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# PREDICTION OF FIRST CARE DURATION WITH ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM IN AN EMERGENCY DEPARTMENT

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The primary mission of an emergency department (ED) is to treat the patients, to find out their diagnosis and to discharge them from system as possible as it can. The patients generally want to be informed the process to be applied and it can be done only with forming a systematic structure in ED. If the duration of the treatments is well-defined, the starting and finishing times of the processes can be known. Also, physicians try to reach the expected durations and they do not loose any unnecessary time. However, the patients who have the same complaints can react differently to the same treatments, and the procedure of the treatments varies from one patient to another, so it is not an easy problem to determine the durations. In this case Adaptive Neuro-Fuzzy Inference System (ANFIS) is used to determine the first care duration, which is the most important phase in an ED. Four effective factors are considered and used as inputs. MATLAB 7.0 fuzzy toolbox is used for the learning procedure. The results are compared with the original data. The results have shown that the predicted and the real values have a high correlation.

**Keywords:** ANFIS, Emergency Department, first care duration

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## 1. INTRODUCTION

Artificial intelligent approaches like fuzzy logic and neural networks have been successfully applied to various fields in recent years and adaptive neuro-fuzzy inference system (ANFIS) is one of the most common techniques that have been used. Some recent literature survey is given in following paragraphs to hold an opinion about the studied areas.

Kwok et. al. (2004) used a non-linear ANFIS model to describe the relationship between the respiratory index and the shunt. The estimated shunts from these models were then used to calculate the fractional inspired oxygen needed to attain the target arterial oxygen level of the patient. Kakar et. al. (2005) used ANFIS for prediction of respiratory motion in breast cancer patients. Übeyli and Güler (2005) presented an adaptive neuro-fuzzy inference system for detection of internal carotid artery stenosis and occlusion. Kazeminezhad et. al. (2005) developed two ANFIS models to predict wave height and period. Gulbag and Temurtas (2006) proposed an ANFIS for quantitative identification of individual gas concentrations (trichloroethylene and acetone) in their gas mixtures. Zaheeruddin and Garima (2006) proposed a neuro-fuzzy model to predict the effects of noise pollution on human work efficiency as a function of noise level, type of task, and exposure time. Daoming and Jie (2006) proposed a method of using ANFIS for the modeling and predicting of high pressure cleaning process.

Wang and Chen (2007) presented a new approach to establish the perception of the product image and the product design by applying ANFIS. Mon (2007) developed a two- stage fuzzy algorithm and used it as the airbag deployment algorithm for identifying the vehicle impact severity. Then, the adaptive-network-based fuzzy inference system is used to train the suitable fuzzy membership functions and fuzzy rules based on crash data for improving the performance of the algorithm. In Das and Kishor's study (2007), a modeling technique based on fuzzy system is used to predict the heat transfer coefficient in pool boiling of distilled water.

Sheu (2008) presented a hybrid neuro-fuzzy approach which integrates Fuzzy-multi-criteria decision-making, the technique for ordering preference by similarity to an ideal solution (TOPSIS), and ANFIS techniques to develop a decision support system used for analyzing and determining global logistics operational modes in the global supply chain environment. Wang and Chen (2008) concerned with the quality of rush order decisions to arrange the capacity reservation mechanism. A neuro-fuzzy model based on ANFIS and KERNEL Systems was established. Uros et. al. (2008) used a trained ANFIS algorithm to predict the flank wear of the cutter during the cutting of steel workpieces. Ho et. al. (2008) used an adaptive network-based fuzzy inference system with the genetic learning algorithm to predict the workpiece surface roughness for the end milling process. Hosseini and Etemadi (2008) proposed a control scheme based on an artificial neuro-fuzzy inference system to optimize and update control gains in real-time according to load variations. Çaydaş et. al. (2008) presented the use of the adaptive neuro-fuzzy inference system method based on the full factorial experimentation for predicting surface roughness and white layer thickness in the A wire electrical discharge machined process. Wang and Elhag (2008) developed an ANFIS for bridge risk assessment. Polat and Güneş (2008) focused on diabetes disease using principal component analysis and ANFIS. The aim of this study was to improve the diagnostic accuracy of diabetes disease combining PCA and ANFIS.

