0.4016	347.15
KA 12	10	1.6400	0.4054	439.89
KA 13	10	1.6400	0.3935	497.82
KA 14	10	1.6000	0.3881	866.75
KA 15	9	1.6400	0.3676	475.59
KA 16	9	1.2500	0.3686	727.06
KA 17	9	1.4000	0.3691	964.25
KA 18	9	1.6400	0.3578	452.79
KA 19	10	1.6400	0.3895	950.11
KA 20	9	1.1000	0.3934	603.89
KA 21	9	1.8300	0.4028	179.31
KA 22	6	1.6400	0.3710	415.31
KA 23	6	1.2500	0.3872	502.54
KA 25	10	1.6400	0.3920	1054.20
KA 26	10	1.6400	0.3920	1023.43
KA 30	10	1.6400	0.3932	1040.24
KA 31	9	1.6000	0.3624	688.69
KA 32	9	1.1100	0.4455	1053.27

KA 34	9	1.6400	0.4295	915.98
KA 35	10	1.6400	0.1918	892.52
KA 36	10	1.6000	0.4039	853.80
KA 37	9	1.6400	0.3592	679.83
KA 38	9	1.2100	0.3969	774.82
KA 39	9	1.6000	0.3962	896.63
KA 40	9	1.6400	0.3847	625.38
KA 41	10	1.6000	0.4003	525.02
KA 42	9	1.6000	0.3905	372.08
KA 43	9	1.6400	0.3934	191.35
KA 44	10	1.6400	0.4022	346.36
KA 46	9	1.6400	0.3961	376.04
KA 47	9	1.6400	0.3873	355.22
KA 48	9	1.6400	0.3853	631.54
KA 49	9	1.6400	0.3882	636.22
KA 50	9	1.6400	0.3868	693.81
KA 51	9	1.6400	0.3905	336.14
KA 27	5	1.6400	0.4042	227.80
KA 28	5	1.6400	0.3344	194.61
KA 29	5	1.6400	0.4001	257.65
BA 01	11	0.5400	0.3767	1509.92
BA 02	9	0.5400	0.3813	1144.63
BA 03	8	1.1600	0.4771	883.50
BA 04	6	1.6400	0.3662	569.52
BA 05	5	1.3700	0.3837	491.30
BA 06	5	1.6400	0.4062	180.24
BA 07	8	1.6400	0.4317	565.09
BA 08	6	1.4000	0.3763	698.95
BA 09	7	1.6400	0.3900	1263.02
BA 10	11	1.6000	0.3666	2143.21
BA 11	8	1.6400	0.3928	770.03
BA 12	6	0.5400	0.3970	460.61
BA 13	5	0.4680	0.4179	271.83
BA 14	5	1.6400	0.3886	234.25
BA 15	7	0.5380	0.3950	342.95
BA 16	6	0.5940	0.3916	472.26
BA 17	7	0.6850	0.3614	916.25
BA 18	7	1.6400	0.1303	510.49
BA 19	7	1.6400	0.1228	646.34
BA 20	10	1.6400	0.4446	860.29
BA 21	10	1.6400	0.4442	175.40
BA 22	10	0.5430	0.3986	1231.59
BA 24	6	1.6400	0.3853	534.78

BA 25	6	1.6400	0.3648	834.96
BA 26	5	0.5670	0.3822	612.17
BA 27	7	1.6400	0.3875	759.70
BA 28	8	0.5240	0.4107	824.42
BA 29	6	1.6400	0.3665	487.67
BA 30	5	0.4790	0.4248	236.20
BA 31	6	1.6400	0.3940	644.32
BA 32	5	1.6400	0.3939	434.77
BA 33	7	1.6400	0.3956	662.15
BA 34	6	1.6400	0.1477	214.67
BA 36	7	1.6400	0.3852	529.26
BA 37	7	1.3700	0.3702	363.98
BA 38	6	1.6400	0.3413	1177.60
BA 39	6	1.6400	0.3605	1042.32
BA 40	7	1.6400	0.3761	1015.58
BA 41	8	1.6400	0.4316	1292.92
BA 42	8	0.4700	0.4500	856.29
BA 43	11	1.6400	0.6404	1626.14
BA 44	5	1.6400	0.1686	440.48
BA 45	5	0.6300	0.3813	528.01
BA 47	8	1.6400	0.3888	1347.85
BA 48	5	1.6400	0.0579	470.44
BA 49-02	9	0.5400	0.1293	798.46
BA 50	7	1.6400	0.3917	660.88
BA 23	7	1.6400	0.3916	576.96
BA 35	7	1.6400	0.4126	505.09
BA 46	7	1.6400	0.3920	576.96

