İleri Teknoloji Bilimleri Dergisi
Cilt 2, Sayı 1, 12-25, 2013

Journal of Advanced Technology Sciences
Vol 2, No 1, 12-25, 2013

PREDICTION OF THE PAVEMENT SERVICEABILITY RATIO OF RIGID HIGHWAY PAVEMENTS BY ARTIFICIAL NEURAL NETWORKS

Nihat MOROVA[1*], Sercan SERİN[2], Serdal TERZİ[3], Mehmet SALTAN[3]

[1]Suleyman Demirel University, Faculty of Technology, Department of Manufacturing Engineering / 32100, ISPARTA
[2] Civil Engineering Department& Faculty of Technology Duzce University 81620, Duzce
[3]Civil Engineering Department& Faculty of Engineering, Suleyman Demirel University 32100, ISPARTA

Abstract-The term ‘‘present serviceability’’ was adopted to represent the momentary ability of pavement to serve traffic, and the performance of the pavement was represented by its serviceability history in conjunction with its load application history. Serviceability was found to be influenced by longitudinal and transverse profile as well as the extent of cracking and patching. The amount of weight to assign to each element in the determination of the over-all serviceability is a matter of subjective opinion.

In this study, the present serviceability index of rigid highway pavements has been predicted by an artificial neural network (ANN) model. For this model, the 49 experimental data obtained from AASHTO include slope variance, faulting, cracking, spalling and patching. The developed ANN model has a higher regression value than the AASHO model. This approach can be easily and realistically performed to solve the problems which do not have a formulation or function for the solution.

Keywords-Artificial Neural Networks, Pavement, Rigid Pavements, Serviceability

1. INTRODUCTION

In the literal sense, the first roads were built through Egypt from the south part of Asia shortly after the invention of the wheel around 3500 B.C. On the other hand, the first roads that depended on a few scientific rules were built by the Romans around 300 B.C. The oldest and the longest known road is the “King’s Road” which was built by Persians. By the end of the eighteenth century, some basic scientific principles about road construction had been defined by engineers. During the 1960’s the American Association of State Highway Officials (AASHO) started to determine theoretical roots of road pavement using “AASHO Road Test” results [1].

The pavement management system (PMS) was first conceived in the late 1960s to 1970s as a result of pioneering work by Hudson et al [2] and Finn et al [3] in the United States, and by Haas [4] in Canada. The pavement management concept was first conceived to organize and coordinate the activities involved in achieving the best value possible for the available funds [5].

AASHTO (1990) defines PMS as follows, “A PMS is a set of tools or methods that assist decision makers in finding optimum strategies for providing, evaluating, and maintaining pavements in a serviceable condition over a period of time.” The products and information that can be obtained and used from a PMS include planning, design, construction, maintenance, budgeting, scheduling, performance evaluation, and research [6,7]. The goal of a PMS is to yield the best possible value for available funds in providing and operating smooth, safe, and economical pavements [8]. The functions of a PMS are to improve the efficiency of decision making, to expand the scope and provide feedback on the consequences of the decisions, to facilitate coordination of activities within the agency, and to ensure consistency of decisions made at different levels within the same organization [9]. A PMS provides a systematic, consistent method for selecting maintenance and rehabilitation (M&R) needs

* nihatmorova@sdu.edu.tr

and determining priorities and the optimal time of repair by predicting future pavement conditions [10].

In response to the growing need for highway rehabilitation and maintenance on one hand and shrinking resources on the other, there has been an increased interest in developing a formal management approach to optimize the utilization of highway construction and maintenance resources. The specific component of this approach related to pavement is termed ‘‘pavement management system’’ (PMS) [11,12].

Hence, optimizing the current pavement condition evaluation practice will be the first and foremost task of efficient pavement management systems [13]. Setting priorities for pavement maintenance and rehabilitation depends on the availability of a universal scale for assessing the condition of every element in the network.

Pavement condition is a generic phrase to describe the ability of a pavement to sustain a certain level of serviceability under given traffic loadings. It is usually represented by various types of condition indices, such as Present Serviceability Index (PSI), Present Serviceability Rating (PSR), Mean Panel Rating (MPR), Pavement Condition Index (PCI), Pavement Condition Rating (PCR), Ride Number (RN), Profile Index (PI), and International Roughness Index (IRI). These indices can be classified into two categories: roughness-based and distress-based.