Sengur (2008) investigated the use of linear discriminant analysis and adaptive neuro-fuzzy inference system to determine the normal and abnormal heart valves from the Doppler heart sounds. Also, Sengur (2008) discussed the effect of the wavelet domain features and ANFIS classifier on the texture classification problem. The main aim of the study is combining the color and texture information to improve the classification of the texture images. Baylar et. al. (2008) obtained ANFIS for predicting air entrainment rate and aeration efficiency of weirs. Varol et. al. (2008) used ANFIS to predict temperature and flow field due to buoyancy-induced heat transfer. Khajeh et. al. (2008) modeled solubility of carbon dioxide in poly (vinyl acetate), poly (2,6-dimethyl-1,4-phenylene ether), polypropylene and high-density polyethylene, poly (butylene succinate), poly (butylene succinate-co-adipate) and polystyrene by ANFIS under wide range of pressure and temperature. Ying and Pan (2008) applied ANFIS model to forecast the regional electricity loads in Taiwan and demonstrate the forecasting performance of this model.

In this paper, ANFIS model is applied to an emergency department to predict the first care durations of the patients. The main aim is to assist the workers, patients and their parents. The paper is organized as follows. In Section 2, the structure of ANFIS is explained. In Section 3, the proposed ANFIS model and outputs for emergency departments are discussed. Finally, in Section 4, conclusion is presented.

## 2. ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS)

Adaptive Neuro-Fuzzy Inference System first proposed by Jang (1992). ANFIS constructs input-output form with fuzzy if then rules and provides an optimization scheme to find the parameters in the fuzzy system that fit the data best. Input and output data is separated to parts according to their distributions, and linear solutions are produced with ANFIS. Membership functions are used, as the individuals are members of the sets in a certain extent between 0 and 1. $\mu ij$ shows the membership of the ith input to the jth fuzzy set.

The rule based on ANFIS contains fuzzy if-then rules of Sugeno type (Jang, 1992). For a first order n-rule Sugeno fuzzy inference system can be stated as:

Rule1: If $x=A_1$ and $y=B_1$ then $f_1(x,y)=p_1x+q_1y+r_1$

Rule 2: If $x=A_2$ and $y=B_2$ then $f_2(x,y)=p_2x+q_2y+r_2$

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Rule n: If $x=A_n$ and $y=B_n$ then $f_n(x,y)=p_nx+q_ny+r_n$

x and y are the inputs of ANFIS, A and B are the fuzzy sets $f_i$ (x, y) is a first order polynomial and represents the outputs of the first order Sugeno fuzzy inference system. The structure of ANFIS is given in Figure 1 and the layers' descriptions are presented in the following paragraphs (Jang, 1993; Gün, 2007; Kiris, 2008).

**Layer 1:** Every node in this layer is a square node with a node function as Eq.1 (membership function). Parameters of membership functions are referred to as premise or antecedent parameters. Membership functions such as bell-shaped, trapezoid, gaussian, triangular can be used. Gaussian function is given in Eq.1.

$$f(x,\sigma,c)=\mu_{ij}=e^{-\frac{(x_j-c_{ij})^2}{2\sigma_{ij}^2}} \quad \ldots \quad (1)$$

**Layer 2:** Every node in this layer is a circle node that multiplies the incoming signals as in Eq.2. Each node's output represents the firing strength of a fuzzy rule.

$$\mu_i=\prod_{j=1}^{n}\mu_{ij}, \quad \ldots \quad (2)$$

$x_j$: jth input

$c_{ij}$: mean

$\sigma_{ij}$: Standard deviation

**Layer 3:** Every node in this layer is a circle node that calculates the ratio of the one firing strength to the sum of all rules' firing strengths as in Eq.3. The output of this layer is called normalized firing strength.