APPENDIX B

MODEL RESULTS

Model predictions					
	Model A	Model B	Model C	Model D	Fuzzy Model
Software	Predicted	Predicted	Predicted	Predicted	Predicted
Energy Consumption	Energy Consumption	Energy Consumption	Energy Consumption	Energy Consumption	Energy Consumption
135.7279	185.3673	138.7279	139.658	201.585	135.3654
164.9043	185.6369	169.695	170.2563	206.895	165.553
108.226	158.2568	107.287	105.6896	165.6978	111.228
90.2191	106.5859	94.2101	96.2593	100.266	95.369
180.0693	201.5868	188.0083	189.3652	231.2987	180.95
91.2327	80.2566	96.574	98.4623	132.7982	105.266
117.4261	135.6589	125.968	128.369	141.269	117.58
118.3082	162.2528	125.369	125.6496	161.269	120.56
119.3865	156.3646	125.2569	131.2563	158.364	126.369
109.7058	107.7898	107.7898	105.3699	105.369	111.58
175.1845	177.1686	177.1686	178.6952	181.792	175.68
108.9191	145.9875	116.688	121.2563	141.2598	109.57
209.8014	260.5895	265.8014	269.365	265.37981	211.569
195.1272	200.5488	196.1892	152.365	224.297	201.56
171.0352	160.2569	173.0896	175.2663	159.382	177.65
133.9657	120.5897	135.998	136.258	118.3725	139.65
181.0217	201.8842	181.745	185.3952	205.2876	180.25
162.5478	195.3694	164.5786	165.3872	194.585	160.68
190.3299	202.8455	194.3879	198.2546	205.3872	188.54
121.1064	119.6859	121.1765	120.286	117.269	120.47
148.1952	167.6985	162.3841	154.532	168.572	149.98
119.6468	99.5741	121.985	135.6812	107.585	120.25
169.708	200.5854	165.398	160.3546	205.347	169.89
220.896	235.6984	222.675	225.452	241.2695	221.25
174.5447	162.5887	176.587	180.2586	165.3789	180.58
107.3083	141.2566	135.3573	136.4221	148.356	111.91
100.6293	118.6985	101.7894	95.6825	121,28775	100.36
155.5992	158.6985	155.452	158,5614	156.3218	158.65
147.8109	151.2566	147.342	145.548	156.3692	145.25
135.6659	162.2589	135.9458	130.4622	189.526	134.68
155.6852	190.2884	155.456	152.586	191.2369	160.58
147.025	149.6982	147.925	148.563	151.2896	145.36

131.4734	152.3695	131.6477	135.845	150,258	131,69
124.9929	160.5885	126,9788	125,975	156,8912	130,58
210.1631	200.9987	211,1865	215,5589	195,3822	220,88
191.792	170.2589	191,675	198,45	181,2982	190,263
136.0392	130.6984	136,5672	130,286	127,3715	132,68
142.1778	146.3699	143.1866	145,96	149,2178	141.599
173.6929	200.259	173.5773	180,5466	201,201	172.36
164.1806	184.557	168,977	165,552	189,3258	168.69
182.9106	179.659	182.768	198,455	174,2813	185.24
185.5002	200.5885	187,5977	189,1486	200,185	185.25
131.8066	120.3256	133,8786	135,5826	121,8962	130.87
175.2049	171.5223	175,9869	165,586	170,2899	170.89
191.2181	190.6585	191,4968	195,456	185,268	195.67
154.5933	132.3698	154,5755	156,5489	135,97852	150.25
160.9324	151.2311	160,8769	164,5855	142,6985	165.41
165.7915	160.6988	165,8675	170,552	158,3289	165.69
175.294	195.6985	176,9881	178,562	196,1855	170.36
364.7031	321.3222	364,7866	360,54698	330,6422	308.64
106.5537	125.6447	110,8679	111,8965	127,58962	102.36
111.2075	100.2354	111,2877	115,686	99,3845	95.36
110.6575	135.6998	121,5896	122,5863	135,6942	115.12
170.8231	192.3644	173,8867	174,5493	180,6954	175.36
99.7412	108.6994	99,86789	100,5865	111,8569	90.652
125.0314	135.6995	126,087	130,855	139,6854	120.58
100.7112	123.3366	100,8765	105,5862	120,8865	100.23
124.8229	121.2556	124,877	125,9722	130,855546	125.84
128.4503	131.2699	129,879	130,596	135,9452	122.36
150.3364	165.3699	150,7688	148,8865	170.289962	159.63
117.6562	121.4445	119,698	120,586	130.97852	185.69
139.7755	146.9822	141,78	141,5896	151.5582	136.365
114.0748	107.5666	114.877	120,586	105.4982	115.25
130.8533	139.6444	133.878	141.286	141.2894	130.8
137.6541	141.2588	137.866	141.5236	156.31278	136.36
162.2228	163.2699	162.8678	153.5522	170.286	162.58
138.7217	141.5289	139,7219	141,8986	140.2989	138.59
146.4795	142.2731	147.8987	149,886	141.2794	169.89
162.9897	180.5439	165.877	170,5536	182.1563	162.8
156.5165	175.9125	159.766	160,39825	170.8764	160.65
123.2453	131.2699	123.7699	125.5862	136.8812	126.87
187.5458	200.2764	187.7558	190.6982	201.589	185.69
107.4149	134.5962	112.589	112.9852	108.9456	110.58

