Journal of Housing and the Built Environment (2023) 38:2005–2027
https://doi.org/10.1007/s10901-023-10022-4

ARTICLE

An adaptive-neuro-fuzzy-inference-system based grading model to estimate the value of the residential real estate considering the quality of property location within the neighborhood

Serhat Yilmaz[1] · **Zeynep Gamze Mert**[2]

Received: 8 March 2022 / Accepted: 17 February 2023 / Published online: 20 March 2023
© The Author(s), under exclusive licence to Springer Nature B.V. 2023

Abstract
In residential real estate, location quality within the neighborhood has considered a very important characteristic. On account of a limited number of studies on novel evaluation methods in real estate literature, an Adaptive-Neuro-Fuzzy-Inference-System Grading Model (ANFISGM) which combines human knowledge-based FIS with optimization skills of ANN is proposed. By 4 location parameters, Distance to Open Space (DtOS), Parcel Size (PS), Excellence of View (EoV), and Distance to Parking (DtP), the model has been applied to grading the location quality of 27 detached properties within the campus region of Kocaeli University. Performance of the proposed model is compared with the Standard Grading Method (SGM), and Fuzzy Grading Model (FGM), which were developed considering the quality of property location (QoPL) within the neighborhood. In this study, the ANFIS model is proposed as the first contribution to the real estate valuations made in terms of location quality in the neighborhood. Since it was not very clear in previous studies, the individual and resultant effects of the parameters on the score are examined and interpreted by correlation surfaces. The lack of nonlinear interpolation, which reduces the sensitivity of traditional and fuzzy methods and causes them to assign the same value throughout the transition regions, is eliminated by the proposed ANFIS method. Hereby, ANFISGM declares an accurate and practical grading model to estimate the value of the residential real estate considering property location within the neighborhood. This paper expects that ANFISGM will contribute to the appraisal process within a minimum of detail and a limited period, especially for tax purposes.

Keywords The value of real estate · Quality of property location · Grading models · Artificial intelligence · Optimization

✉ Serhat Yilmaz
serhaty@kocaeli.edu.tr

Extended author information available on the last page of the article

1 Introduction

There are some significant reasons behind the development capacity of the residential real estate sector. Most of the unqualified antecedents in cities have been substituted by new residences and suburban residential unit transition demand has increased. There are significant studies on the role of deprived suburban as a transition step in individuals' residential journeys over time (Kovacs et al., 2021; Xu & Zhang, 2017). On the other hand, design demands for out-of-town residential and out-of-townhouse have become a wide range. Physical characteristics that include the number of living rooms, bathrooms, etc., production standards, age and wearing of the house, areas allocated to the vehicles, and regional individualities that include the feature of the neighborhood and the feature of the building location have key factors on housing choices (Din et al., 2001). Behind customer preferences lies a complex and non-linear logic that is difficult to predict.

Expert systems including Artificial Intelligence (AI) have a reasonable performance in modeling nonlinear systems. Fuzzy inference systems (FIS) (Zadeh, 1965) and artificial neural networks (ANNs) are such systems. ANN may be insufficient in some cases such as responding adequately to sudden and large variations in input variables. These relations could be realized by ANFIS which connects semantic expression and classification skills of FIS to the learning capability of the ANNs (Dere & Filiz, 2019; Jagtap & Pillai, 2014; Lin, 1996). Several research groups have conclusively confirmed the effectiveness and capabilities of ANFIS in many areas. Petković et al. (2013) designed an ANFIS to predict the coefficient value of wind turbine power for improving the quality of wind energy. The study finds that the proposed ANFIS network is efficient, reliable, and easily adopted. Based on this, an ANFIS control system has been developed to maximize produced energy from the wind turbine. ANFIS controller adjusts wind speed easily and rapidly and extracts more power from wind turbines (Petković et al., 2014). Following these findings, Petković et al. (2016) designed an ANFIS network to predict the efficiency of wind farms through several turbines. They found that the ANFIS method is very advantageous for determining the optimum turbine number quickly. Furthermore, estimation skills of ANFIS methodology have been applied to predict contact forces of the gripper through embedded sensors. Comparing ANFIS results with the existing prediction models, the study shows that the ANFIS model can be used as an alternative model (Petković et al., 2016). To determine influential factors for the mathematics lecture performance, Gavrilović et al. (2018) used ANFIS whereas Stojanovic et al. (2021) applied the same method to analyze the mathematics knowledge of students. Petković et al. (2020) employed ANFIS methodology to estimate kinetic parameters of biomass oxidation, meanwhile Milić et al. (2021) applied ANFIS to optimize the predictors for the fatty acid methyl ester yield and exergy efficiency in situ transesterification of microalgae slurry conversion into biodiesel. Kuzman et al. (2021) developed ANFIS predictive model to analyze fertilizer for the optimum combination in crop production. On the other hand, in order to determine influential factors on brake thermal efficiency, Petković et al. (2021) established the ANFIS network. Thus, Kusum biodiesel performance is optimized by finding the best combination of the inputs. ANFIS methodology was applied to select the most forceful factors for the precipitation concentration index (PCI) prediction in Serbia. This paper shows that ANFIS offers better results than ANN and FIS (Petković et al., 2017). Studies have obtained important results in comparing the performance of ANFIS with other computational intelligence methods. Considering laser power, cutting speed, and water-jet speed, Nikolic´ et al. (2016) investigated the effective parameters on the water-jet assisted underwater laser cutting process through the

ANFIS method. This study shows that ANFIS assists in eliminating some parameters to improve the process. Milovančevića et al. (2018) analyzed the vibration of pumping aggregate using soft computing methods, artificial neural network (ANN), genetic programming (GP), and ANFIS. This paper shows that ANFIS results are the highest precision.

Although ANFIS has been used and adapted easily and quickly in many different research areas, the studies on real estate have increased gradually. Kummerow and Lun (2005) proposed that manipulation of the data structure of real estate possibly will improve allocative efficiency, by drawing attention to information and communication technology effects on real estate activities. Liu and Chen (2011) proposed an evaluation index system that discovers the most favored residential acceptors with the examinations from the viewpoint of the acceptor depending on some criteria. Meaningful improvement in predicting results obtain after employing computational intelligence techniques to decision support systems and real estate evaluations (Lokshina et al., 2003). Research by Kontrimas and Verikas (2011) compared mass appraisal models and demonstrated that the performance of the artificial intelligence-depended methods was significantly better than the classical method. Kusan et al. (2010) suggested a fuzzy inference system (FIS) model for the price of sale estimation of residences positioned in several regions in Eskisehir, Turkey where the model includes comprehensive property factors and related rule base to accomplish a strong evolution. Yalpir and Özkan (2011) compared the FIS model and multiple regression model results for the prediction of real estate existing in Konya, Turkey. The results of the FIS model were found to be more reliable. Liu et al. (2011) established the real estate valuation scheme depends on Geographic Information System (GIS) with Back-Propagation ANNs to prove the ineffectiveness and imprecision of traditional real estate evaluation theory. This new system achieves to process spatial and attributes data as well as increases the real estate's effectiveness and precision. Similarly, Brondino and Silva (1999) processed GIS data through neural networks and an alternative multiple regression model for land valuation of Brazilian medium-sized cities. Kauko (2003) motivated to use of neural networks due to their solution capabilities on nonlinear interactions of different social, environmental, and locational factors and their impacts on prize levels. Rossini (1998) examined the performances of ANN for residential valuation and suggested adding new variables systematically to improve their performances and to derive the appropriate ANN structure. Nishi et al. (2021) proposed an ANN-based automatic segmentation method that would be able to evaluate rental housing in a balanced way for Housing Markets. Chiarazzo et al. (2014) developed an ANN model that has been performed in real-estate assessment. Furthermore, performance comparisons of ANNs for residential selling fee forecasting of the properties are implemented.

