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# Classifying of the Simav Geothermal Waters with Artificial Neural Network Method

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**Keywords:** Simav Geothermal Area, Hydrogeochemistry, Artificially Neural Network (ANN), Turkey.

## ABSTRACT

Simav geothermal field is located within the Aegean Graben System in western Anatolia. Rock units in the study area are mainly the formation of Menderes Massive. The Simav geothermal waters were grouped into types, namely four; Eynal, Citgol, and Naşa geothermal water and cold water. With this study, it is aimed to introduce a method for classifying waters in the study area using some parameters such as temperature, pH, electrical conductivity and major ions by means of Artificial Neural Network (ANN) method.

According to the data obtained from wells drilled for the drinking and irrigation water purposes, ground water flow is toward the desiccated lake. Cold water analysis gave high $CO_3$+$HCO_3$, Ca, Mg ion values, and low $NH_4$, $NO_3$, Fe, $NO_2$, Al and Mn ion values. Hot water analysis gave a cation trend of Na+K>Ca>Mg and an anion trend of $HCO_3+CO_3>SO_4>Cl$.

While preparing the training data set in ANN method, for input, T (°C), EC (μS), pH, Na (mg/l), K (mg/l), Ca (mg/l), Mg (mg/l), $CO_3$ (mg/l), $HCO_3$ (mg/l), Cl (mg/l) and $SO_4$ (mg/l) values of 50 water samples from the study area were used. Four output values were used. In each output value, the known water represented by 1 and others by 0.

A test data set of 15 samples in which the T, EC, pH, Na, K, Ca, Mg, $CO_3$, $HCO_3$, Cl and $SO_4$ values are known but their group are unknown was prepared. And these input values were run in ANN model in order to see how the waters were grouped.

The advantages of artificial neural networks can be exploited to solve this problem. The most common ANN architecture is Multilayered Perceptrons, which was used in this study. For this solution, the first artificial neural network model using Extended Delta-Bar-Delta (EDBD) algorithm has been successfully implemented.

Mean Square Error result of these model obtained by EDBD algorithm is $1.3x10^{-3}$. These results show that the group in which the waters in the study area fall can be determined with high accuracy by using some parameters of water the ion content of water.

## 1. INTRODUCTION

In western Anatolia, there are several graben systems related principally to the active tectonism, in which volcanic activities have been observed. These increase the geothermal potential of Turkey. There are 170 geothermal fields in Turkey, having temperature above 40 °C. One of these important geothermal fields is the Simav geothermal field located in the Simav graben. The Simav geothermal waters were grouped into four; Eynal, Citgol, and Naşa geothermal water and cold water (Figure 1).

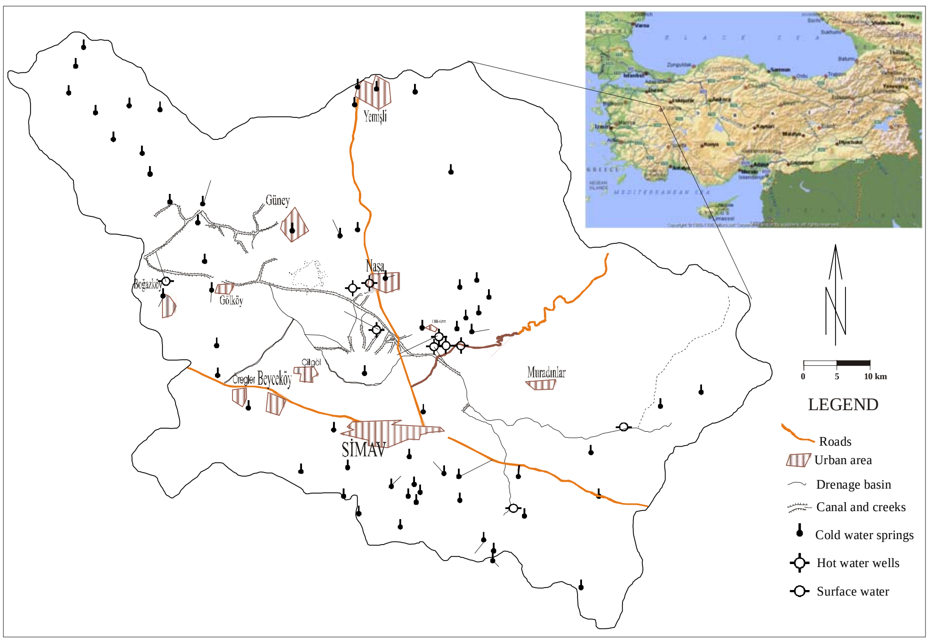


**Figure 1: Location of the study area and locations of samples (from Bayram, 1999).**

## 2. GEOLOGY AND HYDROGEOLOGY

Metamorphics of the Menderes Massive crops out at the base of the sequence in the study area, and comprises of the Precambrian – Paleozoic Kalkan formation and Simav metamorphic (Figure 2). The Kalkan formation begins with migmatite, amphibolite, granitic migmatite which were cut by aplite vein at the base, and passes into biotite gneisse with marble inter beds and pegmatoid veins, migmatitic gneisse and leptite gneisse. The Simav metamorphics tectonically overlap the Kalkan formation and this form "a cataclastic zone" having many kilometers of extension. In this zone, milonite, milonite schist and cataclasits were determined. The Simav metamorphics comprise of metabasics bearing marble bands and lenses and schist having metabasic and metaultramafic interbeds (Akdeniz and Konak, 1979).