183.1912	198.6522	186.87	189.67852	199.4647	180.69
194.1133	215.6522	195.7661	200,5865	206.789552	196.67
146.6232	140.3625	148.999	149,58963	125.6853	146.98
150.9201	158.6922	158.6987	161,289	170.4895	150,78
169.7974	160.5266	169.7777	152,823	126.56	165.589
117.175	105.6941	117.6777	118,5789	102,9786	108.69
192.4865	150.2982	192.5656	190,58856	156,9855	190.58
254.7513	236.5489	256.9889	259.6712	269,34	254.78
147.3345	195.3614	147,3567	148.58996	162.9785	147.29
203.5823	210,2894	207,988	211.5823	223.7125	205.36
134.629	139,3644	134.5667	130.2892	145.9872	135.68
141.6244	149,6523	141.5667	140.58962	151.9953	140.87
237.6924	239,3688	239.2234	238.6942	265.8852	237.89
189.3566	180,5452	189.7775	180.2796	140.8726	189.63
172.5449	200,0125	172,8367	152.585	210.9752	172.58
201.1443	215,6985	203,554	209.486	219.6744	199.83
123.4974	125,6855	123,4777	115.486	149.8456	126.39
88.7961	105,5512	95,6983	95,45321	106,8133	90.25
104.4277	125,3626	105,445	110,5482	120,97445	156.36
115.9569	118,5422	115,7886	129,575	120,57525	120.58
130.1904	151,2863	135,666	141,4786	150,98542	136.78
107.8358	100,0025	107.5969	112,04	99,9952	108.95
200.4176	201,2398	200.7335	218.542	220.8556	205.58
233.5069	230,2889	233.8777	236.97852	200.55625	235.98
180.4446	191.2566	184.776	185.875	196.8745	180.56
251.1884	250.3655	251.88	241.4896	220.6465	240.98
204.1121	208.6542	204.4665	206.9752	212.84546	205.39
238.5199	231.2569	239.556	245.288	265.8445	250.36
208.4327	220.2597	218.887	225.555	229.8416	205.46
211.5182	217.5892	215.655	220.5569	215.95156	211.687
174.3686	184.5633	174.8544	185.6422	190.8415	175.98
157.2875	151.5472	157.1122	165.92636	165.9956	156.54
320.01	336.5236	322.766	326.871	332.9552	320.25
239.2617	241.2964	239,4557	241.4864	245.955	238.847
168.315	165.6933	171.88	175.9982	191.55692	169.52
208.028	201.2882	215.698	215.9752	220.5166	208.56
119.1662	124.5111	121.8	123.6842	131.2852	119.87
164.5841	165.5535	164.6457	165.8422	200.8546	165.82
155.7727	161.3258	155.7645	160.5789	169.5589	156.65
109.7365	135.6822	112.777	115.842	132.8415	105.846
124.8474	125.6842	126.5436	128.9412	180.5662	126.58