$$\overline{\mu}_i=\frac{\mu_i}{\sum_{i=1}^{k}\mu_i} \quad \ldots \quad (3)$$

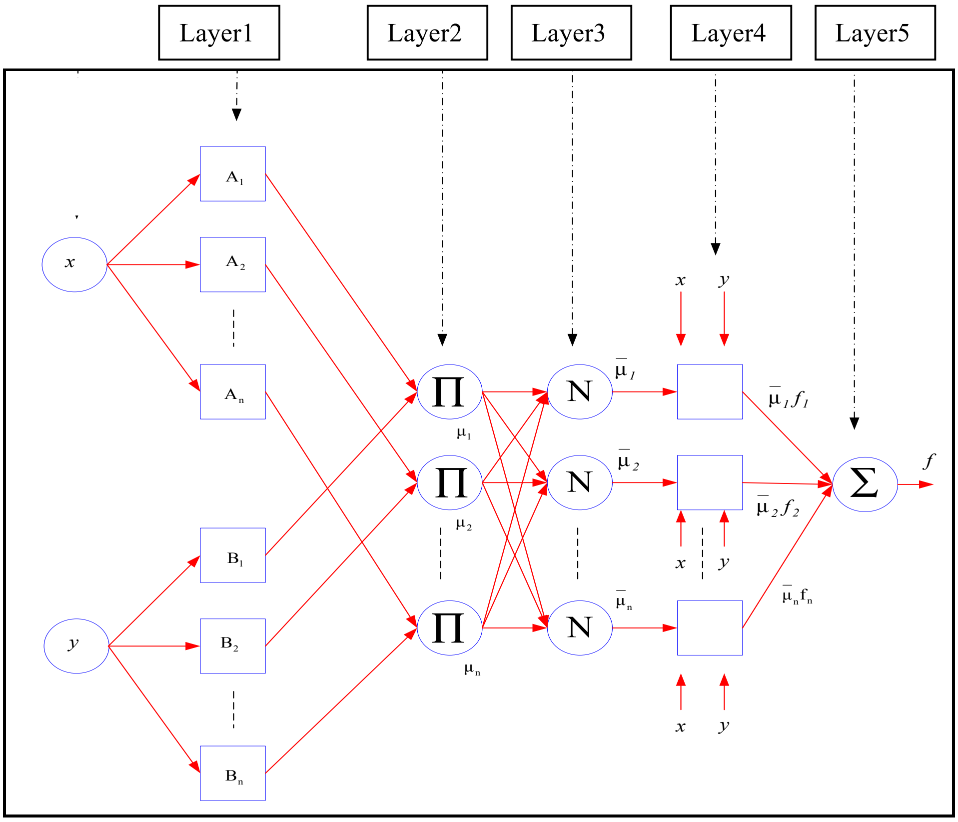



**Figure 1. ANFIS structure**

**Layer 4:** Every node in this layer is a square node with a node function as Eq.4 (linear combination of input variables). Parameters ( $p_n$, $q_n$ and $r_n$) in this layer are referred to as consequent parameters.

$$\bar{\mu}_i f_i = \bar{\mu}_i (p_n x + q_n y + r_n) \quad \ldots \quad (4)$$

**Layer 5:** The single node in this layer is a circle node that computes the overall output with the summation of all incoming signals. Overall output is given in Eq.5.

$$f = \sum_i \bar{\mu}_i f_i = \frac{\sum_i \mu_i f_i}{\sum_i \mu_i} \quad \ldots \quad (5)$$

For premise parameters that define membership functions, ANFIS employs gradient descent to fine-tune them. For consequent parameters that define the coefficients of each output equations, ANFIS uses the least-squares method to identify them. This approach is thus called hybrid learning method since it combines gradient descent and the least-squares method (Jang, 1992).

## 3. MODELING OF AN EMERGENCY DEPARTMENT USING ANFIS

In this section an emergency department (ED) of a university hospital is analyzed. The critical factors are defined based on the process and the ANFIS model is established.

### 3.1. Structure of the system

The most important aim of the system is to reach standardization by serving patients accurately, quickly and in high quality. Standardization in an ED is not an easy work, however becoming closer to the expected values is needed for the efficient process. An ED of University Hospital is investigated to achieve an opinion about the duration of treatments. 250 forms which are used to obtain the information of first treatment durations are filled in two periods by the doctors. The category, age, general situation, starting time and finished time of the processes, consultation, tests and diagnosis data are collected to learn the factors that effect the duration.