The sequence continues upward by the Paleozoic aged formations which have lateral and vertical transitions. These are the Balıkbası formation comprising of quartz-schist, albite- chlorite- muscovite schist, chlorite – quartz-muscovite schist having marble interbeds, the Sarıcasu formation being composed of quartz phillite and the Arıkaya formation comprising of crystallized limestone. The Balıkbası formation crops out in an area of 6 km$^2$ in the study area. It comprises of secondary porous and permeable marble and underlines the Sarıcasu formation having cover rock characteristics. EJ-1 and EJ-2 wells yield hot water at this reservoir (Yücel et al., 1983).

Rocks which are Upper Triassic – Upper Jurassic in age, dolomitized, laminated, cherty and quartzite bearing crystallized limestone is examined as the Budagan limestone. These formations crop out in an area of 25 km$^2$. Therefore higher temperatures were obtained. Hot water from EJ-1, EJ-2, E-2, E-3, E-4, E-5, E-6, E-7, E-8, and E-9 is drawn from this reservoir. The highest temperature (162.47 °C) was measured from EJ-1 well (Yücel et al., 1983). The Egrigoz granite comprises of granite having granite porphir at its peripheral parts and microgranit cut by aplite and pegmatite veins.

The Kızılbük formation is composed of interbedded sandstone tuffite, claystone, and clayey limestone. The Civanadag tuff comprises of riodasit, dasitic and plagiodasitic tuff having sandstone and claystone lenses. Akdag volcanics is made of riyolite, riyodasite, dasite and agglomerate. The Akdag volcanics, the Civanadag tuff and the Kızılbük formation have lateral and vertical transition and are Middle – Upper Miocene in age. The Akdag volcanics, the Civanadag tuff and the Kızılbük formation form a thick cap rock (Bayram and Simsek, 2005).

The Toklargolü formation comprising of gravel, sand and clay consolidated in places, the fine grained. Basic Nasa basalt with flow structure come over the above mentioned units. The Nasa basalt and the Toklargolü formation covers an area of 84 km$^2$ in the study area. The Eynal formation being composed of loosely consolidated pebble, sand and clay rest over them (Erisen, 1989). In Nasa basalt covered by alluvium and Eynal formation, geothermal fluid production is done in C-1, C-2 (abandoned C-3, C-4, C-5) and N-1, N-2 wells. In addition, hot water has been produced from the first reservoir rocks in some of the other boreholes. The highest temperatures in first reservoir rock (105 °C) were measured at 85m of depth in C-1 well (Bayram and Simsek, 2005).