ANN cannot imitate massive differentiation and estimate extremely high peak values that are not real results both in positive and negative directions. Small deflections in a slope estimation would result in divergences in the results. However, FIS can employ separate fuzzy rules each of which can determine critical input and corresponding output points, no matter how different they are, of the nonlinear relation. Around these points, ANN can optimize the corresponding membership functions and rules. ANFIS is an adaptation of ANN learning and fine-tuning capability onto MFs and expressions of the Takagi–Sugeno (T-S) Type FIS Model. One can monitor and interpret each role and its effects on the ANFIS Model. Guan et al. (2008) proposed an adaptive neuro-fuzzy inference system (ANFIS) for the estimation of real estate prices due to its residential properties. In general, physical property features such as neighborhood, construction type, number of baths, number of garages and basements floor areas, percentage of central air, wall type, and historic sale prices constitute the training data. The proposed ANFIS model was compared with

a multiple regression model. Each fuzzy input variable has two membership functions. Parameters which has a lower correlation percentage with the prize are removed from the model. The rest exhibited a linear correlation surface which can be also provided by linear regression analysis. Zhao and Wang (2010) proposed the collaboration of ANFIS and principal component analysis (PCA) for choosing a convenient real estate project. PCA employ to decrease the assessment index dimensions where ANFIS evaluates the real estate projects. These studies motivated for development of a residential real estate valuation model by taking into account the location within the neighborhood. Furthermore, analyzing and interpreting the effect of each parameter on the score through correlation surfaces and comparing the ANFISGM model with classical and computational intelligence methods would fill a gap in the performance analysis of the ANFIS method. Ahn et al. (2012) proposed genetic algorithms joined to ridge regression (GA-Ridge) for forecasting real estate appraisal. Korean real property market focus on an experimental study and its results indicate the effectiveness of GA-Ridge in the estimation of real property assessment. Lewis et al (1997) proposed a Kohonen Neural Network trained with chronological data gathered by official mortgage transactions by years.

These studies show that recent real estate research has focused on novel methods that depend on computational intelligence. However, value estimation models considering the quality of property location which are employed novel methods are deficient in the research. In practice, to estimate residential real estate value, Standard Grading Method (SGM) is conventionally used for grading a property within a neighborhood according to its location quality as a lookup table method. Because the location is the most important factor that makes real estate unique, this study proposes an optimal model for analyzing-grading the quality of the property location (QoPL) by employing novel methods. ANFIS determines optimized parameters which constitute and validates a nonlinear and precise relation between inputs and output. Once the model is determined, real-time estimations can be simulated on the model. In this regard, the motivation of the paper is to introduce an ANFIS based Grading Method (ANFISGM) and compare its performance with SGM and the Fuzzy Grading Method (FGM) models in terms of grading the quality of the property location (QoPL).

ANFIS-based grading model for estimating the value which determines the quality of property location within the neighborhood is first extracted. Standard Grading Models and Fuzzy Inference System Based Models show sharp Score changes in transition regions and constant Score values despite parameter changes in a certain range (Mert & Yılmaz, 2009). In this study, the ANFIS model provides a sensitive evaluation score for each point by means of its' nonlinear and continuous correlation functions composed of membership functions and trained connection weights. The applications of the proposed ANFISGM contribute to more accurate value assignments for the situations.

2 Case study area and grading models for the location quality

2.1 Residential area of Kocaeli University Umuttepe Campus

Kocaeli City is in the center of major locations such as Istanbul, Ankara, and Bursa. It is in the Marmara Region where most imperative industrial and logistic companies are located, and it connects Anatolia to Europe through railways, highways, and Kocaeli Gulf (Mert & Mert, 2000).

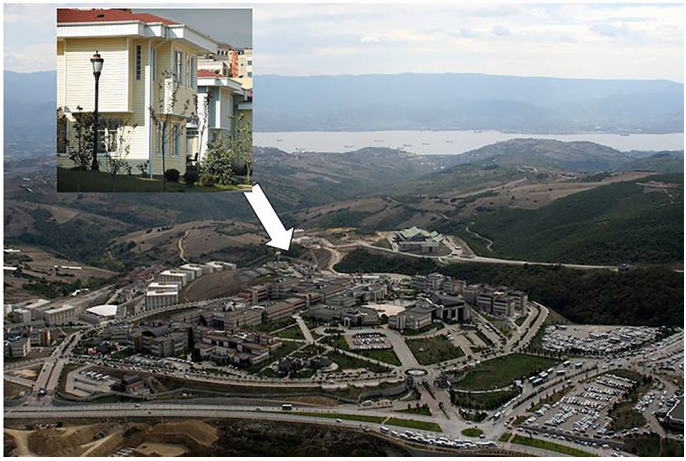


Fig. 1 Location of detached house district in Umuttepe Campus of the Kocaeli University

Table 1 Definition of the location quality parameters

Parameters	Definition
Distance to open space (DtOS)	Distance to open space, playground, or recreational areas
Parcel size (PS)	Parcel size or land lot size around the household
The excellence of view (EoV)	Common free view of surroundings
Distance to parking (DtP)	Distance to the road or parking area

Despite the rapid industrial development, unplanned urbanization paves the way for destructive effects in the August 17th, 1999 Kocaeli Earthquake. The disaster directed the residential real estate demands to new and resistant buildings that have adequate safety regulations. Suburban residential areas are in general composed of detached houses and 2–4 floored townhouses that are especially located around well-developed regions in terms of social and technical properties. The houses should have good construction quality, creative concepts, and be resistant to disaster effects.

The Earthquake (1999) brought about losses in approximately % 75 of the physical properties of Kocaeli University. Following intensive feasibility research and reconstruction works, the new region of the University Campus has been located 5–7 km north of the present Kocaeli city center and named Umuttepe Campus. Today, approximately 40,000 students receive education, and 1600 staff works in this campus area.

The residential area locates in the southeast of the Umuttepe Campus (Fig. 1). It covers 80 000 m^2 area and contains 224 units in 5 different types. In this study, the detached property district is selected to determine the QoPL case study. The district surrounded by roads consists of 27 detached properties. Recreational areas are located in the east of the district which has a dominant view to the south.

While the internal physical characteristics of the buildings are alike, environmental physical characteristics are at variance from each other concerning location quality. For this reason, the definitions of the location quality parameter should read as follows (Table 1).

Although, the model could be greatly improved if other location quality parameters are included in the model, such as if the property is close to public facilities or a bus stop, school, etc., since the location of the buildings is approximately similar far away to these criteria in the campus area, a remarkable effect have not observed.

2.2 Grading models for the location quality

Grading the quality of property location within the neighborhood was investigated through Standard Grading Model (SGM) and Fuzzy Grading Model (FGM) according to the parameters defined above (Mert & Yılmaz, 2009).

2.3 Standard Grading Model (SGM)

SGM evaluates an interval rather than a unique scalar input value of a related parameter. Tables 2, 3, 4, and 5 show the intervals and scores which are determined by an expert for each parameter. Thus, any measured parameter in that interval is assigned to a definite score value. As seen in the structure of SGM (Fig. 2), the total grading score is calculated by the sum of each parameter's grade.

SGM assigns a unique score for a variety of elements in a parameter set (Tables 2, 3, 4, and 5). For example; scores of DtP for 61 steps and 100 steps are the same (Table 5)

Table 2 The distance to open space (DtOS) grades

Distance (by step) Related score	Score
Between 401 and 500	4
Between 301 and 400	8
Between 201 and 300	12
Between 101 and 200	16
Between 1 and 100	20

Table 3 Parcel size (PS) grades

Area (m^2)	Score
<50	0
51–100	5
101–150	10
151–200	15
201–500	20

Table 4 Excellence of view (EoV) grades

	Balcony Score	Bedroom's Balcony Score	Total Score
0–10%	0	0	0
11–50%	2	1	3
51–90%	4	1	5
91–100%	5	2	7

Table 5 Distance to parking (DtP) grades

Distance (by step)	Score
Between 61 and 100	1
Between 31 and 60	2
Between 0 and 30	3

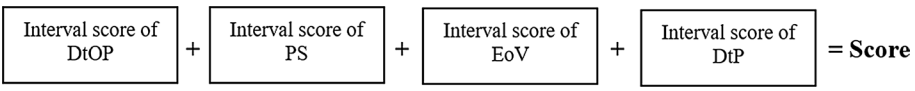


Fig. 2 Structure of the Standart Grading Model (SGM)

which is not a reasonable situation. Any size should have another score for providing a fair evaluation.

2.4 Fuzzy Grading Model (FGM)

The structure of Fuzzy Grading Model (FGM) is a rule-based system comprised of fuzzification, fuzzy inference, and defuzzification stages (Fig. 3).