The present serviceability index (PSI) is one common evaluator used to describe the functional condition with respect to ride quality. The pavement condition index (PCI) is another index commonly used to describe the extent of distress on a pavement section [14].

The pavement condition rating (PCR) method is based upon visual inspection of pavement distresses. Although the relationship between pavement distresses and performance is not well defined, there is general agreement that the ability of a pavement to sustain traffic loads in a safe and smooth manner is adversely affected by the occurrence of observable distress. The rating method provides a procedure for uniformly identifying and describing, in terms of severity and extent, pavement distress. The mathematical expression for PCR provides an index reflecting the composite effects of various distress types, their severity and extent upon the overall condition of the pavement [15].

Prediction of future pavement condition is not only essential for maintenance budget forecasting at the network level but also for determining the most cost-effective rehabilitation strategy at the project level [13].

The knowledge of future pavement performance is essential to sound pavement design and life-cycle economic evaluation at the project level of pavement management. At the network level, such information is important to ensure adequate financial funding and budgeting [16].

Pavement failure is a highly variable event that not only depends on layer material properties, environmental and sub-grade conditions, and traffic loading, but also on the specific definition of failure adopted by the highway agency. Failure can be defined in terms of amount of cracking, rut depth, surface roughness, or combinations of these or other indicators of performance [17].

In recent years, one of the most important and promising research fields has been ‘‘Heuristics from Nature’’, an area utilizing some analogies with natural or social systems and using them to derive non-deterministic heuristic methods and to obtain very good results. Artificial neural Networks (ANN) is among the heuristic methods [18].

Designers utilize principles of science and mathematics to develop specific technologies. These technologies are then used to create engineered tools such as products, structures, machines, processes or entire systems. It has already been seen that different tasks in engineering problem solving require different analysis [19]. Recently, artificial intelligence and statistical analysis have been extensively using in the fields of civil engineering applications such as construction management, building materials, hydraulic, geotechnical and transportation engineering etc. [20-37].

The main purpose of this paper is to develop an ANN methodology for estimating pavement serviceability index without any restrictive assumption by considering slope variance, rut depth, patches, cracking and longitudinal cracking as input variables and the AASHO panel data as an output variable.

2. PAVEMENT SERVICEABILITY RATIO

One of the most famous pavement testing facilities in the world was the AASHO Road Test, which was constructed and operated near Ottawa, Illinois, between 1957 and 1961. This facility was one of the earliest and most experimentally sound efforts to evaluate the effects of various pavement structural designs and loading parameters on overall pavement performance. The basic derived formulae that represent the effects of different axle loads and configurations are still used today, even though vehicle characteristics and pavement designs have changed considerably [38].

The American Association of State Highway Officials “AASHO” Road Test developed a definition of pavement serviceability and the present serviceability rating (PSR) that is based on individual observation. PSR is defined as "the judgment of an observer as to the current ability of a pavement to serve the traffic it is meant to serve. To generate the original AASHO Road Test PSR scores, observers rode around the test tracks and rated their ride using the quantitative scale shown in Fig. 1. This subjective scale ranges from five (excellent) to zero (essentially impassable). Since PSR is based on passenger interpretations of ride quality, it generally reflects road roughness because roughness largely determines ride quality.

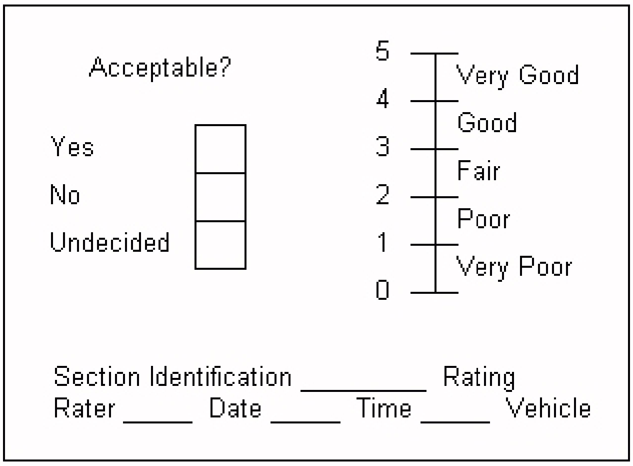


Figure 1. Individual present serviceability rating form

The present serviceability index (PSI) is based on the original AASHO Road Test PSR. Basically, the PSR was a ride quality rating that required a panel of observers to actually ride in an automobile over the pavement in question. Since this type of rating is not practical for large-scale pavement networks, a transition to a non-panel based system is needed. To transition from a PSR serviceability measure (panel developed) to a PSI serviceability measure (no panel required), a panel of raters during 1958 to 1960 rated various roads in the states of Illinois, Minnesota, and Indiana for PSR.