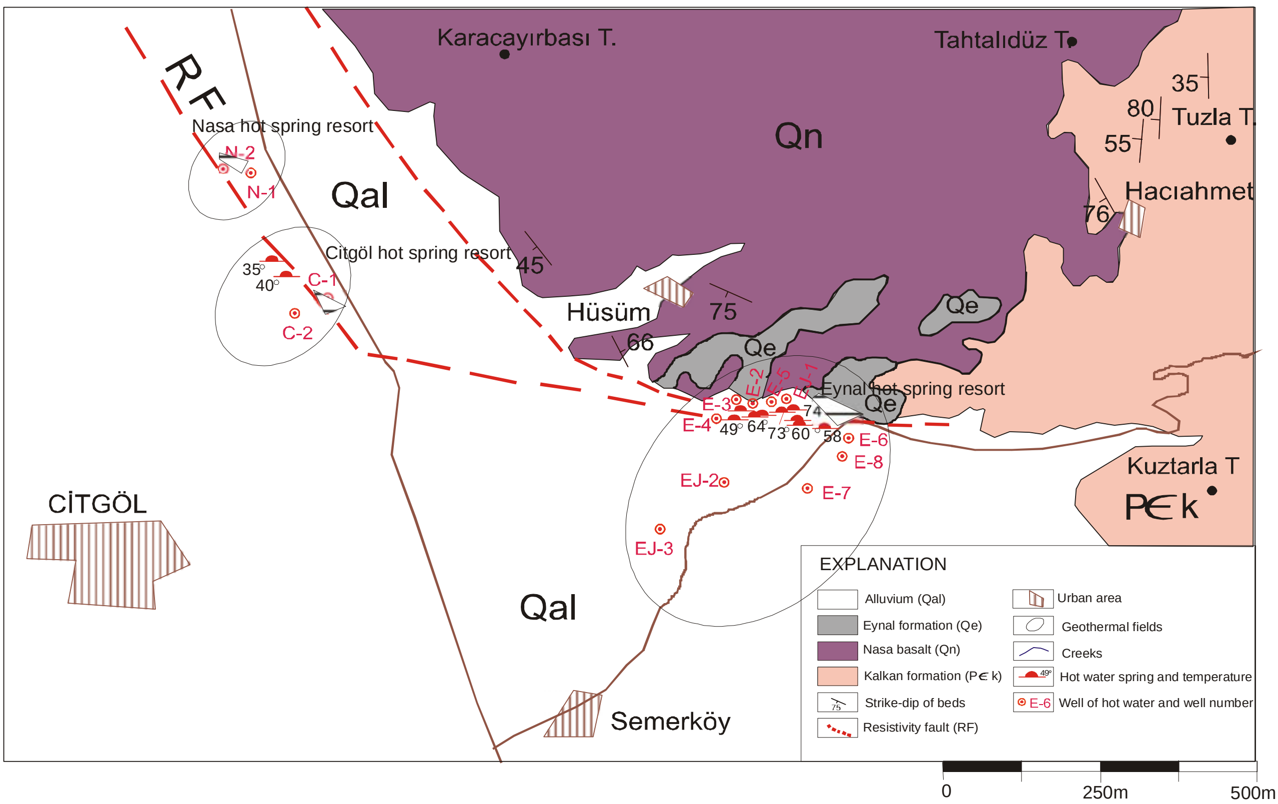


**Figure 2: Geological map of the well site and it's environ (from Bayram, 1999).**

## 2. ARTIFICIAL NEURAL NETWORKS (ANNs)

ANNs are biologically inspired computer programs designed to simulate the way in which the human brain processes information. ANNs gather their knowledge by detecting the patterns and relationships in data and learn (or are trained) through experience, not from programming. An ANN is formed from hundreds of single units, artificial neurons or processing elements connected with weights, which constitute the neural structure and are organized in layers. The power of neural computations comes from weight connection in a network. Each neuron has weighted inputs, summation function, transfer function and one output. The behavior of a neural network is determined by the transfer functions of its neurons, by the learning rule, and by the architecture itself. The weights are the adjustable parameters and, in that sense, a neural network is a parameterized system. The weighted sum of the inputs constitutes the activation of the neuron. The activation signal is passed through a transfer function to produce the output of a neuron. Transfer function introduces non-linearity to the network. During training, the inter-unit connections are optimized until the error in predictions is minimized and the network reaches the specified level of accuracy. Once the network is trained, new unseen input information is entered to the network to calculate the output for test. ANN represents a promising modeling technique, especially for data sets having non-linear relationships that are frequently encountered in engineering. In terms of model specification, artificial neural networks require no knowledge of the data source but, since they often contain many weights that must be estimated, they require large training sets. In addition, ANNs can combine and incorporate both literature-based and experimental data to solve problems. There are many types of neural networks for various applications available in the literature (Maren et al., 1990, Haykin, 1994). Multilayered perceptrons (MLPs) (Rumelhart and McClelland, 1986, Maren et al., 1990, Haykin, 1994) are the simplest and therefore most commonly used neural network architectures. In this work, they have been adopted to determine for Classifying of geothermal areas. As shown in Figure 3, an MLP consists of three layers: an input layer, an output layer and an intermediate or hidden layer. Processing elements (PEs) or neurons (indicated in Figure 3 with the circle) in the input layer only act as buffers for distributing the input signals $x_i$ to PEs in the hidden layer. Each PE j in the hidden layer sums up its input signals $x_i$ after weighting them with the strengths of the respective connections $w_{ji}$ from the input layer and computes its output $y_j$ as a function f of the summation as

$$y_i = f(\sum w_{ji} x_i) \tag{1}$$

where *f* can be a simple threshold function, a sigmoidal or hyperbolic tangent function. The output of PEs in the output layer is computed similarly. MLPs can be trained using many different learning algorithms (Rumelhart and McClelland, 1986, Fahlman, 1988, Jacobs, 1988, Minai and Williams, 1990, Maren et al., 1990, Haykin, 1994, NeuralWare, 1996). A learning algorithm gives the change $\Delta w_{ji}(k)$ in the weight of a connection between PEs *i* and *j*. In this work, MLP is trained with the extended delta-bar-delta (EDBD) algorithm. In the following section, the EDBD algorithm has been explained briefly.

The extended delta-bar-delta algorithm (Minai and Williams, 1990) is an extension of the delta-bar-delta algorithm (Jacobs, 1988) and based on decreasing the training time for multilayered perceptrons

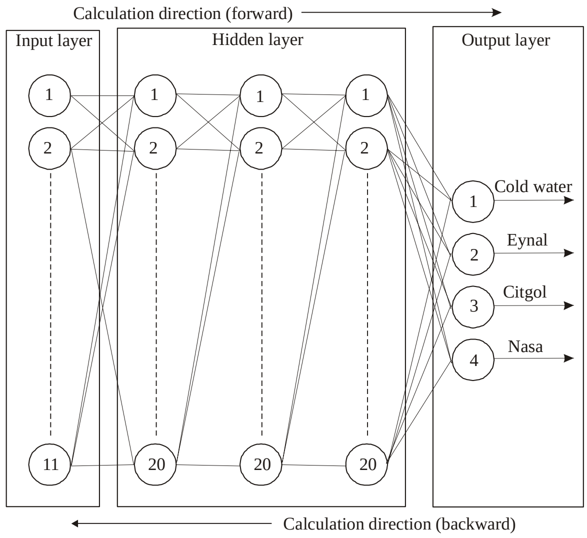


**Figure 3: General form of Multilayered Perceptrons.**

**Extended Delta-Bar-Delta (EDBD) Algorithm**

The use of the momentum heuristics and avoiding the cause of the wild jumps in the weights are the features of the algorithm. The EDBD algorithm includes a little-used "error recovery" feature which calculates the global error of the current epoch during training. If the error measured during the current epoch is greater than the error of the previous epoch, then the network's weights revert back to the last set of weights (the weights which produced the lower error). However, a patience factor has been included into the error recovery feature, which may produce the better performance of the networks through the use of this feature. Instead of testing the error upon every epoch, as was performed previously, the error is now tested upon n-th epoch, where n equals the patience factor. In this algorithm, the changes in weights are calculated as

