# THE MODELLING RECORDED FAULTS IN RAILWAYS AND PREDICTION

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***Abstract:*** *This paper describes the prediction of the accidents and incidents by modelling the faults that are hard to be predicted, and forms the stochastic processes in railways. As it is seen, the root causes of the occurrence of the accidents and incidents in railways are the technical faults, the organizational faults, the staff faults, the third-party faults, the other faults and some parameters affecting these faults holidays, seasonal effects etc. The system model was set up by considering the above-mentioned faults and the causes as the inputs of the model and the accidents and the incidents as the outputs of the model. The real values of the accidents and the incidents were compared with the predicted values by using Artificial Neural Networks-ANN and Support Vector Machines-SVM. The results, which were acquired by this article, are considered as a guide because of the absence of any studies about the prediction of the accidents caused by the faults.*
***Keywords:*** *Railways, Safety Stochastic Processes, Faults, Accidents and Incidents, Artificial Neural Networks, Support Vector Machines.*

## Introduction

The technological innovations and the developments deeply affect the transport and the social lifestyles. The life and the transport possibilities had been restricted in the narrow area but now it enlarges the regional even the global travels with these innovations and developments. In addition, the global competition and the working conditions, the time and the cost factors are still the critical factors to sustain their work effectively for the companies [1].

The importance and the speed of the freight and passenger transportations between long distances are increasing day by day because of the rising up the relations and the communications between the countries. In addition to this, the increase in the welfare levels of the people causes continuous differentiation on passengers' safety and comfort demands. Besides, the passengers and the freights must be carried faster, safer, more economical and more environment – friendly because they are important parameters of the competition for the transportation and logistics activities [2].

The long-term investments and the innovations in railway sector provide the fulfilment of global competition requirements and so that it takes aim at to enhance the image and the market share of the transportation and logistics activities of the railway sector. As a consequence of this, the railway lines' capacity usage rate, the speed of the trains and the traffic density in railway lines has increased significantly in recent years. On the contrary, the headway between trains that is important for safety has decreased considerably because of the increasing of the traffic density. All these factors lead to increase the faults and to arise big risks [3].

In Turkey railways, the accustomed speeds have increased significantly due to the commissioning of High Speed Train (HST). The upper speed limit for the Turkey railways was 120 km/h in the past times but now it is nearly 300 km/h with the HSTs. The conventional safety approach that is based on the experience and the cultural structures causes the falling behind with the rising speed limits and traffic density.

New safety strategies and methods are needed to prevent the loss of the usual safe travel image of the railways and to be kept the risks within the certain limits. For this purpose, the hazards and risks that are caused by the faults must be mitigated to the minimum value.

In this study, the rail line between Sivas-Kayseri (319.75 km) within the boundaries of TCDD IV. Regional Directorate was taken into consideration and a database was created by using the operational data received from Turkish State Railways (TCDD) Traffic Operation records and the real values of the accidents and incidents were compared with the predicted values by using Artificial Neural Networks-ANN and Support Vector Machines-SVM.

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## 1. Safety Concept and Created Safety Model

The organizations, which are constituted by the combination of different disciplines that have many different processes, such as railways have a complex system structure including the accidents and the incidents caused by various faults. In the system approach, the defences and the barriers like alarms, double checks etc. occupy a key position. The function of these defences and barriers is to protect potential victims from local hazards. Mostly they do this very effectively, but there are always weaknesses. According to Reason [4], the difference defence layers can in fact be seen as the slices of a Swiss cheese due to they having many holes. The presence of holes in each slice (i.e. defence layer) does not normally cause a bad outcome. Usually this can happen only when the holes in each layers are aligned to permit a trajectory of accident opportunity – bringing hazards into damaging contact with victims [5].