This information was then correlated with various pavement measurements (such as slope variance (profile), cracking, etc.) to develop PSI equations. Further, the raters were asked to provide an opinion as to whether a specific pavement assessed for PSR was "acceptable" or "unacceptable" as a primary highway.

Although PSI is based on the same 5-point rating system as PSR, it goes beyond a simple assessment of ride quality. About one-half of the panel of raters found a PSR of 3.0 acceptable and a PSR of 2.5 unacceptable. Such information was useful in selecting “terminal” or failure serviceability (PSI) design input for empirical structural design equations. It is interesting to note that the original AASHO Road Test raters opinions were based on car ride dynamics; it is unclear whether such levels are acceptable for trucks. Pavement performance can then be defined as "the serviceability trend of a pavement segment with an increasing number of axle applications" [39]. Figure 2 further demonstrates this concept.

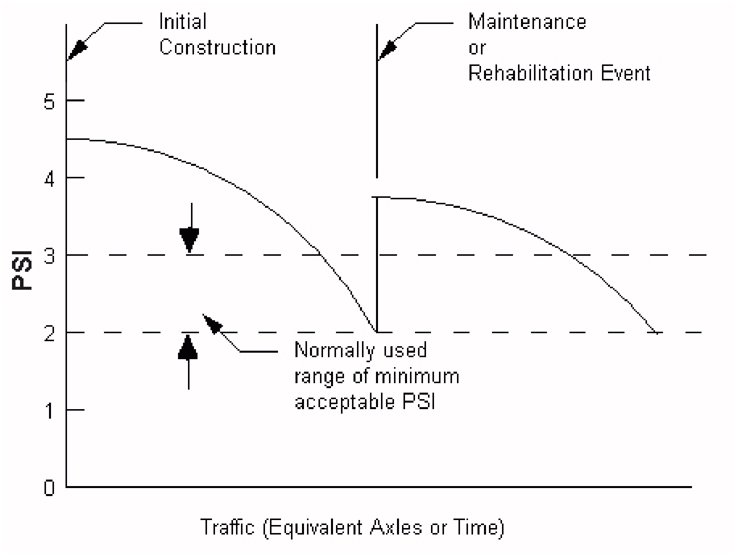


Figure 2. Concept of pavement performance using present serviceability index (PSI) [40].

The Present Serviceability Index "PSI" was established from regression equations, which related user's opinions to objective measurements (AASHO slope profilometer) with the extent of cracking, patching, and rutting.

AASHO test results (1962) showed that serviceability was found to be influenced by longitudinal and transverse profile as well as the extent of cracking and patching. To obtain a good estimate of the opinion of the traveling public in these subjective matters a Pavement Serviceability Rating Panel was appointed by AASHO. Pavement Performance Ratings have been measured for every pavement section by the committee [41].

The concept of serviceability was developed by Carey and Irick at the AASHO Road Test and surface profile and roughness provide nearly 95% of the information about pavement serviceability. With this information, a present serviceability rating from 0 to 5 (very poor to very good) was used by a panel of raters riding in a vehicle over the pavement. These ratings were correlated with objective measurements of pavement condition to develop a regression equation for present serviceability index (PSI). For rigid pavements, the regression equation used slope variance (a summary statistic for wheel path roughness) and the sum of cracking and patching. Slope variance was found to be the dominant variable [42].

The basic equation of PSI is the linear form shown below;

$$\mathrm{PSI} = \mathrm{A}_0 + (\mathrm{A}_1\mathrm{R}_1 + \mathrm{A}_2\mathrm{R}_2 + \ldots) + (\mathrm{B}_1\mathrm{D}_1 + \mathrm{B}_2\mathrm{D}_2 + \ldots) \tag{1}$$

R_1 and R_2 are functions of profile roughness and D_1 and D_2 are functions of surface deformations.