One-month observation is conducted to compare the management of patients by both emergency residents and rotation residents in a university emergency department. In the ED, the most common diagnosis was non-specific abdominal pain. There were not any differences, in patient's descriptions of his complaints, the numbers of tests and consultations, hospitalization, elapsed time to make a diagnosis and results between two residents groups. Therefore features of the doctors in the system are considered same and are not taken as a factor in the system.

In the existing environment, the patients are classified as triage category. Triage is the definition of the priority of the patient based on injury, compliant and diagnosis. While some of the patients have to be cared immediately, some of them have to wait (Noji and Kelen, 2004). The definitions of the triage groups are as follows:

Triage 1: Vital emergency
Triage 2: Organ and/or extremity (arm, leg) disability
Triage 3: The others

These categories are extended according to the thought of the first aid of the patient and specified in six groups as follows with the expert doctors for detailed priority definition (Kiris, 2008):

Category 1: Airway problems and critical situations
Category 2: Respiratory problems
Category 3: Circulation (cardiovascular) problems
Category 4: Neurological problems
Category 5: Extremity (single finger and skin injuries etc.) and high risk mechanism traumas expect the upper categories.
Category 6: Most of the Triage 3 patients and minor extremity complaints.

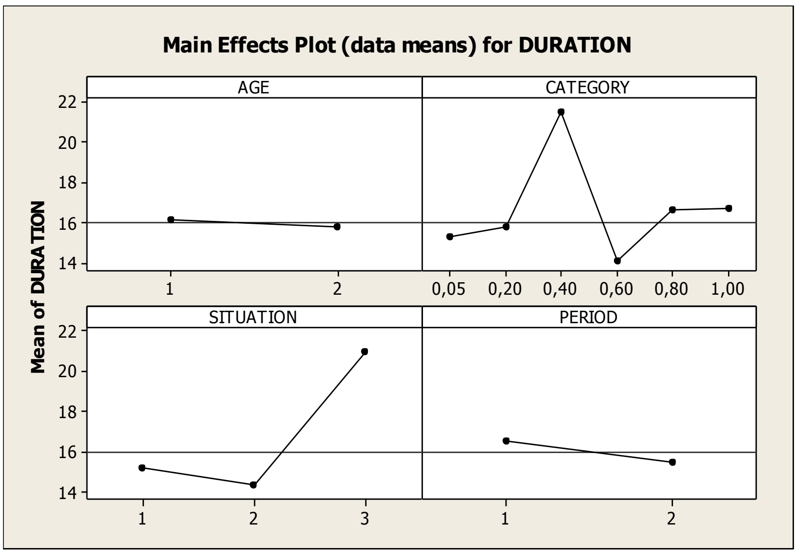
After defining the groups of the priority, scores are given to these categories together with the expert doctor. The experts expected that the gap of the categories has same degree, only the last category has a significant difference from the others. Therefore the scores of the categories are given in Table 1.

**Table 1. Scores of categories**

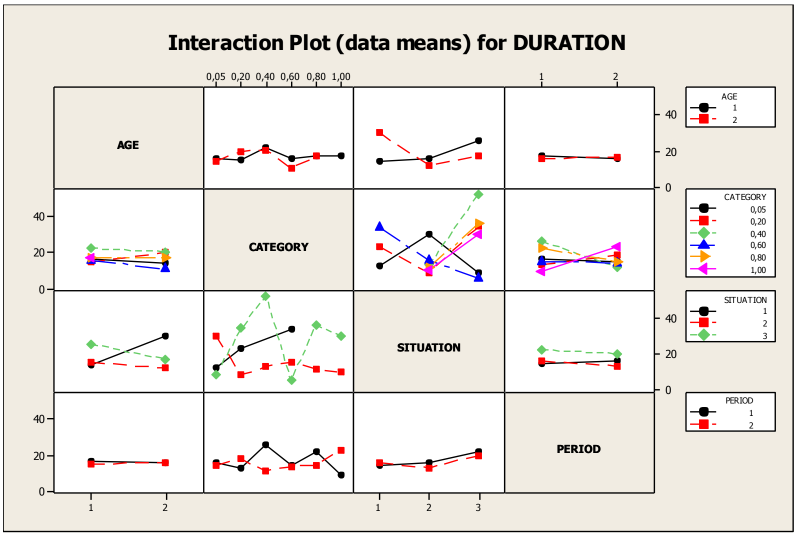
| Category | A | B | C | D | E | F |
|---|---|---|---|---|---|---|
| Score | 1.00 | 0.80 | 0.60 | 0.40 | 0.20 | 0.05 |