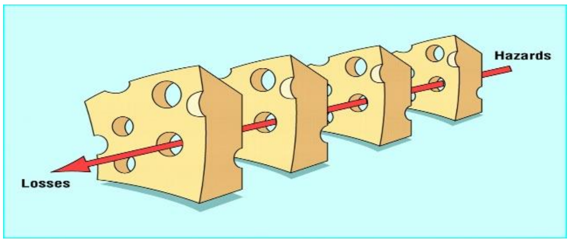


**Figure 1.** Swiss cheese model of accident causation. [4]

The holes in the defences arise from two reasons: the active failures and the latent conditions. Nearly all events involve a combination of these two sets of factors. The active failures are the unsafe acts done by people who have a direct contact with the system (e.g. slips, lapses, mistakes and procedural violations). These active failures have a direct and usually short-lived impact on the integrity of the defences. On the other hand, the latent conditions are the inevitable. They arise from decisions made by the designers, the builders, the procedure writers and the top-level management. The latent conditions have two kinds of adverse effect: the first one is that they can transform into conditions caused the errors within the local workplace (e.g. the time pressure, the understaffing, the inadequate equipment, the fatigue and the inexperience) and the second one is that they can create the long-lasting holes or the weaknesses in the defences (the untrustworthy alarms and the indicators, the unworkable procedures, the design and construction deficiencies etc.). The latent conditions may remain dominant within the system for many years before they combine with the active failures and the local triggers to create an accident probability [4, 6].

If the traffic operational records kept by TCDD IV. Regional Directorate for Sivas – Kayseri rail line are examined, as it was seen the root causes of the occurrence of the accidents and incidents in railways are the technical faults, the organizational faults, the staff faults, the third party faults, the other faults and some parameters affecting these faults holidays, seasonal effects etc. The technical faults, the organizational faults, the staff faults and the third party faults that are observed in the records kept by TCDD can be likened to the holes of the system barriers in the Swiss Cheese model. Therefore, a system model can be set up with the above faults and the causes as the inputs and the accidents and the incidents as the outputs.

### 2.1. Faults and Causes (Inputs)

If the data between the dates 01.01.2007 - 28.12.2014 are analysed, the encountered faults are classified as follows [7];

As the technical faults; broken axle, the change on rail distance, the failure of interlocking system, catenary wire break, and train brake system failure etc., the electrical, mechanical and structural failures were evaluated as technical faults category.

As the organizational faults; untrained staffs, lack/inaccuracy of procedures, information-communication problems, and management priorities etc., these types of faults were evaluated as organizational faults category.

As the staff faults; the excessive self-confidence of staff, negligent behaviours, lack of attention, bad habits, lack of culture etc., these types of faults were evaluated as staff faults category.

As the third parties' faults; their negligent behaviours, lack of attention etc., these types of faults were evaluated as the third parties faults category. Except these faults, the other faults were evaluated as other faults category.

The holidays (the beginning and finishing time of the school, the religious holidays, and the official holidays) and the seasonal factor etc. affecting the frequency of occurrence of the faults were accepted as inputs in the created model.

Table 1 shows the number of the occurrences and the rates of the faults between the above-mentioned dates;

**Table 1.** Number And Rate Of The Faults.

| Occurrence | Technical | Organizational | Staff | Third Party | Other | TOTAL |
|---|---|---|---|---|---|---|
| Number | 145 | 54 | 71 | 101 | 23 | 394 |
| % | 36.80 | 13.71 | 18.02 | 25.63 | 5.84 | 100 |

## 2.2. Accidents and Incidents (Outputs)

If the data between the dates 01.01.2007 - 28.12.2014 are analysed, as it was seen that the railway accidents were collision, person hit by train, derailment, level crossing accident, shunting accident and fallings from the trains and the railway incidents were encountering of trains, fire, theft, attack, stone-throwing, running wagons, railway line closure and the other types [7].

The total of the above-mentioned types of accidents and incidents in order to generate meaningful data set were taken as the output of the system model.

Table 2 shows the number of the occurrences and the rates of the accidents and incidents between the above-mentioned dates; .