113.6555	126.3968	116.6983	117.589	139.4692	120.36
112.2209	116.3968	114.666	116.387421	131.812	115.89
162.9828	160.2685	162.9324	152.4566	151.8452	160.51
103.5931	109.3686	103.2343	142.6412	121.9462	103.674
93.8198	133.3682	93.83424	108.6942	161.225	98.68
99.9742	107.2589	99.2525	102.4525	195.6212	99.36
112.1384	112.5852	112.252	125.684	131.9552	117.36
124.0399	132,3658	130,342	135,9872	149,5852	120,269
133.1808	141,257	135,2432	141,458	156,3845	151,69
119.1366	135,3697	135,698	139,641	141,5875	120,58
97.8748	100,5258	97,82543	108,5552	112,2866	100,87
120.0309	141,2369	123,4342	120,6984	156,3288	119,36
144.0654	200. 2563	144,9349	162,684	200,5565	145,25
111.6415	120.5582	113,4324	125,681	132,572	100,23
194.6839	208.3684	194,2432	205,684	211,2982	200,36
169.6816	209,3664	169,2533	180,6851	200,25985	160,59
164.9999	200,2566	164,9235	198,545	210,596	170,26
107.6561	121,3681	108,242	118,69	123,69425	102,58
138.6461	161,3695	158,66	159,975	160,2825	140,2
151.2774	180,2596	163,3694	165,694	196,3288	160,25
146.9925	175,3695	156,398	196,7475	176,3285	145,236
185.1755	180,5853	197,6986	205,6984	200,552	180,36
190.4075	190,3698	192,432	200,5852	210,5895	180,65
171.0927	196,3885	195,36	187,541	200,28952	181,2862
181.9026	200,2589	200,258	205,9722	208,69452	172,36
173.6684	174,5895	173,2533	205,981	181,2585	171,36
156.5839	140,2566	152,52	132,681	132,395	141,56
132.9616	160,3667	139,687	163,641	165,398785	120,58
177.2895	160,2682	173,2533	153,6984	154,5895	200,26
175.4069	185,2695	182,6592	205,9821	186,328	180,698
161.2863	201,2698	169,25	185,6141	200,28785	150,58
230.1054	241,2896	239,25	263,681	251,3985	220,258
223.6755	240,2566	241,589	265,811	261,288	210,587
221.9106	256,3287	229,6874	298,511	232,3554	235,69

APPENDIX C

MODEL ERRORS
(MEAN ABSOLUTE PERCENTAGE ERRORS)

Model A	Model B	Model C	Model D	Fuzzy Model
36,57273118	2,210304587	2,895572686	48,52141675	0,267078471
12,57250417	2,905139526	3,245518765	25,46367802	0,393379675
46,22807828	0,867628851	2,343614289	53,10350563	2,773825144
18,14116966	4,423675253	6,695034643	11,13611198	5,708214779
11,94956608	4,408858145	5,162401364	28,4498246	0,489089478
12,03088366	5,854589418	7,924351685	45,55987053	15,38187514
15,52704211	7,274277184	9,318967419	20,30460008	0,131061153
37,1441709	5,968140839	6,205317975	36,312614	1,903333835
30,97343502	4,917138872	9,942330163	32,64816374	5,848651229
1,746489247	1,746489247	3,952297873	3,953118249	1,708387341
1,132577368	1,132577368	2,004001496	3,771737796	0,282844658
34,03296575	7,132725114	11,32693898	29,69240473	0,597599503
24,20770309	26,69190959	28,39046832	26,49096241	0,84251106
2,778495258	0,544260359	21,91503799	14,94912037	3,296721318
6,301802202	1,201156253	2,473818255	6,813334331	3,867507975
9,984645323	1,517030105	1,711109635	11,63969583	4,243101033
11,52486138	0,399565356	2,416008688	13,40496747	0,426302482
20,19196815	1,249355574	1,746809246	19,7094024	1,149077379
6,575740333	2,132087496	4,163665299	7,911158467	0,940419766
1,172935534	0,057882986	0,677420846	3,168618669	0,525488331
13,16054771	9,574466649	4,275981948	13,74997301	1,204357496
16,77662921	1,954252015	13,40144492	10,08117225	0,50415055
18,19442808	2,539656351	5,511466755	21,00018856	0,107243029
6,701071998	0,805356367	2,062509054	9,223118572	0,16025641
6,849821278	1,170072766	3,273602693	5,251262284	3,457738906
31,63622944	26,13870502	27,13098614	38,25212029	4,288298296
17,95620162	1,152845145	4,915864465	20,52925937	0,267615893
1,991848287	0,094602029	1,903737294	0,464398275	1,960678461
2,331154198	0,31722965	1,530942576	5,790033076	1,732551524
19,60183067	0,206315662	3,835672781	39,70054376	0,726711723
22,22639018	0,14722016	1,990683764	22,83563242	3,144036813
1,818194185	0,612140792	1,046080599	2,900595137	1,132460466
15,89378536	0,132574346	3,325083249	14,28775707	0,164748154
28,47809756	1,588810244	0,785724629	25,52008954	4,469933892
4,360613257	0,486955132	2,567434531	7,033061465	5,099325238
11,22731918	0,061003587	3,471469092	5,471448236	0,797217819