The ED of a University Hospital in Turkey has been analyzed and opinions of an expert group are received. Then category, age, situation and period are supposed to be the probable affected factors for first care durations. The category that shows the priority of the patients is classified into six groups as told in section 1. Age is divided into two groups as in World Health Organization (WHO) where people of 65 years old and more are classified as the first step of the old age. People that are 64 years old and less are in the first group. The situation is divided into three groups as good (1), moderate (2) and bad (3). In addition, taking the seasonal differences into consideration, the period of 1st May-31st October is defined as first and the period of 1st November-30th April is defined as the second.

Main factor effects and interaction graphics are prepared with MINITAB 14 package programme. Main factor effects and interaction graphics are given in Figure 2 respectively.




(a)




(b)

**Figure 2. (a) Main effects plot for duration (b) Interaction plot for duration**

From Figure 2, ANOVA results show that situation (p=0.016), interaction of category and period (p=0.078), interaction of age and situation (p=0.001) have influences on the first care duration.

### 3.2. ANFIS model for prediction of first care duration

The effective four factors that were determined in Section 3.1 are included as inputs into the model with output of first care duration. Next, the clusters have to be determined. To decrease the variations that will be analyzed, design of experiments is used to form clusters for the membership functions of the factors. Levels of the factors are given in Table 2.

**Table 2. Factor levels**

| Level | Category | Age | Situation | Period | Repetition |
|---|---|---|---|---|---|
| Low | 2 | 2 | 3 | 2 | 50 |
| High | 6 | 4 | 6 | 4 | 200 |

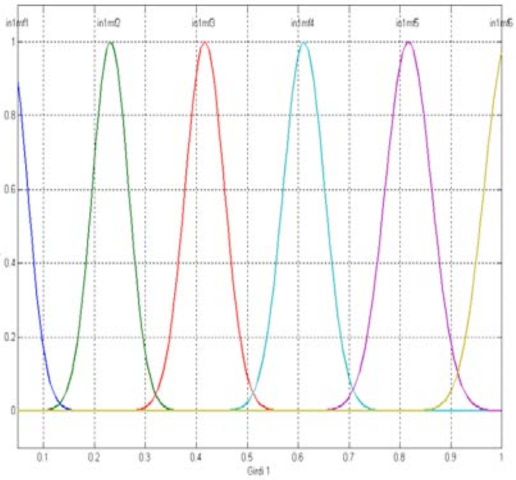
Two levels are defined as low and high for the factors as seen from Table 2. Various conditions are evaluated by ¼ Fractional Factorial Design of Experiment with Minitab 14 and the model with proper results is selected. Variations of factor levels according to correlation, standard deviation and number of rule are given in Table 3.