**Table 2.** Number And Rate Of Accidents/Incidents

| Accident/Incident Type | Number | % |
|---|---|---|
| Train Collision | 1 | 0.41 |
| Person Hit By Train | 11 | 4.55 |
| Derailment | 67 | 27.69 |
| LX Accident | 56 | 23.14 |
| Shunting Accident | 8 | 3.31 |
| Fallings From Trains | 1 | 0.41 |
| Encountering of Trains | 8 | 3.31 |
| Fire | 1 | 0.41 |
| Theft | 4 | 0.65 |
| Attack | 0 | 0.00 |
| Stone-Throwing | 1 | 0.41 |
| Running Wagons | 3 | 1.24 |
| Railway Line Closure | 63 | 26.03 |
| Other | 18 | 7.44 |
| TOTAL: | 242 | 100 |

## 2.3. Definition of Training and Test Data

The all data between 01.01.2007 - 28.12.2014 (2926 days) were analyzed and in question data were evaluated on a weekly basis. There are 418 weeks in time spans in question. For each week, 10 columns were used (technical faults, organizational faults, staff faults, third party faults, other faults, school holidays, religious holidays, official holidays, accidents and incidents with the seasonal factor) and so in total 4180 data were used.

366 weeks' data between 01.01.2007 - 31.12.2013 were defined as the training data in the created model. The training data used are shown in Figure 2;

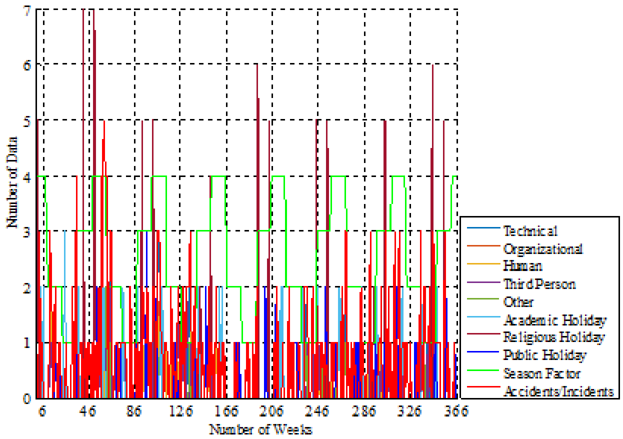


**Figure 2.** Training Data.

52 week's data between 01.01.2014 - 28.12.2014 were defined as the test data. The test data used are shown in Figure 3;

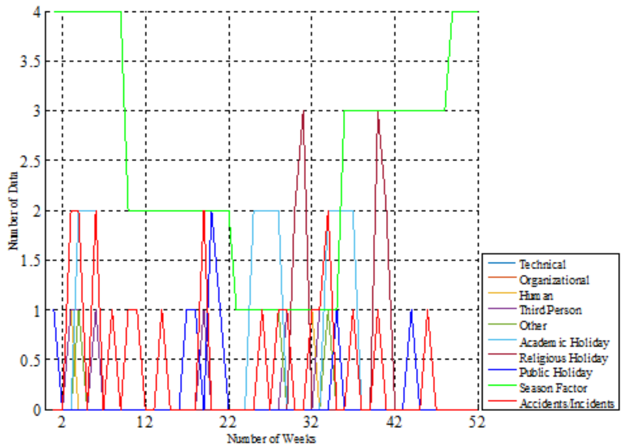


**Figure 3.** Test Data.

As a result, 87.56 % of the data were used in the training and the remaining data 12.44 % were used in the test.

# 3. Methods

## 3.1. Artificial Neural Networks (ANN)

Artificial Neural Networks (ANN) are defined as a system that contains the interconnected neural cells (neurons) and generates an output by processing input data simultaneously in parallel according to the weight functions. It was created with inspiration of biological nervous system's information processing path such as brain and so the system is an information processing series. The widely used algorithm for artificial neural networks is "Feed-Forward Back Propagation" [8].

Feed-Forward Back Propagation involves three different units that the input layer, the hidden layer and the output layer. The nerve cells located in the hidden layer and input - output layers are connected to each other mutually with the cluster weight. The number of cells and type of bindings can be changed.

The mentioned algorithm has two steps. The observed data are spread out to the cells to create output data signals in the feed forward stage. In the back-propagation stage, the observed data and the estimated data are compared continuously and as a result of this process the weights are calculated. This process is repeated several times during the specified number of iterations [9].