3,925927233	0,388123423	4,229075149	6,37147234	2,469288264
2,948491255	0,709534119	2,660190269	4,951546585	0,407095904
15,29486813	0,066554246	3,945872284	15,83720463	0,76738888
12,41096695	2,921417025	0,835299664	15,31557322	2,746609526
1,777699051	0,077961583	8,498359308	4,717769227	1,27351832
8,133845678	1,130726544	1,966790332	7,916325697	0,134878561
8,71048946	1,572000188	2,864803432	7,518895108	0,710586572
2,101881854	0,446334549	5,490086179	2,805286838	2,462773587
0,29265012	0,145749801	2,216265092	3,111682419	2,328179184
14,37546129	0,011514082	1,264996607	12,04112985	2,8095008
6,028183262	0,03448653	2,269959312	11,33016099	2,782286227
3,071749758	0,04584071	2,871377604	4,501195779	0,061221474
11,64015882	0,966433535	1,864296553	11,9179778	2,814699876
11,89485365	0,022895336	1,139589984	9,339350282	15,3722576
17,9167875	4,048850486	5,014185336	19,7420831	3,935761968
9,866330958	0,072117438	4,027156442	10,63147719	14,25038779
22,63045885	9,879221924	10,77992906	22,62539819	4,032713553
12,61029685	1,79343426	2,18132091	5,779253508	2,655905437
8,981443977	0,127018724	0,847493313	12,14713679	9,112783885
8,532336677	0,84426792	4,657709983	11,72025587	3,560225671
22,46562448	0,164132688	4,840573839	20,03282654	0,477801873
2,857889057	0,043341406	0,920744511	4,832964144	0,814834457
2,195090241	1,112258983	1,670451529	5,834863757	4,741366894
9,999906876	0,287621627	0,964437089	13,27260863	6,181869461
3,219804821	1,73539516	2,490136516	11,3230922	57,82423706
5,155910728	1,434085373	1,297866937	8,429731963	2,439984117
5,705203954	0,703222798	5,707833807	7,518400208	1,030201236
6,718286814	2,311519847	7,972821473	7,975419802	0,040732637
2,618665191	0,15393657	2,811031419	13,5547579	0,940110029
0,645470304	0,397601324	5,344871374	4,97044805	0,220190997
2,023619953	0,721011925	2,290124761	1,136952618	0,094938283
2,871664636	0,968872777	2,325581395	3,550053079	15,98209988
10,77012842	1,771461632	4,640722696	11,75939338	0,116387723
12,39230369	2,076138937	2,480089959	9,174687653	2,64093562
6,511079936	0,425655177	1,899382776	11,06403246	2,941045216
6,787995252	0,111972649	1,68086942	7,487877628	0,989518294
25,30496235	4,816929495	5,185779626	1,425035074	2,94661169
8,439815886	2,008175065	3,541283642	8,883341558	1,365349427
11,09604545	0,851461492	3,334753466	6,530336664	1,317117374
4,269924541	1,620343847	2,023165502	14,280073	0,243344846
5,149811059	5,154117974	6,870456619	12,96672875	0,092830577
5,459918703	0,011602062	9,996855076	25,46411194	2,478483181
9,798079795	0,429016428	1,198122466	12,11555366	7,241305739