Regress would be applied to every measured summary as it is not related to the PSR.

This could be successful in different forms to describe measures against PSR and understanding which one is the result with right line.

Rigid pavements do not have rut depth so the equation becomes that which is shown below [43].

$$PSI = A_0 + A_1R_1 + B_1D_1 = A_0 + A_1 \log(1 + SV) + B_1\sqrt{C + P} \tag{2}$$

A_0, A_1 and B_1 coefficients in equation 2 have been determined as multiple linear recreations.

For all sections Error (E) between PSI and PSR can be expressed as shown below.

$E = \sum(PSR - PSI)^{2} = \sum(PSR - A_0 - A_1R_1 - A_2R_2 - B_1D_1)^{2}$ (3)

A_0, A_1 A_2 and B_1 coefficients must be chosen in order for the minimum error to be obtained. E can be minimized to equal 0 and make a partial derivative according to every coefficient.

This results in four equations that can be easily solved and four unknown coefficients [43].

Eq. 4. was used to determine the level of serviceability of the surviving 49 rigid pavement test sections every two weeks during a period of traffic operation [41].

$P = 5.41 - 1.80\ \log(1 + SV) - 0.09\sqrt{C + P}$ (4)

In which,

P= present serviceability index;

SV= mean of the slope variance in the two wheel paths; and

C and P= measures of cracking and patching in the pavement surface. (In this equation and throughout this report, logarithms are to base 10.)

Pavement Performance (Serviceability) decreases over the course of time because of environmental and traffic effects according to the AASHO pavement tests. The serviceability index is a value between 0 and 5.

While the serviceability index is 5 when the pavement is newly built, at the end of a definite period of use it has reached the last serviceability index (PSI) by decrease and when the performance is decreased (or disappears) it is accepted that the life-cycle of the pavement is completed.

Pavement performance is increased by reinforcement of the pavement by increasing the serviceability index [44].

$PSI\ 211 = 5.41 - 1.80\log(1 + SV) - 0.09\sqrt{C + P}$ (5)

The PSI formulation is a mathematical combination that obtained its values as a result of definite physical measurements used for estimating the PSR value of pavement in the limits previously defined. PSR and measurement summaries, after being obtained for all chosen pavements, the last step is to combine those measurement summaries with a satisfactory approach to the PSR user estimates in PSI formulation. Linear recreation technical analysis can be used to reach the formula.

3. ARTIFICIAL NEURAL NETWORK

Artificial neural network is fairly simple and small in size when compared to the human brain, and has some powerful knowledge- and information-processing characteristics due to its similarity to the human brain. The first studies on ANNs were supposed to have started in 1943. In recent years, with the developments in computer technology, ANNs have been applied to many civil engineering problems with some degree of success. In civil engineering, neural networks have been applied to detect structural damage, structural system identification, modeling of material behavior, structural optimization, structural control, groundwater monitoring, prediction of settlement of shallow foundation, and concrete mix proportions [45].

Neural networks are composed of simple elements operating in parallel. These elements are inspired by biological nervous systems. As in nature, the network function is determined largely by the connections between elements. A neural network can be trained to perform a particular function by adjusting the values of the connections (weights) between the elements. Commonly, neural networks are adjusted, or trained, so that a particular input leads to a specific target output. Such a situation is shown in Fig. 3. Here, the network is adjusted, based on a comparison of the output and the target, until the network output matches the target. Typically, many such input/target output pairs are used to train a network. Batch training of a network proceeds by making weight and bias changes based on an entire set (batch) of input vectors. Incremental training changes the weights and biases of a network as needed after the presentation of each individual input vector. Incremental training is sometimes referred to as ‘‘on line’’ or ‘‘adaptive’’ training [46, 47].

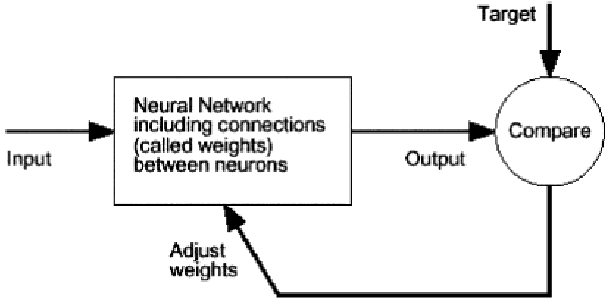


Figure 3. Basic principles of artificial neural networks [47,48].