Many various studies about prediction with the Artificial Neural Networks have been made up to now e.g. disease diagnosis [8], the time series prediction, the tourism demand forecasting, the electricity consumption demand forecasting, the sales balance sheet forecasting, the temperature forecasting, the financial forecasts, the wind speed estimation, the number of allergens bacteria in the atmosphere estimation [11-14].

WEKA 3.6 Multi Layer Perceptron [15] software was used to create the ANN architecture. ANN architecture has been created with one input layer, the number of optimal 9 artificial neural cells in one hidden layer and one output layer. The learning rate optimal 0.3 and momentum optimal 0.2 were taken in optimal 1000 training iterations. Created ANN architecture is shown in Figure 4;

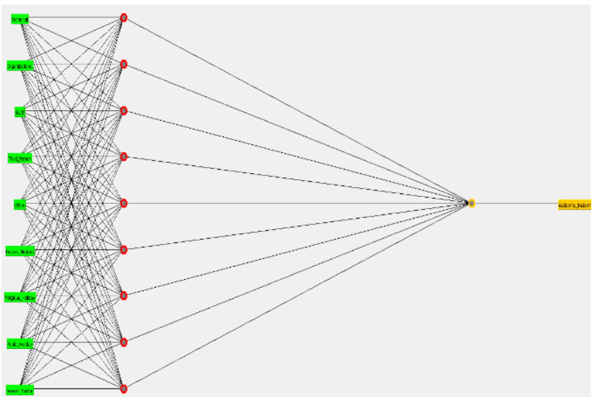

**Figure 4.** ANN architecture.

The logarithmic sigmoid transfer function as shown in Figure 5 was selected as the transfer function.

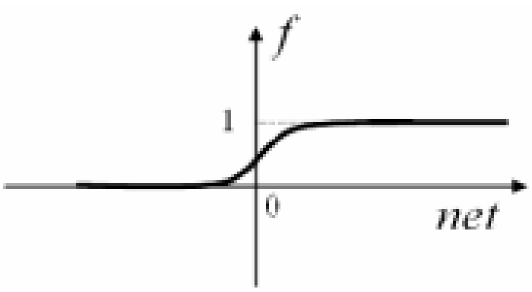


**Figure 5.** Logarithmic Sigmoid Transfer Function.

The mean of the square of errors (MSE) between observations (y) and predictions (d) was used to calculate the weights. These functions are shown in the following equation and n is the number of neural cell used;

$$\boldsymbol{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - d_i)^2 \quad (1)$$

### 3.2. Support Vector Machines (SVM)

Support Vector Machines (SVM) are one of the most important machine-learning algorithms that were developed to solve the problem of classification belonging to the Data Mining. It is proved in the literature that SVM are more successful in comparison with the other techniques. The selections of kernel function and the parameter optimization play an important role in the implementation of SVM.

SVM are a machine-learning algorithm that works in the way of the principle of the structural risk minimization based on the convex optimization. The algorithm is an independent learning algorithm that doesn't need the information of joint distribution function relation to the data [16]. SVM was developed by Vapnik to solve the problem of pattern recognition and classification [17]. The basics of SVM are based on the statistical-learning in other words Vapnik-Chervonenkis (VC) theory [18]. SVM network structure is shown in Figure 6.

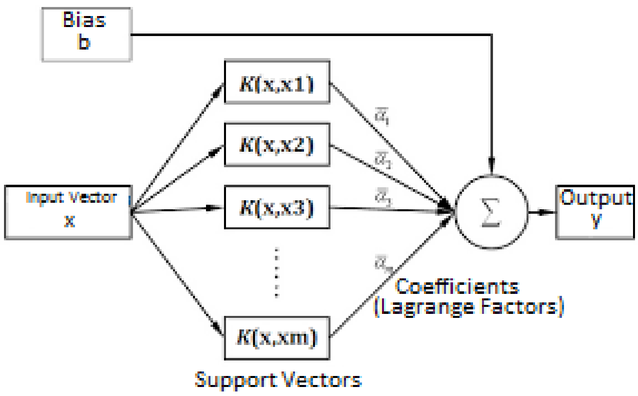


**Figure 6.** General structure of SVM

If it is considered that the network structure shown in Figure 6, K(xi, xi) and α illustrate the kernel function and Lagrange multipliers respectively. The inner product of inputs is calculated with the help of kernel functions. The lagrange multipliers also show the weights. The output value of an example of SVM equals the sum of inner product of the inputs and the independent combination of Lagrange multipliers.