21,91753707	0,041093791	0,986012006	18,44337135	0,990459071
7,145164716	0,878346843	1,931256092	5,726643986	0,01126589
32,59718532	0,015067754	0,852115424	10,61801547	0,030203381
3,294539849	2,164087939	3,929614706	9,887991245	0,873209508
3,517369957	0,04627532	3,223525392	8,436666691	0,780663899
5,668444138	0,040741567	0,730650933	7,322820079	0,532676573
0,70528128	0,644109782	0,421469092	11,86104394	0,083132654
4,653336615	0,222279023	4,793601068	25,6046	0,144383666
15,9191028	0,169115401	11,5679455	22,27263744	0,020342531
7,235700937	1,197995668	4,14712224	9,212341588	0,653411506
1,771778191	0,015951753	6,487100133	21,33502406	2,342235545
18,86918457	7,773089133	7,497074759	20,29053078	1,637346685
20,04726715	0,974166816	5,860992821	15,84517326	49,73038763
2,229535284	0,145140134	11,74410492	3,982816029	3,986912379
16,20388293	4,205840062	8,670531775	15,97277526	5,061509912
7,264099677	0,221540527	3,898705254	7,270869229	1,03323757
0,410243412	0,157620888	9,043317553	10,19770719	2,575821684
1,378117734	0,158796164	1,486731227	14,11121042	1,059112172
5,991866756	2,400404335	3,009455534	9,105232298	0,063953147
0,327602708	0,275331186	3,861165563	12,15896116	4,064041174
2,225296785	0,173630079	1,402709589	4,278707632	0,626077533
3,045028947	0,434387236	2,837541019	11,45589949	4,96398833
5,674253608	5,015671725	8,214785876	10,27137297	1,426215752
2,870202186	1,955765509	4,2732493	2,095970938	0,079804007
5,846637525	0,278605208	6,465384249	9,447171108	0,924134276
3,649558929	0,111451959	5,492400858	5,536422157	0,475244377
5,160338739	0,861223087	2,1439955	4,045248586	0,074997656
0,850407733	0,081082764	0,929818688	2,79748075	0,173324857
1,557615186	2,118052461	4,564774381	13,80858509	0,715919556
3,239852328	3,687003673	3,820254966	6,003326475	0,255734805
4,485248334	2,210190473	3,791343519	10,16983004	0,590603711
0,588999788	0,037427674	0,764411629	22,0376695	0,750923084
3,564873691	0,00526408	3,085393012	8,850202892	0,563192395
23,64363726	2,770728062	5,563782333	21,05498171	3,545310813
0,670258251	1,358618602	3,279043056	44,62952372	1,387774195
11,21045616	2,677213157	3,460897185	22,71223126	5,898966614
3,721142853	2,178827652	3,71278523	17,45762153	3,269533572
1,665390458	0,030923508	6,458472919	6,833604528	1,517215314
5,57517827	0,346355114	37,69372671	17,71652745	0,078094004
42,15357526	0,015391207	15,85422267	71,84538871	5,180356385
7,286579938	0,721886247	2,478939566	95,67168329	0,614358504
0,398436218	0,101303389	12,07935908	17,67173421	4,656388891
6,712275647	5,08070387	9,631820084	20,59442163	3,040070171

6,064087316	1,548571566	6,215009971	17,42270658	13,89779908
13,62561967	13,9011857	17,21083194	18,84467074	1,211550439
2,708562367	0,050441993	10,91230838	14,72472996	3,060236138
17,66711738	2,83535323	0,556106802	30,24046308	0,558939406
39,00374413	0,603545334	12,92371381	39,21212172	0,822265443
7,986904511	1,604152578	12,57552075	18,74795663	10,2215574
7,029086637	0,226366947	5,650236101	8,533987659	2,915546689
23,38780398	0,252413933	6,484792694	18,02095808	5,358035285
21,36770992	0,046303058	20,33037596	27,63401675	3,187941326
12,73685374	0,544232979	10,24921022	14,89757664	4,715106715
16,38949815	14,43524196	15,38369994	15,60548764	1,120767191
19,15831446	7,993262708	9,529909954	29,78065461	5,931223038
19,30506659	6,39862578	33,84866575	19,95748082	1,194958926
2,478837643	6,762827696	11,08294564	8,303744286	2,600506006
0,01979964	1,063245933	5,34522012	10,5993724	5,124535536
14,78485055	14,18371444	9,613677264	17,06491276	5,957881312
10,09127962	10,09078485	13,23213632	14,72871746	5,245994285
0,530378584	0,239018728	18,60591794	4,37045542	1,329199785
10,42718951	2,595349841	15,2652348	15,44788449	9,594792313
20,61128927	5,058152128	23,07387998	24,39590453	9,312162309
9,600850586	2,276615366	13,306541	12,80391676	12,95649207
5,622697853	4,134557991	17,43101326	6,226151879	3,016471986
24,79038827	4,937617144	15,08361219	24,18156409	6,638071554
4,86046829	3,974091873	14,59140029	9,253628989	4,279517126
7,41301573	8,008700103	18,83778062	16,81565482	5,851557278
15,50989453	3,504474324	34,51858541	4,70676029	6,209437494

APPENDIX D

MODEL ERRORS
(MEAN ABSOLUTE DEVIATION)