Inputs and outputs are combined with linguistic rules as;

Rule1. If DtOS = = "Very Close" ∧ PS = = "Broad" ∧ EoV = = "Good View" ∧ DtP = = "Very Close" ⇒ Score = "Very High" (Mert & Yılmaz, 2009).

Where symbols ∧⇒, = = are AND, IMPLICATION, and IS EQUAL TO operators, respectively. The whole relation is defined by 300 rules. The defuzzification method is selected as mean_of_maxima (Mert & Yılmaz, 2009).

The SGM proposes a lookup table organization as a quantitative decision support system to classify real estate in terms of qualitative variables. In such a structure, some qualitative parameters may be substituted. On the other hand, fuzzy systems can produce a nonlinear mapping between their inputs and related outputs. In this way, they could serve as precise quantitative decision support systems. Although fuzzy systems refer to imprecise or ambiguous information, their results are further realistic. It had been observed that the SGM had some deficiencies stemming from the sharp variations near boundary values

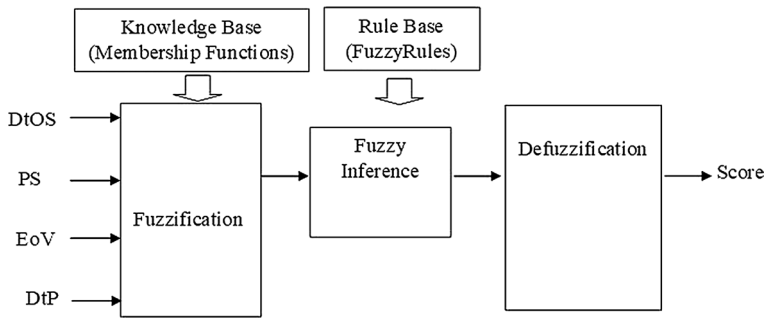


Fig. 3 Structure of the Fuzzy Grading Model (FGM)

since the grading value is constant through a wide range. As a consequence of taking the slightest changes into account, the results of the FGM are more realistic. Thus the study proved the success of the Fuzzy Inference System (FIS) method on QoPL.

3 Designing an adaptive-neuro-fuzzy-inference-system based grading model

Human knowledge-based FIS is improved by the optimization skills of ANN and the results bring about neuro-fuzzy systems (Shamshirband et al., 2015). Numerous methods exist that piece together the abilities of ANN and FIS. The decision-making is based on Takagi–Sugeno Model (Takagi & Sugeno, 1985). Each processing node shares a particular function of the FIS. Coefficient weights of the network are simultaneously the center or width parameters of the fuzzy membership functions in the ANFIS. These parameters are adjusted iteratively for matching the input and output vectors of the system (Walia et al., 2015; Yılmaz et al., 2011). Nodes in the If Part and Then Part of the ANFIS Structure execute a task of the weights (Nguyen et al., 2003) and determine the behavior of ANFIS. Although there are more connections in the real ANFIS Structure, a brief representative model is shown in Fig. 4. In this study, ANFIS Grading Model has 4 inputs, Distance to Open Space (DtOS), Parcel Size (PS), Excellence of View (EoV), and Distance to Parking (DtP), and one output as Score.

3.1 Forward calculations

ANFIS provides forward calculations to obtain a score estimation from inputs. Compare the estimation with training data. The error is propagated back to adjust parameters.

Hybrid and back-propagation-based techniques are used for updating parameters which afford FIS to acquire the behavior of the process (Mesbahi et al., 2012). There are 5 layers where outputs are represented by O_{ij}. Here i and j represent layer number and related output in that layer, respectively. The tasks of each layer are as follows.

Fuzzification Layer: Initially input training data of EoV, DtOS, DtP, and PS are acquired and are brought to Fuzzification Layer. This layer is composed of membership functions (MF) such as the sigmoid function (SF) and determines the active MFs regions in which the inputs exist and returns the related membership degree (Eq. 1).

$$\mu_{\underset{\sim}{A}}(x) = \frac{1}{\left(1 + e^{-(x-m)\sigma}\right)} \tag{1}$$

SF's center, slope, and slope direction are represented by m, σ, and the sign of σ, respectively.

Multiplication Layer: Logical operator AND is employed to connect IF prepositions in the instructions. AND operation is functioned by multiplication of weights (w_i) of the related rules, such as Eq. 2;

$$\text{Rule 1}: \; O_{21} = w_1 = \mu_{A1}(x) * \mu_{B1}(x) \tag{2}$$

Normalization (N) Layer: It could be accepted as an early calculation of the average center of gravity in the defuzzification stage (Kosko, 1992). Total weight is used as a divisor of the related rule weight. An example is given in (Eq. 3).

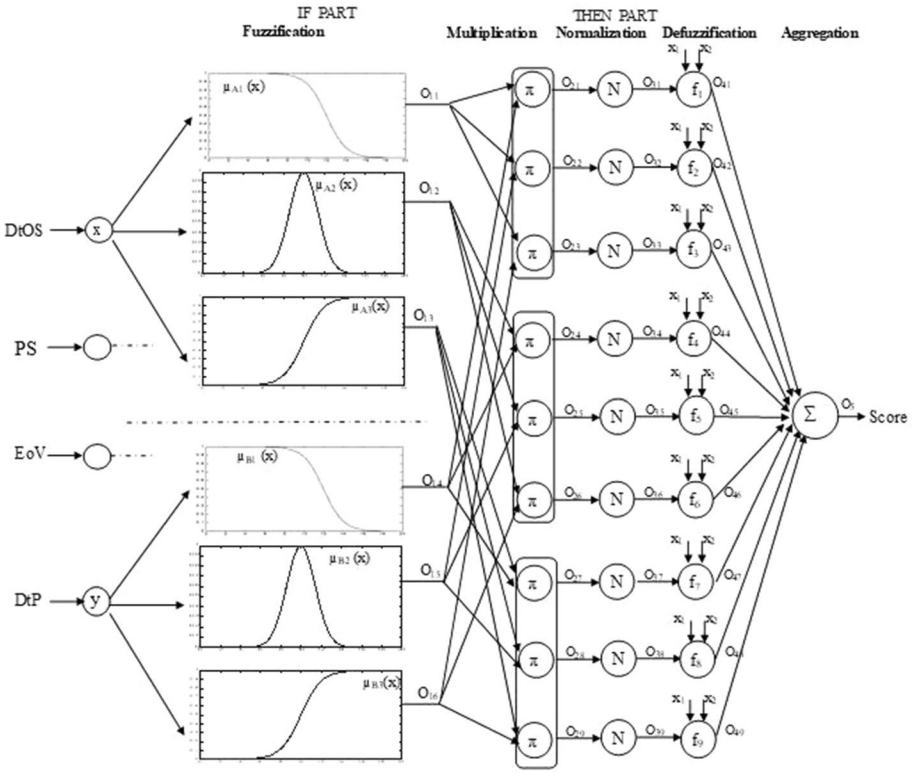


Fig. 4 Structure of the Adaptive-Neuro-Fuzzy-Inference-System based grading model (ANFISGM)

$$w_1 = w_1 / \left(\sum_{(i=1)}^{9} w_i \right) \tag{3}$$

Defuzzification Layer: Each rule has a consequent (THEN) preposition. This proposition is represented by an output MF which is a function of current inputs, x,y, etc., (Eq. 4).

$$z_i = p_i * x + q_i * y + r_i \tag{4}$$

where p_i, q_i, and r_i are weighted parameters. This layer determines the position of the output MFs and implies (Kosko, 1992) the normalized impact degree of related rule ($\overline{w}_i$) to the output (Nguyen et al, 2003). O_{4i} refers to the weighted output of the ith rule in the 4th (Defuzzification) Layer (Eq. 5).

$$O_{4i} = \overline{w}_i * z_i \tag{5}$$

Aggregation Layer: If it is compared with classical FIS defuzzification formulas (Kosko, 1992), this layer could be accepted as the conclusion step of the Defuzzification Stage. The output vector of the previous layer is aggregated, and it yields a scalar output (Eq. 6).