The aim of SVM is to achieve optimal separation hyper plane. In other words, the aim of SVM is to maximize the distance between the support vectors belonging to the different classes. SVM was developed a machine-learning algorithms to solve problems of two-class and multi-class classification.

WEKA 3.6 SMOreg [15] software was used to create the SVM architecture. Many attempts were done to achieve the best result. At the end of the attempts, SVM parameters that give us the best prediction result are as follows: the complexity parameter “c=1” was selected. The data were normalized. The polynomial kernel function as the kernel function and the exponent value “e=1” was selected.

## 4. Numerical Results and Discussion

The generated data sets by using Artificial Neural Networks and Support Vector Machines respectively in the WEKA 3.6 [15] software was processed. Firstly, the training has been done for each method and afterwards the test data have been used.

The assessments of the success between the predicted values and the real values, the following performance evaluation criteria were used [19];

- **Corrected correlation coefficient ($R^2$adj ):** R2adj value gets the value 0-1 range. If the result were close to 1, it would assess as good.
- **Mean absolute error (MAE):** The result is assessed as good if the MAE value was close to 0.
- **Root mean square error (RMS):** The result is assessed as good if the RMS value was close to 0.

The training and the test prediction results were shown in the following tables comparatively;

**Table 3.** Number And Rate Of Accidents/Incidents

| | **Training** | | | **Test** | | |
|---|---|---|---|---|---|---|
| | **$R^2_{adj}$** | **MAE** | **RMS** | **$R^2_{adj}$** | **MAE** | **RMS** |
| **ANN** | 0.9885 | 0.4685 | 0.5222 | **0.9870** | 0.4433 | **0.5169** |
| **SVM** | 0.9257 | **0.1812** | **0.5077** | 0.8792 | **0.2629** | 0.5747 |

Various methods were used to access the information in data mining. There were many algorithms for these methods. Several studies were completed which one is superior, and in these studies different results were obtained. The reason of the different results is that the processing performance is dependent on the used data source, the pre-processing performed on the data and the choice of algorithm parameters. It is natural that the studies made by the different people on the different data sources and with the different parameters result in the different results. The performance/success evaluation criteria mentioned above sometimes fail to find which method is the most successful. Therefore, when evaluating the success of the model, it is also necessary to examine the error rate, precision, sensitivity and F-measure criteria [20]. The success of the model according to the criteria is associated with the number of sample assigned to the correct class and the number of sample assigned to the wrong class.

### 4.1. Model Performance Criteria

The performance information achieved in the test result can be expressed by complexity matrix. In the complexity matrix, the rows refer to the actual numbers belonging to the samples in the test set, and the columns refer to the estimation of the model. However, firstly the error tolerance must be determined to make compatible the complexity matrix with the model. Therefore, firstly the test results obtained for each method are classified into four classes as follows;

- Error value less than 0.5 in the positive direction - True Positive (TP)
- Error value less than 0.5 in the negative direction - True Negative (TN)
- Error value bigger than 0.5 in the positive direction - False Positive (FP)
- Error value bigger than 0.5 in the negative direction - False Negative (FN)

Accordingly, the complexity matrix of Artificial Neural Networks that was created according to the test results is shown in Table 4 below;

**Table 4.** ANN Complexity Matrix

| | |
|---|---|
| TP<br>43 | FN<br>0 |
| FP<br>0 | TN<br>9 |

As it is seen there are a total of 52 the test prediction
As it is seen there are a total of 52 the test prediction results placed in the matrix. The number of **43** the prediction results in the positive direction less than 0,5 (**TP**), the number of **9** the test prediction results in the negative direction less than 0,5 (**TN**), the number of **0** the prediction results in the positive direction bigger than 0,5 (**FP**) and the number of **0** the prediction result in the negative direction bigger than 0,5 (**FN**).