Model A	Model B	Model C	Model D	Fuzzy Model
49,6394	3	3,9301	65,8571	0,3625
20,7326	4,7907	5,352	41,9907	0,6487
50,0308	0,939	2,5364	57,4718	3,002
16,3668	3,991	6,0402	10,0469	5,1499
21,5175	7,939	9,2959	51,2294	0,8807
10,9761	5,3413	7,2296	41,5655	14,0333
18,2328	8,5419	10,9429	23,8429	0,1539
43,9446	7,0608	7,3414	42,9608	2,2518
36,9781	5,8704	11,8698	38,9775	6,9825
1,916	1,916	4,3359	4,3368	1,8742
1,9841	1,9841	3,5107	6,6075	0,4955
37,0684	7,7689	12,3372	32,3407	0,6509
50,7881	56	59,5636	55,57841	1,7676
5,4216	1,062	42,7622	29,1698	6,4328
10,7783	2,0544	4,2311	11,6532	6,6148
13,376	2,0323	2,2923	15,5932	5,6843
20,8625	0,7233	4,3735	24,2659	0,7717
32,8216	2,0308	2,8394	32,0372	1,8678
12,5156	4,058	7,9247	15,0573	1,7899
1,4205	0,0701	0,8204	3,8374	0,6364
19,5033	14,1889	6,3368	20,3768	1,7848
20,0727	2,3382	16,0344	12,0618	0,6032
30,8774	4,31	9,3534	35,639	0,182
14,8024	1,779	4,556	20,3735	0,354
11,956	2,0423	5,7139	9,1658	6,0353
33,9483	28,049	29,1138	41,0477	4,6017
18,0692	1,1601	4,9468	20,65845	0,2693
3,0993	0,1472	2,9622	0,7226	3,0508
3,4457	0,4689	2,2629	8,5583	2,5609
26,593	0,2799	5,2037	53,8601	0,9859
34,6032	0,2292	3,0992	35,5517	4,8948
2,6732	0,9	1,538	4,2646	1,665
20,8961	0,1743	4,3716	18,7846	0,2166
35,5956	1,9859	0,9821	31,8983	5,5871
9,1644	1,0234	5,3958	14,7809	10,7169

21,5331	0,117	6,658	10,4938	1,529
5,3408	0,528	5,7532	8,6677	3,3592
4,1921	1,0088	3,7822	7,04	0,5788
26,5661	0,1156	6,8537	27,5081	1,3329
20,3764	4,7964	1,3714	25,1452	4,5094
3,2516	0,1426	15,5444	8,6293	2,3294
15,0883	2,0975	3,6484	14,6848	0,2502
11,481	2,072	3,776	9,9104	0,9366
3,6826	0,782	9,6189	4,915	4,3149
0,5596	0,2787	4,2379	5,9501	4,4519
22,2235	0,0178	1,9556	18,61478	4,3433
9,7013	0,0555	3,6531	18,2339	4,4776
5,0927	0,076	4,7605	7,4626	0,1015
20,4045	1,6941	3,268	20,8915	4,934
43,3809	0,0835	4,15612	34,0609	56,0631
19,091	4,3142	5,3428	21,03592	4,1937
10,9721	0,0802	4,4785	11,823	15,8475
25,0423	10,9321	11,9288	25,0367	4,4625
21,5413	3,0636	3,7262	9,8723	4,5369
8,9582	0,12669	0,8453	12,1157	9,0892
10,6681	1,0556	5,8236	14,654	4,4514
22,6254	0,1653	4,875	20,1753	0,4812
3,5673	0,0541	1,1493	6,032646	1,0171
2,8196	1,4287	2,1457	7,4949	6,0903
15,0335	0,4324	1,4499	19,953562	9,2936
3,7883	2,0418	2,9298	13,32232	68,0338
7,2067	2,0045	1,8141	11,7827	3,4105
6,5082	0,8022	6,5112	8,5766	1,1752
8,7911	3,0247	10,4327	10,4361	0,0533
3,6047	0,2119	3,8695	18,65868	1,2941
1,0471	0,645	8,6706	8,0632	0,3572
2,8072	1,0002	3,1769	1,5772	0,1317
4,2064	1,4192	3,4065	5,2001	23,4105
17,5542	2,8873	7,5639	19,1666	0,1897
19,396	3,2495	3,88175	14,3599	4,1335
8,0246	0,5246	2,3409	13,6359	3,6247
12,7306	0,21	3,1524	14,0432	1,8558
27,1813	5,1741	5,5703	1,5307	3,1651
15,461	3,6788	6,48732	16,2735	2,5012
21,5389	1,6528	6,4732	12,676252	2,5567
6,2607	2,3758	2,96643	20,9379	0,3568
7,7721	7,7786	10,3689	19,5694	0,1401
9,2708	0,0197	16,9744	43,2374	4,2084