$$z = O_5 = \sum_{(i=1)}^{9} O_4 i \tag{6}$$

Table 6 Training data of DtOS

Input data	Output (interval scores) data
50 (mean of 0 and 100)	20
150 (mean of 101 and 200)	16
250 (mean of 201 and 300)	12
350 (mean of 301 and 400)	8
450 (mean of 401 and 500)	4

Table 7 Training Data of ANFISGM

DtOS	50	50	50	50	50	50	50	50	……	……
PS	350	350	350	350	350	350	350	350	……	……
EoV	95	95	95	70	70	70	30	30	……	……
DtP	15	45	80	15	45	80	15	45	……	……
Total Score	50	49	48	48	47	46	46	45	……	……

3.2 Backward calculations

The learning stage is an optimization of related ANFIS parameters according to the error between model output or outputs (O^k), such as the actual Score determined by the ANFIS and training set outputs (y^k), the expected Score. Through some methods of optimization, these parameters determine the location and form of the output and input MFs (Walia et al., 2015). As an example, Output MFs of the Defuzzification Layer could be reorganized as follows (Eq. 7).

$$zi(t+1) = zi(t) - \eta(O^k - y^k)\,\overline{w}_i(x^k) \tag{7}$$

The neural network is a numerical optimization method, which could map a relation between the training input–output pairs. ANFIS refers to numerical training information and combines it with the power of FIS. However, the ANFIS rule base and MFs have been generated automatically in general. When it is compared to Fuzzy Systems, ANFIS systems could serve as basically established, easily used, but realistic models.

ANFISGM inputs of the training data are the mean of the SGM intervals. ANFISGM outputs of the training data are the sum of corresponding interval scores. Table 6 shows the input and output data of DtOS used in the training process of ANFISGM.

The earliest 8 training data out of 420 are given (Table 7).

4 Results

Subsequent to the training process and interpreting the surfaces, ANFISGM is tested for grading the residential real estate of Kocaeli University.

4.1 Training the ANFISGM data

ANFISGM provides a sub-clustering training method for hybrid optimization. The training data is uploaded to the ANFIS editing toolbox in MATLAB ®. The tolerance for training Error is 10^{-5} where and highest epoch is selected as 10,000 in order to obtain higher iteration and lower training error (Fig. 5). The simulations were performed on a computer with an i7-2.00 GHz processor and 8 GB RAM.

The structure of the ANFISGM is provided in detail (Table 8).

Reached mean square error of the training stage, trained ANFISGM structure, created rules after the training stage and example trained Membership Functions for the EoV are given in the Appendix as Figs. 13, 14, 15, and 16, respectively.

4.2 Interpretation of the ANFISGM surfaces

Input–output relation surfaces of the trained ANFISGM reveal the interaction and compound effect of each input on the Score.

Other parameters kept constant PS and DtOS are proportional to Score as directly and inversely, respectively. Higher PS values result in optimum Score values for DtOS between

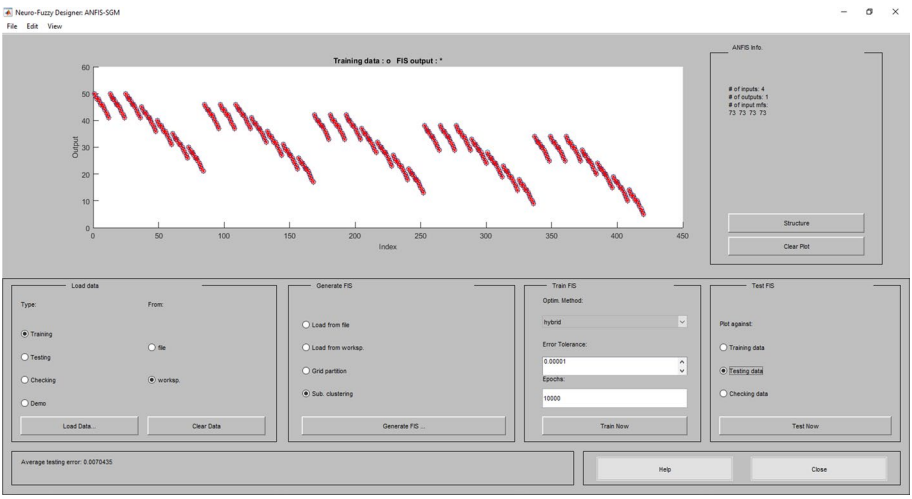


Fig. 5 Neurofuzzy designing interface for the ANFISGM

Table 8 Structural parameters used in ANFISGM

Provided FIS Structure in the ANFIS Model	Sugeno
Inputs used in the ANFIS	4
Outputs used in the ANFIS	1
Rules	73
Training Data	420
Number of Test Data	27
Conjunction Function for the AND Method	Minimum
The function used for ANFIS Implication Method	Minimum
ANFIS Aggregation Function	Maximum
Defuzzification Function of ANFIS	Averaged Weight of all rule outputs (Wtaver)
Method of FIS Generation	Sub-Clustering
Tolerance for training Error	10^{-5}
Maximum epochs of the ANFIS Training Stage	10.000 iterations
Optimization Method of the ANFIS Training	Hybrid
Range of Influence	0.5
Squash Factor	1.25
Accept Ratio	0.5
Reject Ratio	0.15

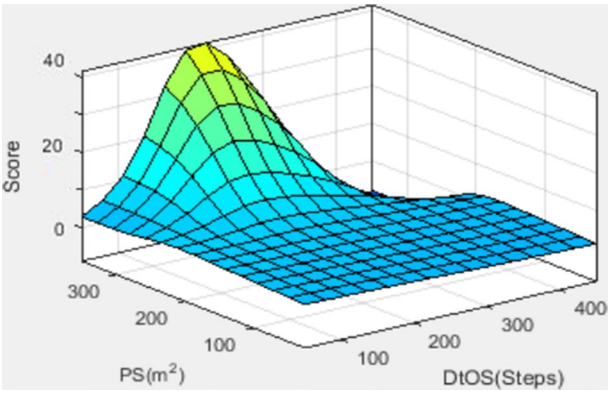


Fig. 6 Correlation surface of ANFIS showing Score variation depending on PS and DtOS

150 and 250 steps. However, the Score decreases significantly after 300 steps where the effects of high PS on the Score diminish. In narrow PS regions, the increase in DtOS causes only a very slight decrease in the Score (Fig. 6).

EoV is directly proportional to Score. Because DtOS has a higher score region (4 to 20 points) than that of EoV (0 to 7 points), the effects of EoV paled in the course of DtOS which becomes more effective after 300 steps. In addition to the required 100% EoV and 0 Steps pair, the Score is higher in the areas of 150–230 steps with 50–60% EoV and 300 steps with 90–100% EoV (Fig. 7).

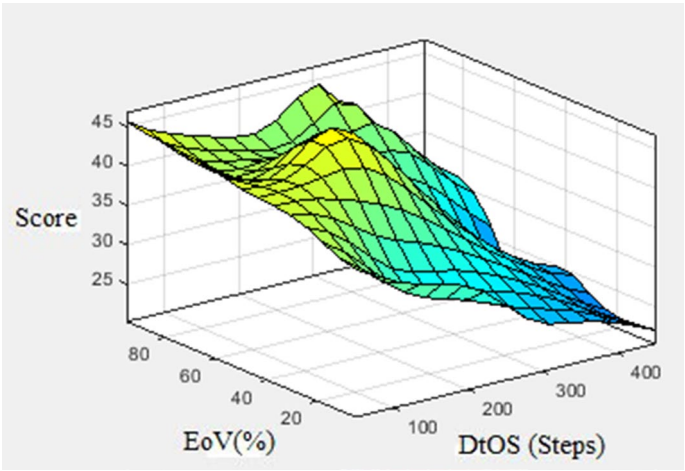
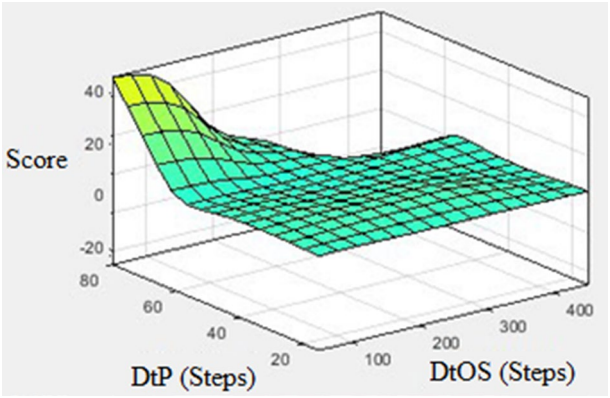


Fig. 7 Correlation surface of ANFIS showing Score variation depending on EoV and DtOS. Other parameters kept constant

Fig. 8 Correlation surface of ANFIS showing Score variation depending on DtP and DtOS. Other parameters kept constant



The score is inversely proportional both with DtP and DtOS and this situation reflects the relation surface (Fig. 8). Although there are some interactive nonlinear regions exist, Score is proportional to both EoV and PS. The score is high in large sizes of PS regardless of EoV (Fig. 9).