Neural networks have been trained to perform complex functions in various fields of application including pattern recognition, identification, classification, speech, vision and control systems. Today, neural networks can be trained to solve problems that are difficult for conventional computers or human beings [48].

4. STRUCTURE OF DEVELOPED ANN MODEL, PARAMETERS, AND FINDINGS

A flowchart summarizing the ANN model was given in Fig. 4. The Artificial neural networks model developed in this research has five neurons (variables) in the input layer and one neuron in the output layer, as illustrated in Fig. 5. One hidden layer with three neurons was used in the architecture because of its minimum percentage error values for training and testing sets. Some of the architectures with different numbers of neurons were studied here in hidden layers and their correlations with experimental results were investigated, while modeling slope variance, faulting, cracking, spalling and patching were used as inputs and PSR (panel data) was used as an output. In this study, data sets were taken from AASHO test results [41]. For training sets, 39 samples (80% of all samples) were selected and the residual data (10–20% of all samples) were selected as a test set. The values of the training and test data were normalized between 0 and 1 using Eq. 6.

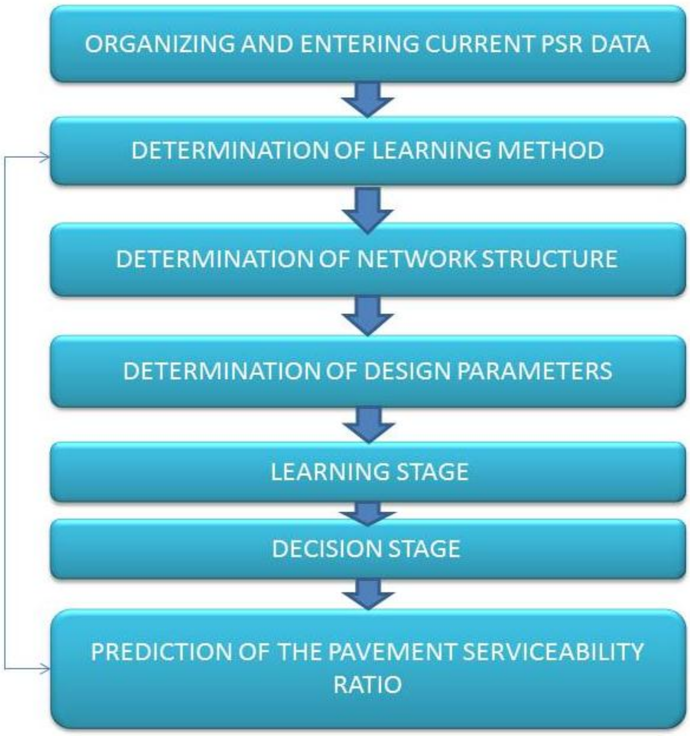


Figure 4. Flow chart of the prediction model

$$F = (F_i - F_{\min})/(F_{\max} - F_{\min}) \tag{6}$$

In this equation, F represents the normalized value, Fi represents i. Value of measured values and Fmax and Fmin represent maximum and minimum values of measured values.

Levenberg-Marquardt back-propagation training was repeatedly applied until the evaluation standard was reached [48].

The back-propagation learning algorithm was used in feed-forward with one hidden layer. The logarithmic sigmoid transfer function was used as the activation function for hidden layers and output layers. The learning rate and momentum are the parameters that affect the speed of convergence of the back-propagation algorithm. 5000 learning cycles were used while training all networks.

A learning rate of 0.001 and momentum of 0.1, were fixed for the selected network after training and model selection was completed for the training set. The trained networks were used to run a set of test data. All of the developed networks (521-531-541-551-561-571- 581-591) were compared with experimental results and the R^2 values of testing results are shown in Table 1.

Various combinations of network architecture to develop an optimum ANN model were examined. ANN (i, j, k) indicates a network architecture with i, j and k neurons in input, hidden and output layers, respectively. The ANN (5, 3, 1) appeared to be most optimal topology; the configuration is shown in Fig. 5. A comparison of panel data between PSI that was obtained from Eq. (5) and the ANN model are given in Figs. 6 (a), (b), (c), (d) and 7 (a), (b), (c), (d) for training and testing sets, respectively. The R^2 values of PSI and the ANN model are obtained as 0.92 and 0.95 for the training set, and 0.91 and 0.92 for the testing set, respectively. The ANN model has better results than PSI for the AASHO panel data for both training and testing sets.