**Table 3. ¼ Fractional Factorial Design of Experiment results**

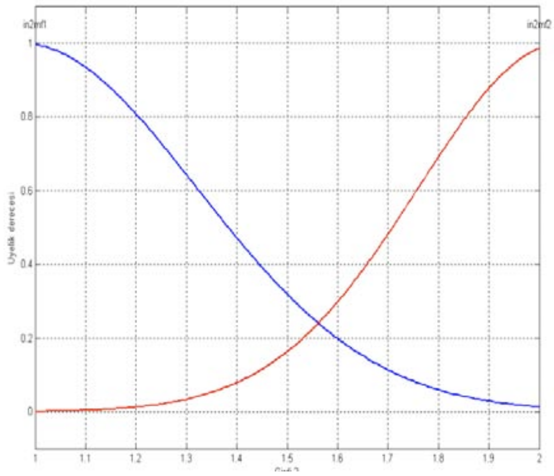
| No | Category | Age | Situation | Period | Repetition | Std.Dev. | Correlation | Number of rule |
|---|---|---|---|---|---|---|---|---|
| 1 | 6 | 2 | 3 | 2 | 50 | 6.38366 | 0.8652 | 72 |
| 2 | 2 | 4 | 3 | 2 | 200 | 6.84866 | 0.8429 | 48 |
| 3 | 6 | 2 | 6 | 2 | 200 | 6.38366 | 0.8652 | 144 |
| 4 | 6 | 4 | 6 | 4 | 200 | 6.38366 | 0.8652 | 576 |
| 5 | 2 | 2 | 6 | 4 | 50 | 6.86088 | 0.8423 | 96 |
| 6 | 2 | 4 | 6 | 2 | 50 | 6.86087 | 0.8423 | 96 |
| 7 | 6 | 4 | 3 | 4 | 50 | 6.38366 | 0.8652 | 288 |
| 8 | 2 | 2 | 3 | 4 | 200 | 6.84865 | 0.8429 | 48 |

As it was told before, becoming closer to expected time for first care duration is an important step in an ED. Therefore first experiment results are acceptable by the experts in ED. The correlation between real and system values of first care duration is 86% and it can be said that there is a high correlation between them. In this case high category level with 6 clusters, low age level with 2 clusters, low situation with 3 clusters, low period level with 2 clusters and low repetition level with 50 iteration can be determined.

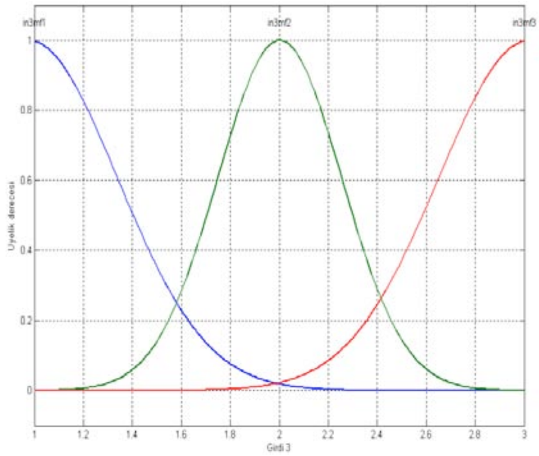
By defining the critical factors for first care duration and the clusters of them, the inputs of ANFIS model are appeared. The membership functions of factors with defined clusters are shown in Figure 3.



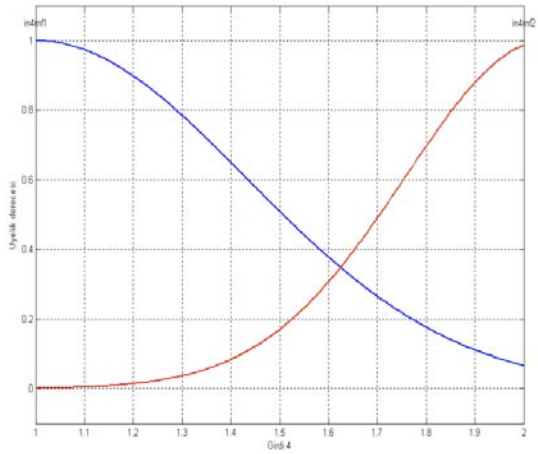
a.Membership function for category



b.Membership function for age



c.Membership function for g.appearance



d.Membership function for period

**Figure 3. Membership functions of factors**

In Figure 3, as calculated earlier, category membership function is divided into three clusters; age membership function is divided into two clusters; situation membership function is divided into three clusters and period membership function is divided into two clusters with the optimized parameters.

The linear and non-linear parameters are optimized in ANFIS as seen in Figure 3. The Sugeno fuzzy model is established based on these data and solved with Matlab 7.0. The ANFIS structure with 4 inputs, 1 output and 72 rules is shown in Figure 4.

Blue points show the real system outputs and red points show the estimated outputs in Figure 2. There are especially two peak points seen in real system. While dealing with this patient, the patient that has more priority can enter to the system and the same doctor has to deal with the new patient. So the process times of first care are too long in these peak points.