Inverse effects of DtP could be noticed especially for lower PS values: Increasing PS intervention result in nonlinearity in the ANFISGM relation surface (Fig. 10). However, the Score generally increases in parallel with PS and reaches peak values beyond 300 m^2.

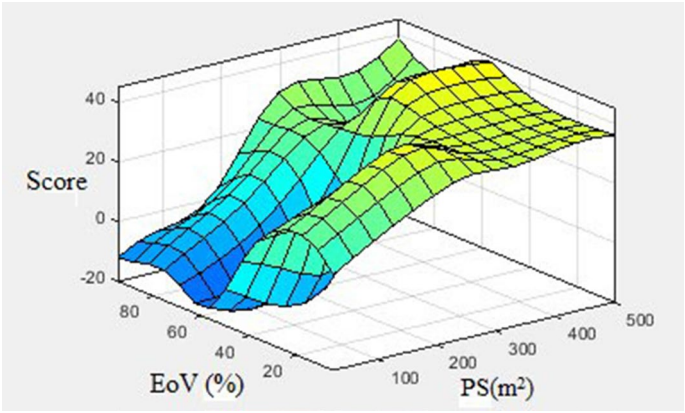


Fig. 9 Correlation surface of ANFIS showing Score variation depending on EoV and PS. Other parameters kept constant

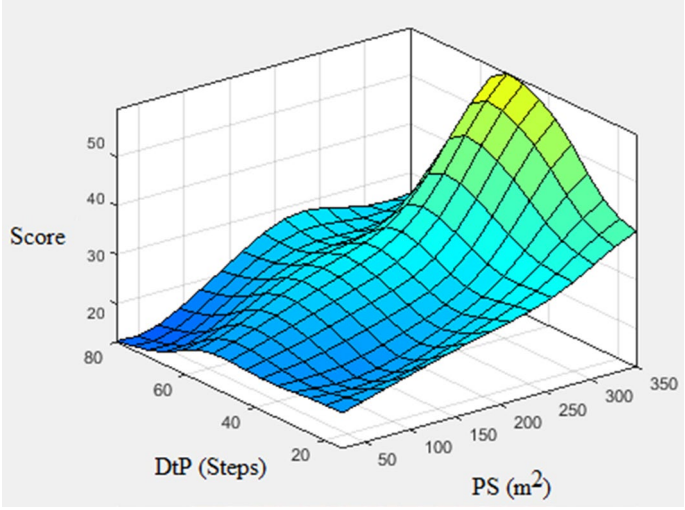


Fig. 10 Correlation surface of ANFIS showing Score variation depending on DtP and PS. Other parameters are kept constant

4.3 Testing the trained ANFISGM

27 testing data is scored by the trained ANFISGM for the detached properties of Kocaeli University. Matlab rule viewer tool shows inputs and output scores in Fig. 11.

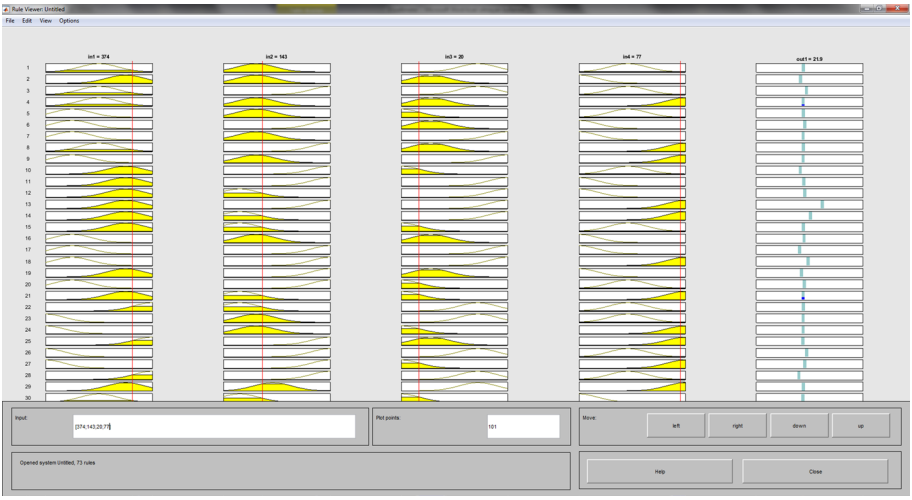


Fig. 11 Matlab rule viewer tool figures out ANFISGM scores (in1:DtOS, in2:PS,in3:EoV,in4:DtP)

5 Discussion

In this study, designing stages of ANFISGM are addressed and every detached property within the campus region of Kocaeli University is evaluated due to its location. To investigate an accurate and practical grading method, this study discusses ANFISGM by comparing with the grading models including SGM and FGM (Mert & Yılmaz, 2009).

Table 9 shows the SGM, FGM, and ANFISGM grading scores of property location to estimate the value of real estate.

Case.2 is scored as 23, 19.7, and 19.3 for the SGM, FGM, and ANFISGM, respectively. The SGM made a rougher evaluation and it converges the case score to the nearest value in the table, which results in a higher value. Similarly, Case.17 scores with SGM as 25, FGM as 29.2, and ANFISGM as 27.1, where the variance reaches 4.2 units. This means the SGM offers a lower value.

Alternatively, FGM is constituted due to expert experiences extracted from the SGM tables. Although the general trend is similar, FGM results have some abrupt changes around rule changes or transitions between two neighborhood membership functions. On the other hand, interpolation capability of the ANFISGS made these transitions smoother by filling the interspecies. A graphical illustration of the scores for 27 cases based on the three models is shown in Fig. 12. It shows that ANFISGM follows the trend of SGM and FGM and it can be used as an alternative models.

This study compares the models, in terms of sensitivity and analysis rates. Sensitivity is a clear indicator of the resolution and hence accuracy of model decisions. Because whether a model is insensitive to changing parameter values and continues to assign the same value, it does not make a fair and accurate evaluation. An ideal model should respond to an increasing parcel size with an increasing value, taking into account the relationships with other variables. The SGM method is a classical lookup table method, and it does not make a precise valuation because it assigns the same value in a very wide range despite parameter changes. On the other hand, lesser but still flat areas are seen in the rule

Table 9 Grading scores of property location by SGM, FGM, and ANFISGM

Case Number	Property Name	DtOS	PS	EoV	DtP	GRADING SCORES		
Number	Name	Step	m^2	%	Step	SGM	FGM	ANFISGM
1	1. A	322	110	90	43	25	26,1	26
2	1. B	322	102	30	43	23	19,7	19,3
3	2. A	291	50	30	44	17	17,7	17,6
4	2. B	291	173	80	44	34	33,5	32,4
5	3. A	419	276	30	19	30	29,1	31,2
6	3. B	419	94	70	19	17	19,5	17,3
7	3. C	419	118	10	19	17	17,4	16,8
8	4. A	426	144	10	19	17	21	18,8
9	4. B	426	104	10	19	17	16	12,5
10	4. C	426	122	10	19	17	17,8	15,3
11	5. A	374	294	30	77	32	33,1	30
12	5. B	374	129	20	77	22	20,6	20,8
13	5. C	374	143	20	77	22	22,1	21,9
14	6. A	309	115	10	57	20	22,1	24,6
15	6. B	309	106	85	57	25	25.3	24,2
16	6. C	309	125	30	57	23	24	24,4
17	7. A	349	143	90	48	25	29,2	27,1
18	7. B	349	189	100	48	32	36,3	33,3
19	7. C	349	219	100	48	37	38,8	35,9
20	8. A	429	194	60	19	27	29,7	28,7
21	8. B	429	208	100	19	34	33,1	36,2
22	10. A	386	162	10	75	24	22,3	23,2
23	10. B	386	252	90	75	34	35,4	35,8
24	10. C	386	150	90	75	29	28,8	26,9
25	11. A	417	166	40	43	24	22,9	25
26	11. B	417	185	40	43	24	27	28,2
27	11. C	417	181	20	43	24	25	23,8