$$\Delta w(k+1) = \alpha(k)\delta(k) + \mu(k)\Delta w(k) \tag{2}$$

and the weights are then found as

$$w(k+1) = w(k) + \Delta w(k+1) \tag{3}$$

In eq. (2), $\delta(k)$ is the gradient component of the weight change, and $\alpha(k)$ and $\mu(k)$ are the learning and momentum coefficients, respectively. $\delta(k)$ is employed to implement the heuristic for incrementing and decrementing the learning coefficients for each connection. The weighted average $\bar{\delta}(k)$ is formed as

$$\bar{\delta}(k) = (1-\theta)\delta(k) + \theta\delta(k-1) \tag{4}$$

where $\theta$ is the convex weighting factor. The learning coefficient change is given as

$$\Delta\alpha(k) = \begin{cases} \kappa_\alpha \exp\left(-\gamma_\alpha \left|\bar{\delta}(k)\right|\right) & \text{if} \quad \bar{\delta}(k-1)\delta(k) > 0 \\ -\varphi_\alpha \alpha(k) & \text{if} \quad \bar{\delta}(k-1)\delta(k) < 0 \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

where $\kappa_\alpha$ is the constant learning coefficient scale factor, exp is the exponential function, $\varphi_\alpha$ is the constant learning coefficient decrement factor, and $\gamma_\alpha$ is the constant learning coefficient exponential factor. The momentum coefficient change is also written as

$$\Delta\mu(k)=\begin{cases}\kappa_\mu \exp\left(-\gamma_\mu\left|\bar{\delta}(k)\right|\right) & \text{if} \quad \bar{\delta}(k-1)\delta(k)>0\\ -\varphi_\mu\mu(k) & \text{if} \quad \bar{\delta}(k-1)\delta(k)<0\\ 0 & \text{otherwise}\end{cases} \qquad (6)$$

where $\kappa_\mu$ is the constant momentum coefficient scale factor, $\varphi_\mu$ is the constant momentum coefficient decrement factor, and $\gamma_\mu$ is the constant momentum coefficient exponential factor. As can be seen from eqns. (5-6), the learning and the momentum coefficients have separate constants controlling their increase and decrease. $\delta(k)$ is used whether an increase or decrease is appropriate. The adjustment for decrease is identical in form to that for the delta-bar-delta algorithm. Therefore, the increases in the both coefficients were modified to be exponentially decreasing functions of the magnitude of the weighted gradient components $\left|\bar{\delta}(k)\right|$.

Thus, greater increases will be applied in areas of small slope or curvature than in areas of high curvature. This is partial solution to the jump problem. In order to take a step further to prevent wild jumps and oscillations in the weight space, ceilings are placed on the individual connection learning and momentum coefficients. For this,

$$\alpha(k) \le \alpha_{max}$$

$$\mu(k) \le \mu_{max} \qquad (7)$$

must be for all connections, where $\alpha_{max}$ is the upper bound on the learning coefficient, and $\mu_{max}$ is the upper bound on the momentum coefficient. Finally, after each epoch presentation of training tuples, the accumulated error is evaluated. If the error E(k) is less than the previous minimum error, the weights are saved as the current best. A recovery tolerance parameter $\lambda$ controls this phase. Specifically, if the current error exceeds the minimum previous error such that

$$E(k) > E_{min}\,\lambda \qquad (8)$$

All connection weights revert to the stored best set of weights in memory. Further, the both coefficients are decreased to begin the recovery.

## 4. APPLICATION OF ANNs TO CLASSIFYING

In the ANN model, the inputs are T (°C), EC (μS), pH, Na (mg/l), K (mg/l), Ca (mg/l), Mg (mg/l), $CO_3$ (mg/l), $HCO_3$ (mg/l), Cl (mg/l) and $SO_4$ (mg/l). Four output values were used. The outputs are cold water, Eynal, Citgol, and Nasa geothermal water. In each output values the known water represented by 1 and others by 0.

In this ANN model, out of 75 data sets generated, 50 data sets were used for training (Table 1) and the rest were used for testing (Table 2) the network. A set of random values distributed uniformly between -0.1 and +0.1 was used to initialize the weights of the networks. However, the input data tuples were scaled between -1.0 and +1.0 and the output data tuples were also scaled between –0.8 and +0.8 before training. After several trials, it was found that three hidden layers network achieved the task with high accuracy.

The most suitable network configuration found was 20 processing elements for both first, second and third hidden layers. The seed number was fixed to 257. Both random procedures were used in training. The number of iteration for training is 370,000. For EDBD, κα=0.095, κμ=0.01, γμ=0.0, γα=0.0, □μ=0.01, □α=0.1, θ=0.7, and λ=1.5.