The equations and rules are formed with derived parameters based on ANFIS logic. In this case, first care durations can be estimated by entering input values to the model. Two of the surface graphics are also given in Figure 6 to see the trend of the durations.

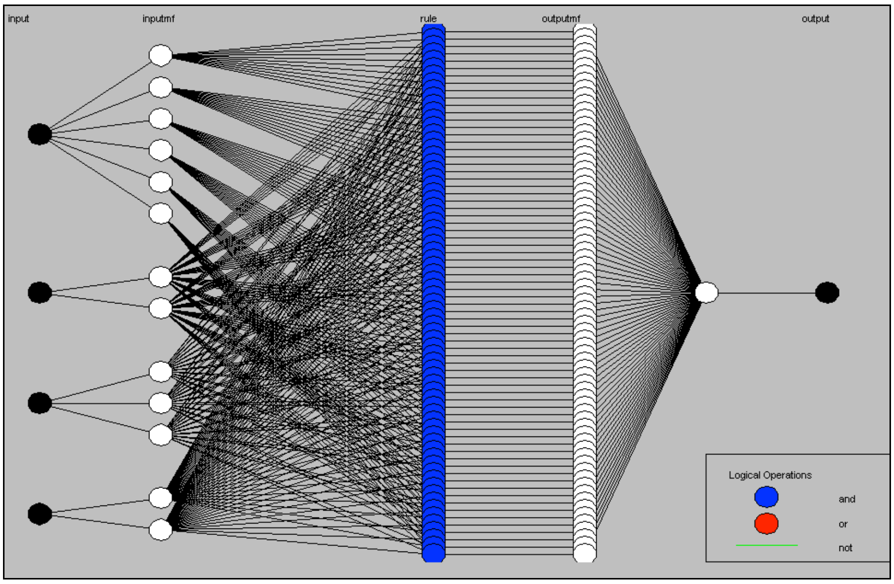



**Figure 4. ANFIS structure with 4 inputs, 1 output and 72 rules**

The graph of real and system values is shown in Figure 5.

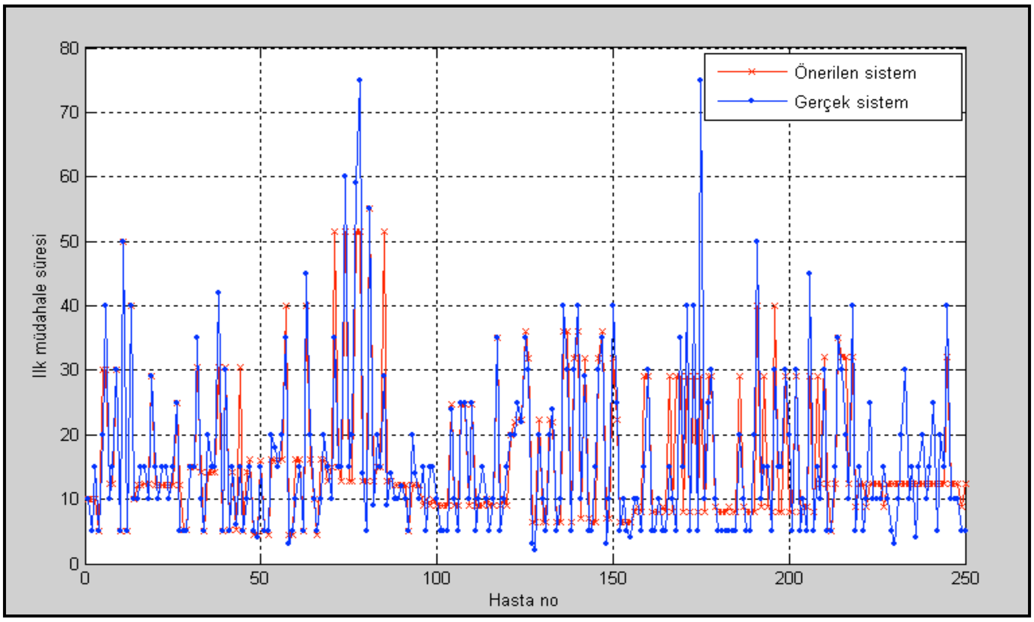
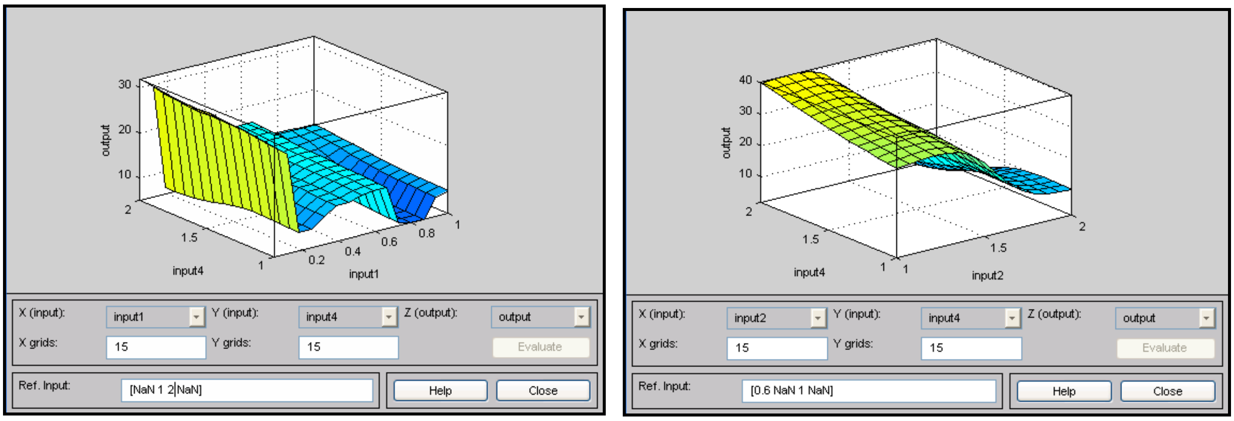