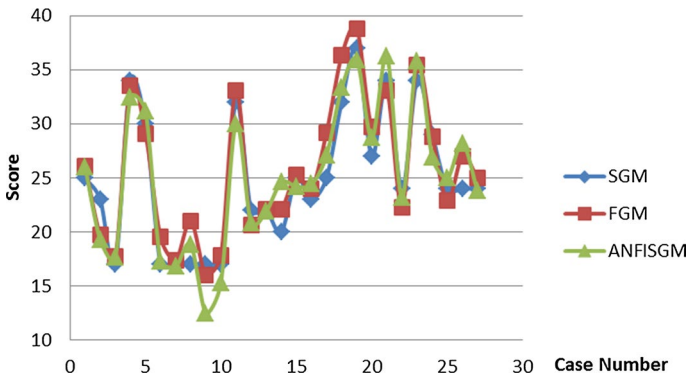


Fig.12 Graphical comparison of the SGM, FGM, and ANFISGM scores for each case

transition regions in FGM correlation surfaces (Mert & Yılmaz, 2009) which indicates that despite the parameter value changes, it continues to assign the same value in these regions. Alternatively, the correlation surface results point to the sensitivity of ANFISGM to parameter changes which allows assigning a more accurate value that responds to the house properties.

In terms of analysis rates, the 300 rules of Fuzzy Inference System (FIS), which require expert knowledge, could be established by the authors in 4 days. These will be repeated at any model change. Generating the training dataset in Adaptive-Neuro-Fuzzy-Inference-System (ANFIS) and training the model at 10–5 sensitivity for 10,000 iterations takes about 2 h on a computer. On the other hand, traditional method directly assigns the score from a look-up table.

6 Conclusions

In residential real estate, the quality of property location (QoPL) is the major factor to estimate the value due to the grade within neighborhood. This paper investigates an Adaptive-Neuro-Fuzzy-Inference-System Grading Model (ANFISGM) for an accurate and practical grading method to estimate the value of residential real estate considering the quality of property location within the neighborhood and compares it with SGM and FGM.

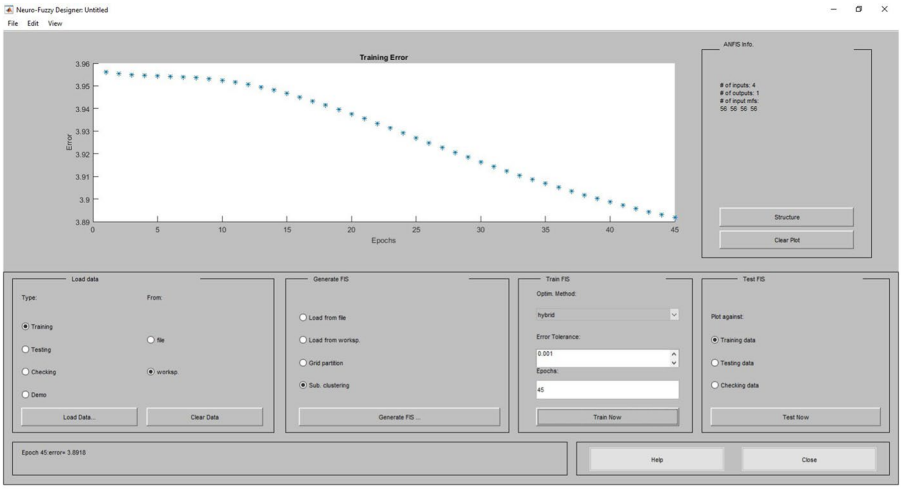
According to the findings, when the correlation surfaces are examined in terms of sensitivity, sharp variations near boundary values are observed in SGM Model, since the grading value is constant through a wide range. Less but still existing flat areas are also observed in FGM relation surfaces, ANFISGM provides more realistic results in correlation surfaces since it takes the slightest changes into account. Misevaluation of the SGM has reached up to 4.2 units in the QoPL scores. Since ANFISGM consider each variation through the parameters, they could assign appropriate values for each input. Thus, the applications of ANFISGM deliver us more accurate value assignments for the situations.

In terms of analyzing rates, SGM is directly looked up from the tables. The mentioned FGM Rule Base had been constructed within several days employing expert experiences which should be reconsidered in a model change. The trained ANFISGM model is created from the training data for 10^{-5} error tolerance and 10.000 iterations in several hours. Results indicate that FGM model is not practical for adaptation to new situations because of intuition and experience demands and expressing these demands in terms of linguistic rules. On the other hand, quantitative training data makes ANFISGM handier.

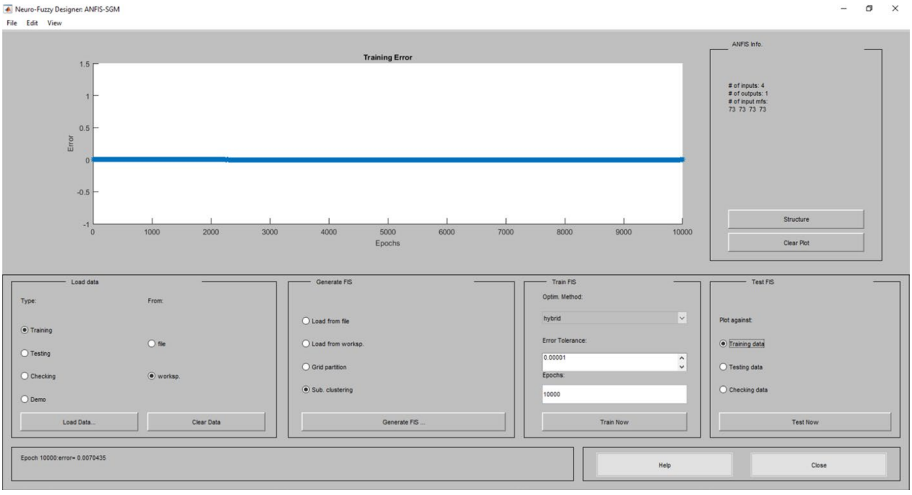
The proposed ANFISGM method provides a meaningful contribution to the real estate experts' applications in serving more precise, equitable, and rapid appraisals that is potentially beneficial for real estate customers, owners, and markets. ANFIS-based grading model for estimating the value which determines the quality of property location within the neighborhood is introduced for the first time and it is worthwhile to reference in the instant and accurate assessment of real estates. In line with the results obtained, ANFISGM is expected to contribute to the appraisal process within a minimum of detail and a limited period, especially for accurate tax purposes.