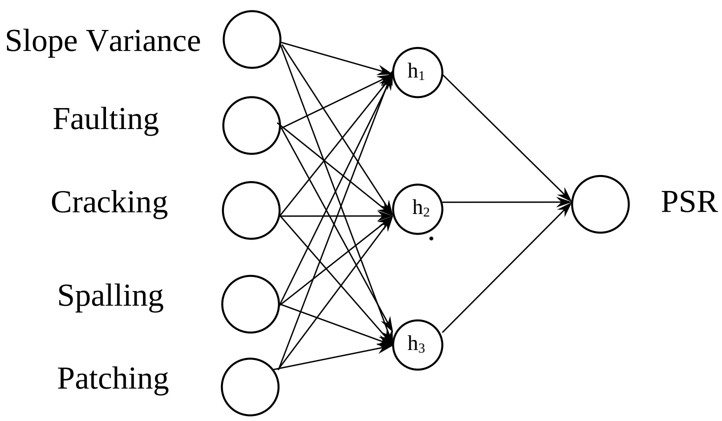
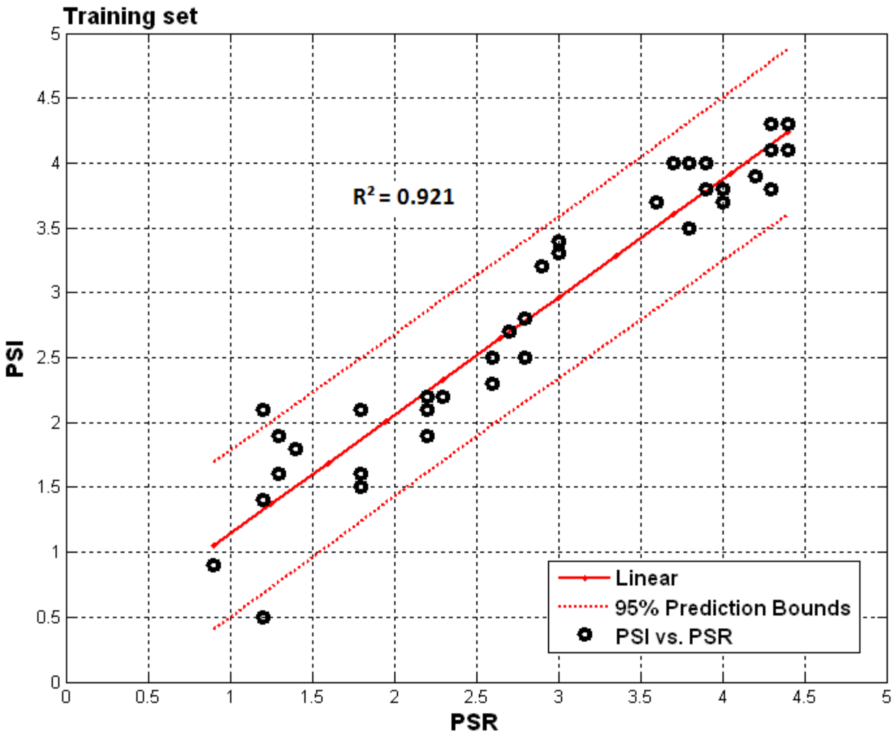