**Figure 5. Real and system values of first care duration**




(a) (b)

**Figure 6. Surface graphics based on (a) category and period (b) age and period**

For patients that are less than 65 years old and in moderate class we observed that while patients of category B are having lower durations, the durations of category A, E, D, C and F patients have higher durations respectively. Especially F category patients need more process times. Generally treatments for these patients' can be finished through this duration and patients discharge from ED.

As for the patients with circulation problems and good situation, first care durations are expected approximately 30-40 minutes for patients who are 64 or under, approximately 5-10 minutes for patients older than 64 years old. These interpretations can be expanded.

## 4. CONCLUSIONS AND FUTURE WORKS

The standardization of service systems are hard to be discussed because of human beings factors. Just like the customers of a restaurant or a hairdresser who have different requirements, each of the patients at hospitals can have different requirements in treatment.. Also these customers and patients can have same requirements but their processes may have different durations. This variation could be related to the customers and/or service givers. So even if it is not easy to predict process durations for these kinds of systems, it has a special importance. In this phase, a neuro-fuzzy system is suggested to be appropriate for prediction. ANFIS applications can be seen in various areas in literature, but this study suggests to use ANFIS to predict the first care durations in EDs for the first time. In this case it can be said that this study gives ideas about standardization and processes in EDs.

ED is an extreme field of the service systems and redundant faults can cause people's deaths. In this study ED is selected as an application area, as EDs have a different and much more important structure from other service systems. So it could be thought that if analyzed outputs of EDs found appropriate, then the system can be adapted to the other EDs and other systems easily.

In the study, the inputs of ANFIS are also determined by determining the effective factors of first care duration .After examining the collected data, correlation of real and estimated outputs are found high. Then these results were accepted by the experts and starting point of prediction for first care durations in EDs is developed. This approach can be applied to other service systems in the same way. Firstly effective factors have to be determined as inputs and results for prediction of durations have to be analyzed to see whether the real system is reflected.

When the durations of processes are predicted, they can be used to schedule the customers/patients. The information of starting times and finishing times of patients to be processed can be obtained. The customers/patients can be assigned to workers/doctors based on defined priorities, eg six classes in EDs. On the other hand the workloads of workers/doctors can be defined, and also these values can be used in assigning the customers/patients to the workers/doctors, trying to balance the workload. According to these applications undesired time loss can be minimized, workers in the system and the customers/patients can be motivated.

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