Appendix

See Figures 13, 14, 15 and 16



(a) For 45 iterations



(b) For 10.000 iterations

Fig. 13 Training stages of ANFISGM. Training error reduces in each iteration

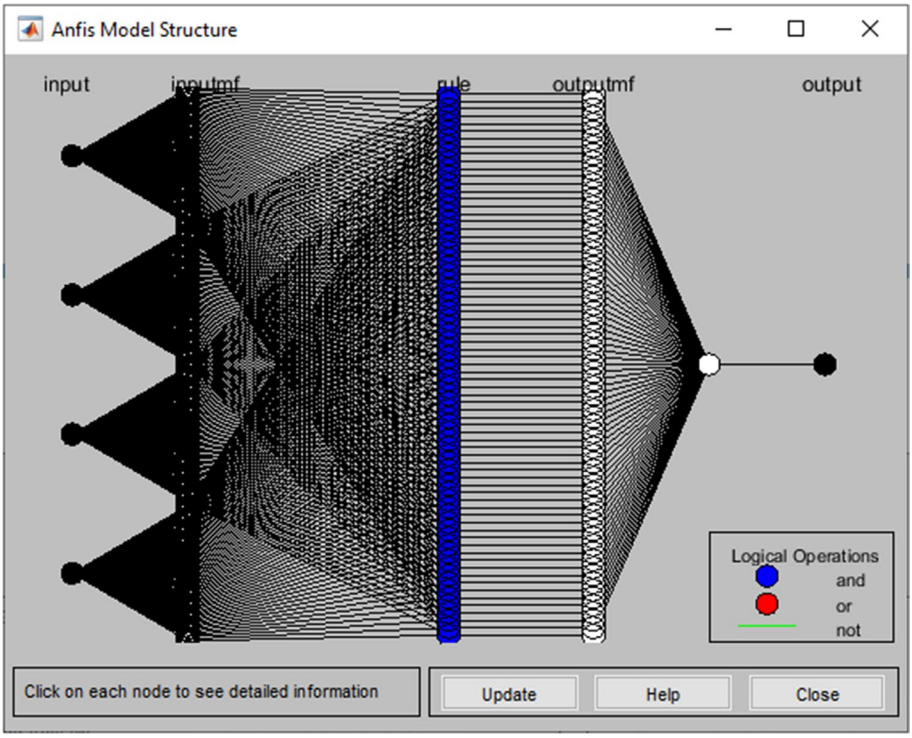


Fig. 14 Trained ANFISGM structure

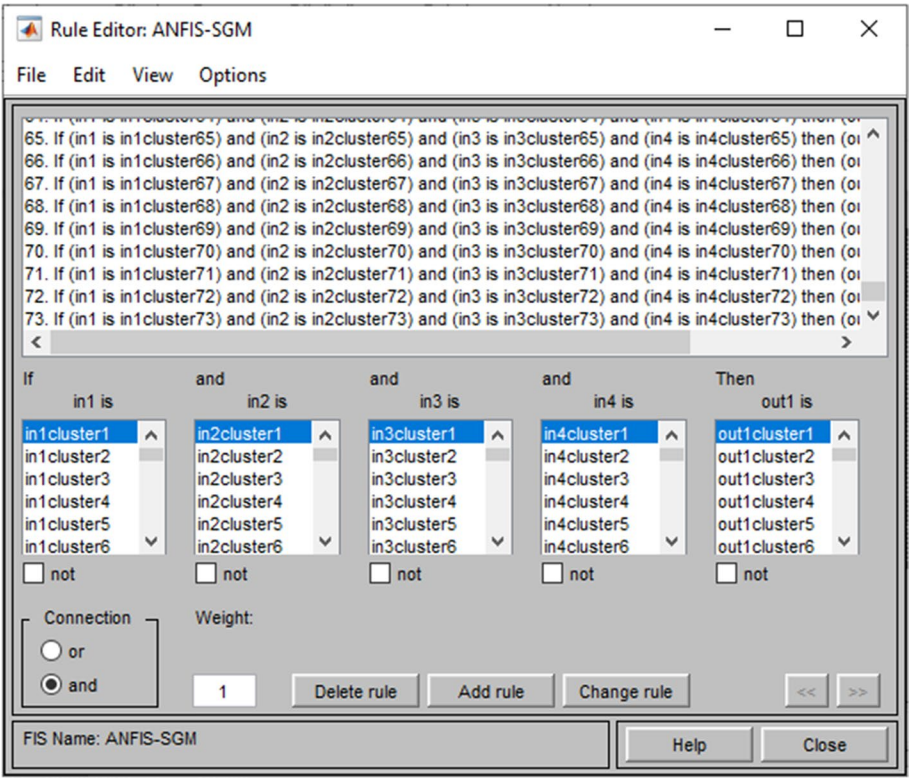


Fig. 15 ANFISGM rule table

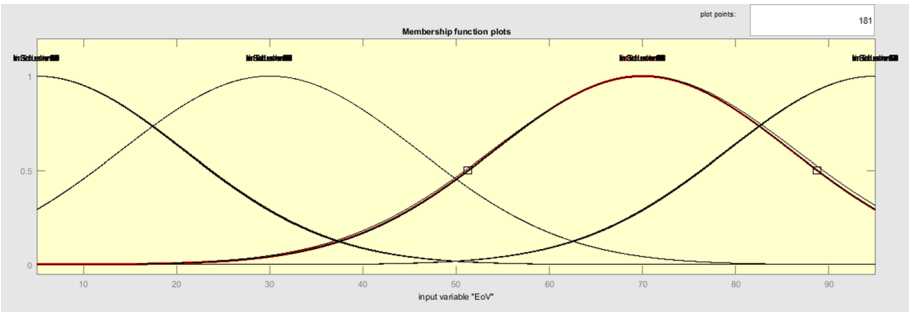


Fig. 16 MFs of the variable EoV

References

Ahn, J. J., Byun, H. W., Oh, K. J., & Kim, T. Y. (2012). Using ridge regression with genetic algorithm to enhance real estate appraisal forecasting. *Expert Systems with Applications, 39*(9), 8369–8379. https://doi.org/10.1016/j.eswa.2012.01.183

Brondino, N. C. M., & Silva, A. N. R. (1999). Combining artificial neural networks and GIS for land valuation purposes. *Proceedings of the 6th International Conference Computers in Urban Planning and Urban Management,* Franco Angeli.

Chiarazzo, V., Caggiani, L., Marinelli, M., & Ottomanelli, M. (2014). A neural network-based model for real estate price estimation considering environmental quality of property location. *Transportation Research Procedia, 3*, 810–817. https://doi.org/10.1016/j.trpro.2014.10.067

Dere, M., & Filiz, İH. (2019). Experimental investigation of the effects of workpiece diameter and overhang length on the surface roughness in turning of free machining steel and modelling of surface roughness by using ANFIS. *Journal of the Faculty of Engineering and Architecture of Gazi University, 34*(2), 675–686.

Din, A., Hoesli, M., & Bender, A. (2001). Environmental variables and real estate prices. *Urban Studies, 38*(11), 1989–2000. https://doi.org/10.1080/00420980120080899

Gavrilović, S., Denić, N., Petković, D., Živić V, N., & Vujičić, S. (2018). Statistical evaluation of mathematics lecture performances by soft computing approach. *Computer Applications in Engineering Education, 26*, 902–905. https://doi.org/10.1002/cae.21931

Guan, J., Zurada, J., & Levitan, A. (2008). An adaptive neuro-fuzzy inference system based approach to real estate property assessment. *Journal of Real Estate Research, 30*(4), 395–422. https://doi.org/10.1080/10835547.2008.12091225

Jagtap, P., & Pillai, G. N. (2014). Comparison of extreme-ANFIS and ANFIS networks for regression problems. *In: IEEE International Advance Computing Conference (IACC),* 1190–1194. https://doi.org/10.1109/IAdCC.2014.6779496

Kauko, T. (2003). On current neural network applications involving spatial modelling of property prices. *Journal of Housing and the Built Environment, 18*, 159–181. https://doi.org/10.1023/A:1023977111302

Kontrimas, V., & Verikas, A. (2011). The mass appraisal of the real estate by computational intelligence. *Applied Soft Computing, 11*(1), 443–448. https://doi.org/10.1016/j.asoc.2009.12.003

Kosko, B. (1992). *Neural networks and fuzzy systems: A dynamical approach to machine intelligence*. Prentice Hall Inc.

Kovacs, B. B., Pedersen, A. E., & Weatherall, C. D. (2021). Residential mobility and persistent neighborhood deprivation. *Journal of Housing Economics*. https://doi.org/10.1016/j.jhe.2021.101771(early access)

Kummerow, M., & Lun, J. C. (2005). Information and communication technology in the real estate industry: Productivity, industry structure and market efficiency. *Telecommunications Policy, 29*(2–3), 173–190. https://doi.org/10.1016/j.telpol.2004.12.003

Kusan, H., Aytekin, O., & Özdemir, I. (2010). The use of fuzzy logic in predicting house selling price. *Expert Systems with Applications, 37*(3), 1808–1813. https://doi.org/10.1016/j.eswa.2009.07.031

Kuzman, B., Petković, B., Nebojsa, D., Petković, D., Cirkovic, B., Stojanovic, J., & Milić, M. (2021). Estimation of optimal fertilizers for optimal crop yield by adaptive neuro fuzzy logic. *Rhizosphere*. https://doi.org/10.1016/j.rhisph.2021.100358

Lewis, O. M., Ware, J. A., & Jenkins, D. (1997). A novel neural network technique for the valuation of residential property. *Neural Computing & Applications, 5*, 224–229. https://doi.org/10.1007/BF01424227

Lin, C. T. (1996). *Neural fuzzy systems: a neuro-fuzzy synergism to intelligent systems*. Prentice Hall PTR.