**Table 1. Data set for training.**

| Rank | Inputs | | | | | | | | | | | Outputs | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | T | $EC_{25}$ | pH | Ca | Mg | Na | K | $CO_3$ | $HCO_3$ | Cl | $SO_4$ | Cold | Eynal | Citgol | Nasa |
| 1 | 11.7 | 479 | 7.18 | 50.41 | 22.34 | 13.20 | 13.37 | 21.00 | 157.80 | 8.00 | 27.00 | 1 | 0 | 0 | 0 |
| 2 | 9.4 | 299 | 7.01 | 37.24 | 6.59 | 13.80 | 13.12 | 10.50 | 126.20 | 7.00 | 17.00 | 1 | 0 | 0 | 0 |
| 3 | 8.1 | 68 | 5.93 | 6.57 | 0.00 | 14.64 | 12.62 | 0.00 | 47.30 | 7.00 | 6.00 | 1 | 0 | 0 | 0 |
| 4 | 12.1 | 104 | 5.80 | 8.77 | 5.26 | 15.48 | 13.45 | 0.00 | 47.30 | 4.00 | 8.00 | 1 | 0 | 0 | 0 |
| 5 | 17.6 | 0 | 7.15 | 70.15 | 17.06 | 14.64 | 12.62 | 10.50 | 200.00 | 7.00 | 25.00 | 1 | 0 | 0 | 0 |
| 6 | 18.5 | 782 | 7.52 | 87.69 | 42.05 | 13.37 | 12.62 | 31.50 | 284.00 | 8.00 | 42.00 | 1 | 0 | 0 | 0 |
| 7 | 10.1 | 120 | 5.90 | 6.57 | 2.62 | 21.39 | 14.28 | 0.00 | 57.80 | 8.00 | 6.00 | 1 | 0 | 0 | 0 |
| 8 | 12.1 | 86 | 5.75 | 2.20 | 2.62 | 15.48 | 15.52 | 0.00 | 42.00 | 6.00 | 5.00 | 1 | 0 | 0 | 0 |
| 9 | 9.7 | 64 | 6.10 | 2.20 | 2.62 | 14.64 | 17.18 | 0.00 | 42.00 | 4.00 | 2.50 | 1 | 0 | 0 | 0 |
| 10 | 10.5 | 76 | 5.95 | 2.20 | 2.62 | 16.33 | 13.53 | 0.00 | 42.00 | 4.00 | 5.00 | 1 | 0 | 0 | 0 |
| 11 | 17 | 1068 | 6.51 | 120.52 | 49.92 | 24.17 | 18.42 | 42.00 | 352.40 | 17.00 | 90.00 | 1 | 0 | 0 | 0 |
| 12 | 20 | 730 | 7.80 | 65.75 | 6.58 | 69.91 | 16.76 | 52.60 | 200.00 | 16.00 | 15.00 | 1 | 0 | 0 | 0 |
| 13 | 16.7 | 725 | 7.68 | 65.75 | 26.28 | 32.36 | 13.62 | 42.00 | 184.00 | 10.00 | 66.00 | 1 | 0 | 0 | 0 |
| 14 | 13.5 | 600 | 7.65 | 65.75 | 32.83 | 12.95 | 12.62 | 21.00 | 210.00 | 10.00 | 16.00 | 1 | 0 | 0 | 0 |
| 15 | 14.9 | 489 | 6.95 | 59.18 | 14.45 | 27.30 | 12.62 | 31.60 | 121.00 | 10.00 | 16.00 | 1 | 0 | 0 | 0 |
| 16 | 17.2 | 347 | 6.91 | 35.08 | 11.81 | 34.05 | 14.03 | 21.00 | 115.70 | 10.00 | 12.00 | 1 | 0 | 0 | 0 |
| 17 | 19.2 | 574 | 7.91 | 87.69 | 3.94 | 14.64 | 14.86 | 42.00 | 136.70 | 7.00 | 25.00 | 1 | 0 | 0 | 0 |
| 18 | 18.4 | 200 | 6.08 | 15.34 | 13.13 | 29.41 | 14.28 | 0.00 | 63.00 | 13.00 | 19.00 | 1 | 0 | 0 | 0 |
| 19 | 18.1 | 1019 | 7.53 | 105.23 | 35.47 | 34.05 | 18.50 | 21.00 | 363.00 | 13.00 | 17.00 | 1 | 0 | 0 | 0 |
| 20 | 21.4 | 1730 | 7.35 | 92.09 | 30.19 | 23.08 | 13.12 | 52.60 | 221.00 | 11.00 | 40.00 | 1 | 0 | 0 | 0 |
| 21 | 16.8 | 771 | 7.65 | 87.69 | 22.32 | 18.01 | 13.70 | 21.00 | 231.00 | 18.00 | 16.00 | 1 | 0 | 0 | 0 |
| 22 | 18.4 | 355 | 7.25 | 26.31 | 15.77 | 31.52 | 14.03 | 21.00 | 100.00 | 12.00 | 5.00 | 1 | 0 | 0 | 0 |
| 23 | 20.5 | 939 | 6.76 | 113.99 | 3.84 | 38.27 | 26.87 | 115.70 | 152.50 | 30.00 | 80.00 | 1 | 0 | 0 | 0 |
| 24 | 17.3 | 868 | 6.82 | 65.75 | 26.28 | 50.08 | 16.93 | 52.60 | 131.50 | 53.00 | 19.00 | 1 | 0 | 0 | 0 |
| 25 | 13.7 | 472 | 7.20 | 65.75 | 3.94 | 26.45 | 13.78 | 21.00 | 152.50 | 10.00 | 6.00 | 1 | 0 | 0 | 0 |
| 26 | 16.2 | 745 | 6.74 | 94.25 | 19.68 | 28.14 | 12.71 | 21.00 | 294.50 | 12.00 | 33.00 | 1 | 0 | 0 | 0 |