Similarly, the complexity matrix that was created according to the test results of Support Vector Machines is shown in Table 5 below;

**Table 5.** SVM Complexity Matrix

| | |
|---|---|
| TP<br>41 | FN<br>3 |
| FP<br>0 | TN<br>8 |

As you can see there are a total of 52 the test prediction results placed in the matrix. The number of **41** the prediction results in the positive direction less than 0,5 (**TP**), the number of **8** the test prediction results in the negative direction less than 0,5 (**TN**), the number of **0** the prediction results in the positive direction bigger than 0,5 (**FP**) and the number of **3** the prediction result in the negative direction bigger than 0,5 (**FN**).

#### 4.1.1. Accuracy – Error Rate

The most popular and simplest method that is used to measure the success of the model is the accuracy rate of the model. This is the ratio of the correct classified number of sample (TP +TN) to the total sample number (TP+TN+FP+FN). The error rate is 1’s complement of that value. In other words, this is the ratio of the incorrect classified sample number (FP+FN) to the total sample number (TP+TN+FP+FN) [20].

$$\boldsymbol{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN} \quad (2)$$

$$\boldsymbol{Error\ Rate} = \frac{FP + FN}{TP + FP + TN + FN} \quad (3)$$

### 4.1.2. Precision

Precision is the ratio of the correct classification predicted True Positive sample number to the correct classification predicted all sample [20].

$$\boldsymbol{Precision} = \frac{TP}{TP + FP} \quad (4)$$

### 4.1.3. Sensitivity

That is the ratio of the correct classification predicted True Positive sample number to total of the correct classification predicted True Positive sample number and the incorrect classification predicted False Negative sample number [20].

$$\boldsymbol{Sensitivity} = \frac{TP}{TP + FN} \quad (5)$$

### 4.1.4. F-Measure

Precision and sensitivity criteria are not sufficient to achieve a meaningful comparison of results alone. Evaluation of both criteria together gives more accurate results. For this, F-Measure was defined. F-measure is the harmonic mean of precision and sensitivity [20].

$$\boldsymbol{F - Measure} = 2\,x\,\frac{Sensitivity\ x\ Precision}{Sensitivity +\ Precision} \quad (6)$$

The model performance measures calculated with each method and the values were given in Table 6;

**Table 6.** Comparison of Model Performance Criteria.

| | Accuracy | Precision | Sensitivity | F-Measure |
|---|---|---|---|---|
| ANN | 1.0000 | 1.0000 | 1.0000 | 1.0000 |
| SVM | 0.9423 | 1.0000 | 0.9318 | 0.9647 |

## 5. Conclusion

If it is looked at the first results Table 3, the **ANN** method, whose **$R^2$adj** value is the highest and **RMS** value is the smallest, is in the first row. The **SVM** method, whose **MAE** value is the smallest, is in the second row. And if the results compared with each other according to the model performance criteria Table 6, generally the **ANN** is better than the **SVM**. As a result, according to the comparison result; the ANN method was found to be more successful than the SVM method.

The railways have gained importance in the recent years in Turkey. In order to avoid from the hazards that are occurred in railways, identification of the hazards, such as in this work, should be proceed in detail and the reasons for these hazards should be classified clearly. At the end of this identification and classification process, in the future with a correctly created model faults, the accidents and incidents can be predicted. Thanks to this study that has high percentage of success, before the occurrence of accidents and incidents, it seems to be able to prevent these hazards with a proactive approach.

There are no studies in the literature related to the prediction of accidents and incidents caused by faults. From this perspective, this study is the first of its kind in the world. Besides, the overlapping of the predictions at the high rates with the real data shows that the model was set up correctly.

It is planned in the future that the similar models and a prediction software, such as in this study, will be created for every region and sub-region by using Turkish State Railways (TCDD) Traffic Operation records to predict accidents and incidents before they happen.