11,4809	0,5027	1,4039	14,1964	8,485
42,1883	0,0791	1,89794	35,501	1,9065
18,2024	2,2376	4,9199	14,5887	0,0287
48,0269	0,0222	1,25546	15,644	0,0445
6,7071	4,4057	8	20,1302	1,7777
4,7354	0,0623	4,3398	11,3582	1,051
8,0279	0,0577	1,03478	10,3709	0,7544
1,6764	1,531	1,0018	28,1928	0,1976
8,8114	0,4209	9,077	48,484	0,2734
27,4676	0,2918	19,9599	38,4303	0,0351
14,5542	2,4097	8,3417	18,5301	1,3143
2,1881	0,0197	8,0114	26,3482	2,8926
16,7551	6,9022	6,65711	18,0172	1,4539
20,9349	1,0173	6,1205	16,54675	51,9323
2,5853	0,1683	13,6181	4,61835	4,6231
21,0959	5,4756	11,2882	20,79502	6,5896
7,8333	0,2389	4,2042	7,8406	1,1142
0,8222	0,3159	18,1244	20,438	5,1624
3,218	0,3708	3,47162	32,95065	2,4731
10,812	4,3314	5,4304	16,4299	0,1154
0,8229	0,6916	9,6988	30,5419	10,2084
4,5421	0,3544	2,8631	8,73336	1,2779
7,263	1,0361	6,7681	27,3246	11,8401
11,827	10,4543	17,1223	21,4089	2,9727
6,071	4,1368	9,0387	4,43336	0,1688
10,1947	0,4858	11,2736	16,4729	1,6114
5,7403	0,1753	8,63886	8,7081	0,7475
16,5136	2,756	6,861	12,9452	0,24
2,0347	0,194	2,2247	6,6933	0,4147
2,6217	3,565	7,6832	23,24192	1,205
6,7398	7,67	7,9472	12,4886	0,532
5,3449	2,6338	4,518	12,119	0,7038
0,9694	0,0616	1,2581	36,2705	1,2359
5,5531	0,0082	4,8062	13,7862	0,8773
25,9457	3,0405	6,1055	23,105	3,8905
0,8368	1,6962	4,0938	55,7188	1,7326
12,7413	3,0428	3,9335	25,8137	6,7045
4,1759	2,4451	4,166521	19,5911	3,6691
2,7143	0,0504	10,5262	11,1376	2,4728
5,7755	0,3588	39,0481	18,3531	0,0809
39,5484	0,01444	14,8744	67,4052	4,8602
7,2847	0,7217	2,4783	95,647	0,6142
0,4468	0,1136	13,5456	19,8168	5,2216

8,3259	6,3021	11,9473	25,5453	3,7709
8,0762	2,0624	8,2772	23,2037	18,5092
16,2331	16,5614	20,5044	22,4509	1,4434
2,651	0,04937	10,6804	14,4118	2,9952
21,206	3,4033	0,6675	36,2979	0,6709
56,1909	0,8695	18,6186	56,4911	1,1846
8,9167	1,7909	14,0395	20,9305	11,4115
13,6845	0,4407	11,0001	16,6143	5,6761
39,6848	0,4283	11,0035	30,57825	9,0916
35,2567	0,0764	33,5451	45,5961	5,2601
13,712	0,5859	11,0339	16,03815	5,0761
22,7234	20,0139	21,3289	21,6364	1,5539
28,9822	12,092	14,4166	45,0514	8,9726
28,377	9,4055	49,755	29,336	1,7565
4,5902	12,5231	20,5229	15,3765	4,8155
0,0377	2,0245	10,1777	20,182	9,7575
25,2958	24,2673	16,4483	29,19682	10,1935
18,3563	18,3554	24,0696	26,79192	9,5426
0,9211	0,4151	32,3126	7,5901	2,3084
16,3273	4,0639	23,9029	24,1889	15,0239
27,4051	6,7254	30,6794	32,437185	12,3816
17,0213	4,0362	23,5911	22,7	22,9705
9,8626	7,2523	30,5752	10,9211	5,2911
39,9835	7,9637	24,3278	39,00155	10,7063
11,1842	9,1446	33,5756	21,2931	9,8474
16,5811	17,9135	42,1355	37,6125	13,0885
34,4181	7,7768	76,6004	10,4448	13,7794