**Table 1 (Continued)**

| | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 27 | 15.6 | 402 | 6.73 | 35.08 | 9.22 | 24.26 | 14.36 | 10.50 | 115.70 | 17.00 | 27.00 | 1 | 0 | 0 | 0 |
| 28 | 16.7 | 1497 | 7.01 | 98.70 | 72.29 | 18.52 | 13.12 | 73.60 | 273.50 | 13.00 | 168.00 | 1 | 0 | 0 | 0 |
| 29 | 19.2 | 113 | 7.67 | 0.56 | 0.31 | 16.33 | 12.62 | 0.00 | 52.60 | 10.00 | 22.00 | 1 | 0 | 0 | 0 |
| 30 | 16.9 | 373 | 7.03 | 41.64 | 3.94 | 18.86 | 13.04 | 21.00 | 126.20 | 8.00 | 165.00 | 1 | 0 | 0 | 0 |
| 31 | 18.8 | 193 | 7.03 | 21.90 | 5.26 | 23.08 | 13.87 | 10.50 | 73.60 | 100.00 | 11.00 | 1 | 0 | 0 | 0 |
| 37 | 67.4 | 2520 | 8.79 | 25.00 | 10.00 | 450.00 | 75.00 | 84.90 | 498.98 | 83.31 | 308.85 | 0 | 1 | 0 | 0 |
| 38 | 65.4 | 3020 | 6.59 | 70.00 | 15.00 | 302.50 | 30.00 | 0.00 | 566.69 | 60.27 | 254.20 | 0 | 0 | 0 | 1 |
| 39 | 87.7 | 2040 | 9.14 | 35.00 | 5.00 | 360.00 | 35.00 | 84.90 | 403.21 | 69.13 | 285.14 | 0 | 0 | 1 | 0 |
| 40 | 18.1 | 535 | 7.60 | 86.00 | 19.00 | 14.97 | 9.00 | 18.30 | 307.44 | 30.13 | 22.48 | 1 | 0 | 0 | 0 |
| 41 | 16.7 | 579 | 7.47 | 97.00 | 29.00 | 8.00 | 8.00 | 18.30 | 387.35 | 10.64 | 28.05 | 1 | 0 | 0 | 0 |
| 42 | 14.5 | 494 | 7.65 | 87.00 | 14.00 | 14.30 | 7.00 | 18.30 | 270.23 | 23.04 | 8.99 | 1 | 0 | 0 | 0 |
| 43 | 64.3 | 2060 | 8.47 | 25.00 | 7.50 | 380.10 | 42.50 | 64.71 | 552.78 | 63.81 | 377.82 | 0 | 1 | 0 | 0 |
| 44 | 87 | 250 | 7.35 | 39.00 | 2.00 | 2.30 | 5.00 | 0.00 | 125.60 | 1.77 | 7.55 | 0 | 1 | 0 | 0 |
| 45 | 56.7 | 2100 | 6.13 | 60.00 | 10.00 | 325.00 | 35.00 | 0.00 | 604.02 | 54.55 | 324.87 | 0 | 0 | 0 | 1 |
| 46 | 12.9 | 489 | 7.04 | 57.00 | 31.00 | 3.50 | 8.00 | 0.00 | 322.93 | 3.55 | 29.07 | 1 | 0 | 0 | 0 |
| 47 | 8.9 | 256 | 7.80 | 42.00 | 11.00 | 2.50 | 7.00 | 0.00 | 173.42 | 1.77 | 13.35 | 1 | 0 | 0 | 0 |
| 48 | 16.4 | 225 | 6.90 | 29.00 | 4.00 | 3.80 | 6.00 | 0.00 | 113.64 | 3.55 | 7.72 | 1 | 0 | 0 | 0 |
| 49 | 21.4 | 680 | 7.35 | 90.00 | 27.00 | 9.20 | 4.00 | 0.00 | 370.75 | 5.32 | 42.22 | 1 | 0 | 0 | 0 |
| 50 | 81.2 | 1519 | 7.50 | 53.00 | 5.00 | 510.00 | 40.00 | 34.62 | 744.99 | 81.53 | 448.52 | 0 | 1 | 0 | 0 |