Liu, X., & Chen, B. (2011). Based on gray comprehensive evaluation method of real estate. *Systems Engineering Procedia, 1*, 189–194. https://doi.org/10.1016/j.sepro.2011.08.031

Liu, X. S., Deng, Z., & Wang, T. (2011). Real estate appraisal system based on GIS and BP neural network. *Transactions of Nonferrous Metals Society of China, 21*(3), 626–630. https://doi.org/10.1016/S1003-6326(12)61652-5

Lokshina, I.V., Hammerslag, M. D., & Insinga, R.C. (2003). *Applications of artificial intelligence methods for real estate valuation and decision support.* Hawaii International Conference on Business

Mert, Z.G., & Mert, E. (2000, August 29-September 1). *Land-use evaluation of Kocaeli University Main Campus Area*. 40th Congress of European Regional Science Association

Mert, Z. G., & Yılmaz, S. (2009). Fuzzy modelling approach based on quality of property location for grading neighborhood level of family housing units. *Expert Systems with Applications, 36*(2), 3603–3613. https://doi.org/10.1016/j.eswa.2008.02.023

Mesbahi, A. H., Semnani, D., & Khorasani, S. N. (2012). Performance prediction of a specific wear rate in epoxy nanocomposites with various composition content of polytetrafluoroethylen (PTFE), graphite, short carbon fibers (CF) and nano-TiO2 using adaptive neuro-fuzzy inference system (ANFIS). *Composites: Part B-Engineering, 43*, 549–558. https://doi.org/10.1016/j.compositesb.2011.11.026

Milić, M., Petković, B., Selmi, A., Petković, D., Jermsittiparsert, K., Radivojević, A., Milovancevic, M., Khan, A., Vidosavljević, S., Denić N, T., & Kuzman, B. (2021). Computational evaluation of microalgae biomass conversion to biodiesel. *Biomass Conversion and Biorefinery*. https://doi.org/10.1007/s13399-021-01314-2

Milovančevića, M., Nikolića, V., Petković, D., Vracarc, L., Vege, E., Tomica, N., & Jović, S. (2018). Vibration analyzing in horizontal pumping aggregate by soft computing. *Measurement, 125*, 454–462. https://doi.org/10.1016/j.measurement.2018.04.100

Nguyen, H. T., Prasad, N. R, & Walker, C. L. (2003). *A first course in fuzzy and neural control.* Chapman&Hall/CRC,.

NikolicPetkovićLazovMilovančević, V. D. L. M. (2016). Selection of the most influential factors on the water-jet assisted underwater laser process by adaptive neuro-fuzzy technique. *Infrared Physics & Technology, 77*, 45–50. https://doi.org/10.1016/j.infrared.2016.05.021

Nishi, H., Asami, Y., & Shimizu, C. (2021). The illusion of a hedonic price function: Nonparametric interpretable segmentation for hedonic inference. *Journal of Housing Economics*. https://doi.org/10.1016/j.jhe.2021.101764

Petković, D., Ćojbašič, Ž., Nikolić, V., Shamshirband, S., Kiah, M., L., M., Anuar, N., B., & Wahab, A., W., A. (2014). Adaptive neuro-fuzzy maximal power extraction of wind turbine with continuously variable transmission. *Energy*, 64, 868-874

Petković, D., Pavlovic´, N., T., & Cojbašic, Z. (2016). Wind farm efficiency by adaptive neuro-fuzzy strategy. Electrical Power and Energy Systems, 81, 215–221

Petković, D., Barjaktarovic, M., Milosevic, S., Denic, N., Spasic, B., Stojanovic, J., & Milovančević, M. (2021). Neuro fuzzy estimation of the most influential parameters for Kusum biodiesel performance. *Energy*. https://doi.org/10.1016/j.energy.2021.120621

Petković, D., Ćojbašič, Ž, & Nikolić, V. (2013). Adaptive neuro-fuzzy approach for wind turbine power coefficient estimation. *Renewable and Sustainable Energy Reviews, 28*, 191–195. https://doi.org/10.1016/j.rser.2013.07.049

Petković, D., Gocic, M., Trajkovic, S., Milovančević, M., & Šević, D. (2017). Precipitation concentration index management by adaptive neuro-fuzzy methodology. *Climatic Change, 141*, 655–669. https://doi.org/10.1007/s10584-017-1907-2

Petković, D., Jovic, S., Anicic, O., Nedic, B., & Petković, B. (2016). Analyzing of flexible gripper by computational intelligence approach. *Mechatronics, 40*, 1–16. https://doi.org/10.1016/j.mechatronics.2016.09.001

Petković, D., Petković, B., & Kuzman, B. (2020). Appraisal of information system for evaluation of kinetic parameters of biomass oxidation. *Biomass Conversion and Biorefinery*. https://doi.org/10.1007/s13399-020-01014-3

Rossini, P. (1998). *Improving the results of artificial neural network models for residential valuation.* Fourth Annual Pacific-Rim Real Estate Society Conference, Perth

Shamshirband, S., Malvandi, A., & Karimipour, A. (2015). Performance investigation of micro- and nano-sized particle erosion in a 90° elbow using an ANFIS model. *Powder Technology, 284*, 336–343. https://doi.org/10.1016/j.powtec.2015.06.073

Stojanovic, J., Petković, D., Alarifi, I., M., Cao, Y., Denic, N., Ilic, J., Assilzadeh, H., Resic, S., Petković, B., Khan, A., & Milickovic, M. (2021). Application of distance learning in mathematics through adaptive neuro-fuzzy learning method. *Computers and Electrical Engineering*, 93. https://doi.org/10.1016/j.compeleceng.2021.107270

Takagi, T., & Sugeno, M. (1985). Fuzzy identification of systems and its applications to modelling and control. *IEEE Transactions on Systems, Man, and Cybernetics, 15*(1), 116–132. https://doi.org/10.1109/TSMC.1985.6313399

Walia, N., Singh, H., & Sharma, A. (2015). ANFIS: Adaptive neuro-fuzzy inference system- a survey. *International Journal of Computer Applications, 123*(13), 32–38. https://doi.org/10.5120/ijca2015905635

Xu, Y., & Zhang, X. (2017). The residential resettlement in suburbs of Chinese cities: A case study of changsha. *Cities, 69*, 46–55. https://doi.org/10.1016/j.cities.2017.06.002

Yalpir, Ş, & Özkan, G. (2011). Fuzzy logic methodology and multiple regressions for residential real-estates valuation in urban areas. *Scientific Research and Essays, 6*(12), 2431–2436.

Yılmaz, S., Arici, A. A., & Feyzullahoglu, E. (2011). Surface roughness prediction in machining of cast polyamide using neural network. *Neural Computing & Applications, 20*, 1249–1254. https://doi.org/10.1007/s00521-011-0557-y

Zadeh, L. A. (1965). Fuzzy sets. *Information, and Control, 8*(3), 338–353. https://doi.org/10.1016/S0019-9958(65)90241-X

Zhao, H., & Wang, X. (2010). Study on real estate project investment decision-making based on principal component analysis and adaptive network-based fuzzy inference system. *In: International Conference on Biomedical Engineering and Computer Science*, pp. 1–4. https://doi.org/10.1109/ICBECS.2010.5462375

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Springer Nature or its licensor (e.g. a society or other partner) holds exclusive rights to this article under a publishing agreement with the author(s) or other rightsholder(s); author self-archiving of the accepted manuscript version of this article is solely governed by the terms of such publishing agreement and applicable law.

Authors and Affiliations

Serhat Yilmaz[1] · Zeynep Gamze Mert[2]

Zeynep Gamze Mert
gamzemert@gtu.edu.tr

[1] Department of Electronics and Telecommunication, Faculty of Engineering, Kocaeli University, 41380 İzmit, , Kocaeli, Turkey

[2] Department of City and Regional Planning, Faculty of Architecture, Gebze Technical University, 41400 Çayırova, Kocaeli, Turkey