## 6. References

[1] Markovic N., Milinkovic S., Tikhonov K. S., Schonfeld P., “Analyzing passenger train arrival delays with support vector regression”, Transportation Research Part C, vol. 56, 2015, 251–262.

[2] Islam D. M. Z., Laparidou K., Burgess A., “Cost effective future derailment mitigation techniques for rail freight traffic management in Europe”, Transportation Research Part C, Accepted 19 June 2015.

[3] Kocaarslan İ., Karaman S., Apaydın İ., Gör E. , “Demiryolu Emniyet Yönetim Sistemi ve TCDD’de Uygulanması”, I. Uluslararası Raylı Sistemler Çalıştayı, Karabük /TURKEY, 2012. (In Turkish)

[4] Reason J.T., “Human Error: Models And Management”, British Medical Journal, vol. 320, 2000, 768-770.

[5] Karabacak S. A., “Implementation of Monitoring and Analysis Method on Railway Safety Management System”, Master Thesis, Istanbul University, 2014. (In Turkish)

[6] Reason J.T., “ Human Error”, Cambridge University Press, New York, 1990, ISBN: 978-0521314190.

[7] Karaman S., Kocaarslan İ., Tiryaki H., “Application of Artificial Neural Networks for Safety Management Systems in Railways”, International Congress on Advanced Railway Engineering, 2-4 March 2015, İstanbul, 262-267.

[8] Sivri N. , Özcan K. , Uçan O. N. , Akıncılar O. , “Estimation of Stream Temperature in Değirmendere River (Trabzon-Turkey) Using Artificial Neural Network Model”, Turkish Journal of Fisheries and Aquatic Sciences, vol. 9, 2009, 145-150.

[9] Alp M., Cığızoğlu K., “Rainfall-Runoff Relation to Different Methods of Artificial Neural Network Modeling.”, İTU Journal/ d engineering, vol. 3(1), 2004, 80-88. (In Turkish)

[10] Akgundogdu A., “Trabecular Bones Structure Analyzing Using Artificial Intelligence Methods”, Ph.D. Thesis, Istanbul University, 2009. (In Turkish)

[11] Cannas B., Montisci A., Fanni A., See A., Sechi G. M., "Comparing Artificial Neural Networks and Support Vector Machines for Modelling Rainfall-Runoff", 6th International Conference on Hydroinformatics - Liong, Phoon &Babovic (eds) © 2004 World Scientific Publishing Company, 2004, ISBN 981-238-787-0.
[12] Dawson C.W., Wilby R., "An Artificial Neural Network Approach to Rainfall-runoff Modelling. Hydrological", Sciences—Journal—des Sciences Hydrologiques, 43(1) 47, February 1998, ISSN 1019-101145.
[13] Kayaalp N., Hamidi N., "Dicle Nehrinde Taşınan Aylık Süspanse-Sediment Miktarının Yapay Sinir Ağları ile Belirlenmesi", IV. Ulusal Hidroloji Kongresi ve Hidrolojide Yeni Yöntemler Semineri, 21-25 June 2004. (In Turkish)
[14] Sivri N., Kilic N., Ucan O. N. , "Estimation of stream temperature in Firtina Creek (Rize-Turkiye) using artificial neural network model", Journal of Environmental Biology, vol. 28(1), 2007, 67-72.
[15] WEKA 3.6 Reference Manual, 2014.
[16] Soman K.P., Loganathan R., Ajay V. thods. PHI Learning Pvt. Ltd., 2011, 486 s.
[17] Cortes C., Vapnik V., Support vector networks, Machine Learning, 1995, 20, 1-25.
[18] Li S., Li H., Li M., Shyr Y., Xie L., Li, Y., Improved prediction of lysine acetylation by support vector machines. Protein and peptide letters, 2009, 16, 977-983.
[19] Erdal H. I., "Predictive Modeling With Support Vector Machines and an Application", Ph.D. Thesis, Istanbul University, 2011. (In Turkish)
[20] Catal C., "Performance Evaluation Metrics for Software Fault Prediction Studies", Acta Polytechnica ungarica, 2012, vol. 9, No.4, 193-206.

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