**Table 2. Data set for testing.**

| Rank | Inputs | | | | | | | | | | | Outputs | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | T | $EC_{25}$ | pH | Ca | Mg | Na | K | $CO_3$ | $HCO_3$ | Cl | $SO_4$ | Cold | Eynal | Citgol | Nasa |
| 1 | 19.7 | 213 | 7.04 | 15.34 | 10.51 | 26.45 | 14.03 | 0.00 | 42.00 | 12.00 | 35.00 | 1 | 0 | 0 | 0 |
| 2 | 11.3 | 569 | 6.57 | 61.38 | 28.90 | 12.95 | 12.95 | 21.00 | 205.00 | 10.00 | 15.00 | 1 | 0 | 0 | 0 |
| 3 | 45.4 | 1800 | 6.79 | 80.00 | 15.00 | 362.50 | 30.00 | 0.00 | 782.63 | 65.58 | 256.36 | 0 | 0 | 0 | 1 |
| 4 | 8.4 | 252 | 7.97 | 48.00 | 11.00 | 2.30 | 10.00 | 12.00 | 160.43 | 3.55 | 10.80 | 1 | 0 | 0 | 0 |
| 5 | 11.8 | 445 | 7.25 | 68.00 | 31.00 | 4.40 | 9.00 | 18.30 | 283.04 | 8.86 | 27.69 | 1 | 0 | 0 | 0 |
| 6 | 13.9 | 270 | 6.15 | 36.00 | 6.00 | 7.10 | 10.00 | 0.00 | 117.12 | 13.47 | 8.10 | 1 | 0 | 0 | 0 |
| 7 | 79 | 2646 | 8.16 | 57.50 | 10.00 | 300.00 | 57.50 | 0.00 | 556.20 | 58.49 | 350.49 | 0 | 1 | 0 | 0 |
| 8 | 88.5 | 2560 | 9.68 | 30.00 | 5.00 | 342.60 | 42.50 | 64.71 | 421.21 | 62.04 | 352.20 | 0 | 0 | 1 | 0 |
| 9 | 50.4 | 2230 | 6.62 | 72.50 | 12.50 | 306.10 | 45.00 | 0.00 | 669.78 | 54.94 | 309.49 | 0 | 0 | 0 | 1 |
| 10 | 17.3 | 540 | 7.09 | 48.00 | 19.00 | 29.10 | 12.00 | 0.00 | 179.40 | 58.49 | 35.73 | 1 | 0 | 0 | 0 |
| 11 | 18.5 | 735 | 8.70 | 92.00 | 26.00 | 8.10 | 7.00 | 0.00 | 394.73 | 5.32 | 37.95 | 1 | 0 | 0 | 0 |
| 12 | 96 | 2504 | 8.32 | 65.00 | 7.50 | 520.00 | 40.00 | 121.17 | 592.43 | 77.99 | 529.53 | 0 | 1 | 0 | 0 |
| 13 | 90.1 | 2808 | 8.77 | 127.50 | 7.50 | 535.00 | 55.00 | 213.45 | 445.78 | 88.62 | 610.01 | 0 | 1 | 0 | 0 |
| 14 | 70.1 | 1574 | 7.86 | 54.00 | 7.00 | 277.50 | 20.00 | 28.86 | 416.44 | 53.17 | 323.54 | 0 | 0 | 1 | 0 |
| 15 | 50.5 | 1882 | 6.10 | 88.00 | 9.00 | 335.00 | 25.00 | 0.00 | 680.39 | 56.72 | 346.26 | 0 | 0 | 0 | 1 |

## 5. RESULTS AND CONCLUSIONS

Simav geothermal waters are grouped into 4 categories, namely Eynal, Citgol, Nasa geothermal water and cold waters. The classification is impossible employing only chemical analysis results of any water in the field. However, in this study, it has been shown this can be possible employing ANN. For this purpose, different MLP training algorithms have been tried, and among them EDBD algorithm has given very promising results. This success can be appreciated examining $R^2$ values which are close to 1 and RMS error values which are close to 0 (Table 3).

As a model aid, the model test results obtained from the neural model versus water samples used to classify Cold Water, Eynal, Citgol and Nasa are plotted in Figure 4-7.

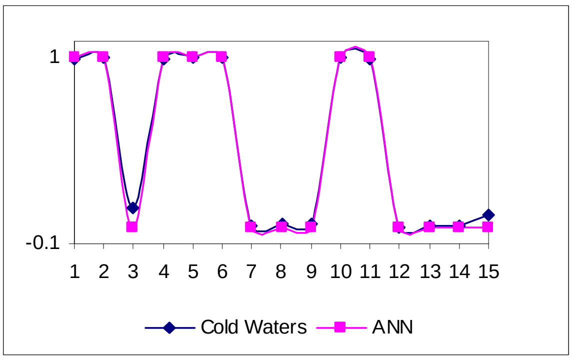


**Figure 4. Results of ANNs versus of cold waters.**

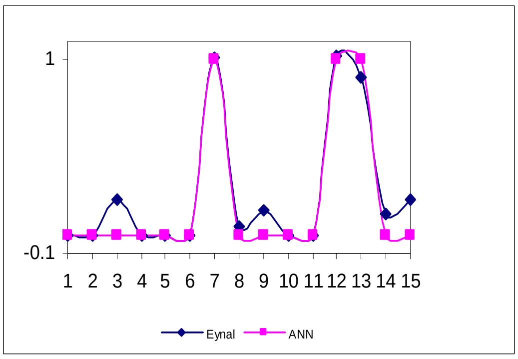


**Figure 5. Results of ANNs versus of Eynal hot waters.**

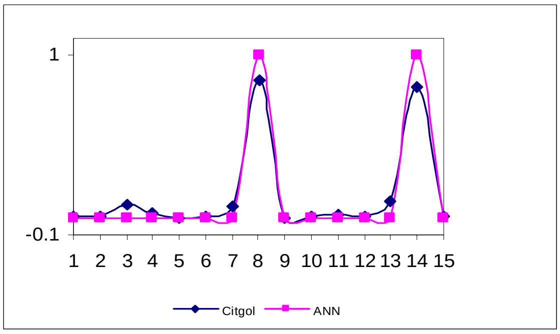


**Figure 6. Results of ANNs versus of Citgol hot waters.**

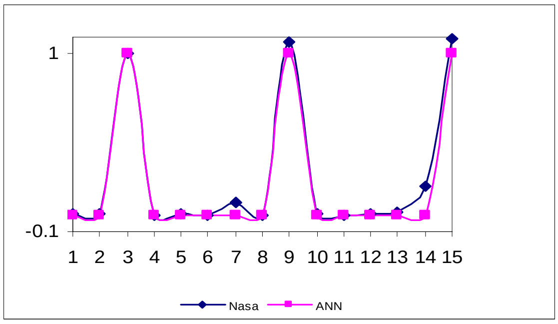


**Figure 7. Results of ANNs versus of Nasa hot waters.**

The good agreement in classifying supports the validity of the neural model. The multiple outputs are calculated successfully.

A distinct advantage of neural computation is that, after proper training, a neural network completely bypasses the repeated use of complex iterative processes for new cases presented to it. For engineering applications, the simple models are very usable. Thus the neural model given in this work can also be used for many engineering applications and purposes.

**Table 3. Results of testing data.**

| Rank | Cold Water | Eynal | Citgol | Nasa | ANN Results: Cold Water | ANN Results: Eynal | ANN Results: Citgol | ANN Results: Nasa |
|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 0 | 0 | 0 | 0.99804400 | 0.000998 | 0.011822 | 0.006572 |
| 2 | 1 | 0 | 0 | 0 | 1.00066100 | 0.001256 | 0.008838 | 0.006238 |
| 3 | 0 | 0 | 0 | 1 | 0.11520100 | 0.201969 | 0.085768 | 0.995589 |
| 4 | 1 | 0 | 0 | 0 | 0.99532500 | 0.003462 | 0.033024 | 0.002820 |
| 5 | 1 | 0 | 0 | 0 | 0.99933000 | 0.000285 | 0.000136 | 0.010423 |
| 6 | 1 | 0 | 0 | 0 | 1.00411000 | 0.001930 | 0.016542 | 0.001056 |
| 7 | 0 | 1 | 0 | 0 | 0.00981000 | 1.008581 | 0.075474 | 0.079860 |
| 8 | 0 | 0 | 1 | 0 | 0.02154400 | 0.051459 | 0.841020 | 0.000050 |
| 9 | 0 | 0 | 0 | 1 | 0.01346100 | 0.140292 | 0.003232 | 1.069376 |
| 10 | 1 | 0 | 0 | 0 | 1.00419200 | 0.002397 | 0.008398 | 0.010776 |
| 11 | 1 | 0 | 0 | 0 | 0.99794600 | 0.002626 | 0.021971 | 0.000068 |
| 12 | 0 | 1 | 0 | 0 | 0.00031600 | 1.020478 | 0.016052 | 0.014458 |
| 13 | 0 | 1 | 0 | 0 | 0.00502400 | 0.897110 | 0.108780 | 0.017972 |
| 14 | 0 | 0 | 1 | 0 | 0.00489200 | 0.127045 | 0.804645 | 0.181239 |
| 15 | 0 | 0 | 0 | 1 | 0.07396900 | 0.208245 | 0.017703 | 1.088651 |

| | | | | | |
|---|---|---|---|---|---|
| Average | | 0.482921667 | 0.244542 | 0.136894 | 0.232343 |
| Standard Deviation | | 0.50147032 | 0.386288 | 0.280468 | 0.426803 |
| Sum Square Error | | 0.019598785 | 0.133738 | 0.091041 | 0.052765 |
| Mean Square Error | | 0.001306586 | 0.008916 | 0.006069 | 0.003518 |
| Root Mean Square Error | | 0.036146724 | 0.094424 | 0.077906 | 0.059310 |
| $R^2$ | | 0.9966 | 0.9588 | 0.9859 | 0.9860 |

**REFERENCES**


A. Minai and R.D. Williams, “Acceleration of Back Propagation Through Learning Rate and Momentum Adaptation”, Int. Joint Conf. on Neural Networks, Washington DC, Vol. 1, pp. 676-679, Jan. 1990.

A. Maren, C. Harston, and R. Pap, “Handbook of Neural Computing Applications”, Academic Press, London, 1990.

Bayram, F. “Simav jeotermal Alanının Hidrojeoloji Incelemesi” S.Ü. Fen Bilimleri Enstitüsü Doktora Tezi, 156 s (1999).

Bayram, F. and Simsek, S., “Hydrogeochemical and Isotopic Survey of Kütahya-Simav Geothermal Field” World Geothermal Congress’05, Antalya-Turkey (2005)

D.E. Rumelhart and J.L. McClelland, “Parallel Distributed Processing”, The MIT Press, Cambridge, Vol. 1, 1986.

Neural computing, “A Technology Handbook for Professional II/Plus and Neuralworks Explorer”, Pittsburgh: Neural Ware, Inc., Technical Publications Group, 1996.S.E. Fahlman, “An Emprical Study of Learning Speed in Back Propagation Networks”, Technical Report CMU-CS-88-162, Carnegie Mellon University, June 1988.

R.A. Jacobs, “Increased Rate of Convergence Through Learning Rate Adaptation”, Neural Networks 1, 295-307, 1988.

S. Haykin, “Neural networks: A Comprehensive Foundation”, Macmillan College Publishing Company, New York, 1994.