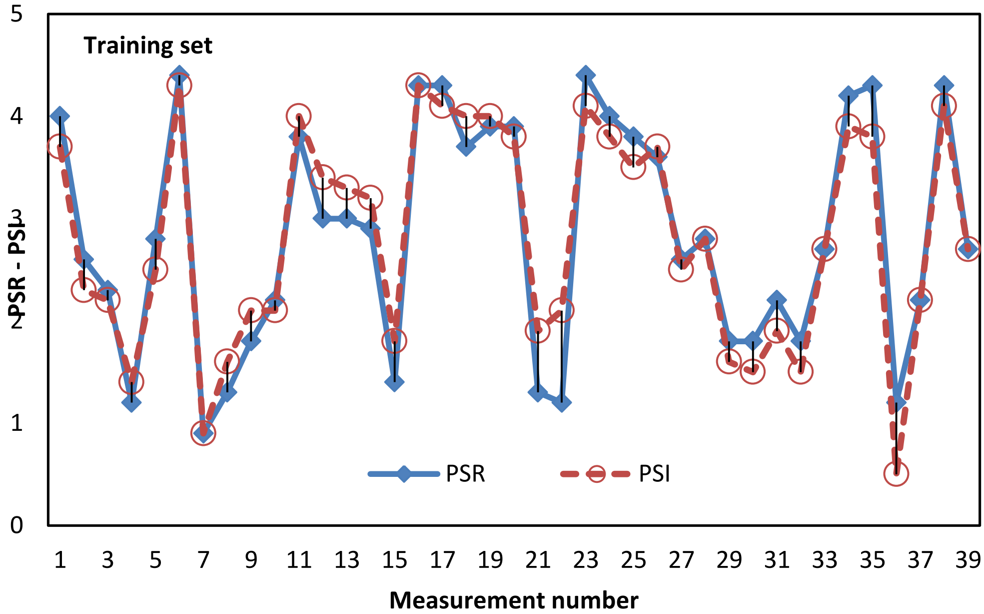
Figure 5. The structure of the 531 model (5 input, 3 hidden and 1 output)

Table 1. Results obtained from testing the ANN and correlations between experimental results

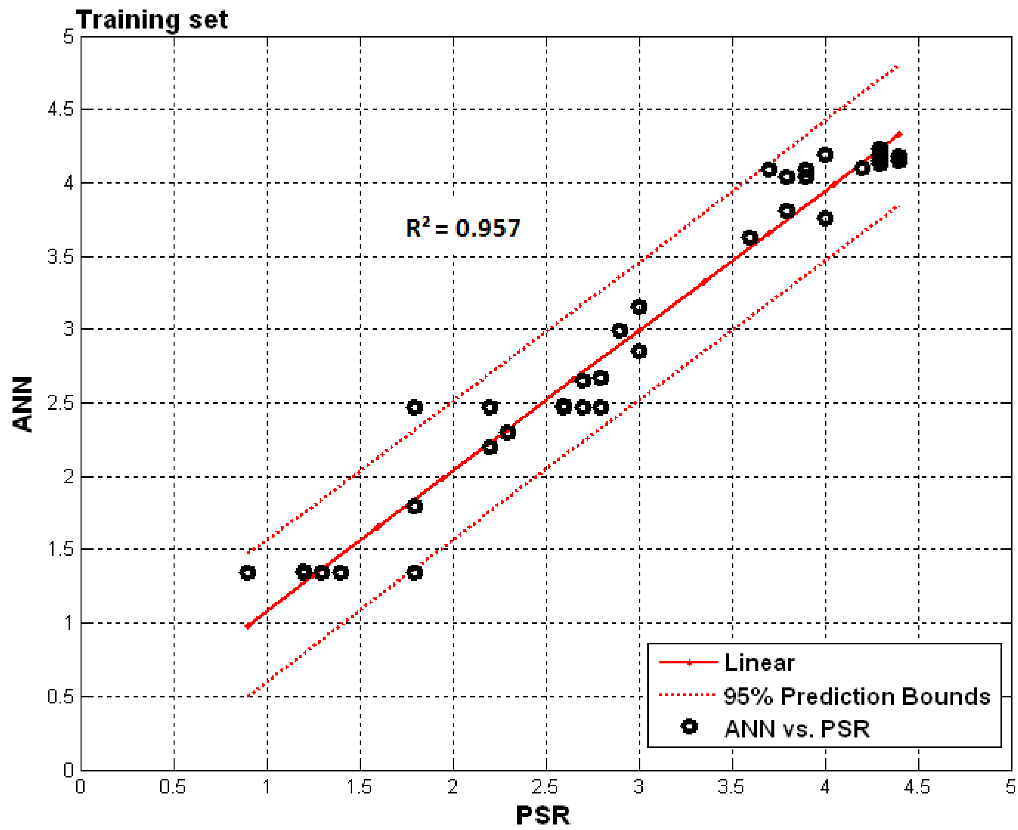
Model	Model 521	Model 531	Model 541	Model 551	Model 561	Model 571	Model 581	Model 591
R^2	0.617	0.925	0.821	0.914	0.776	0.848	0.701	0.566


Training set
R² = 0.921
Linear
95% Prediction Bounds
PSI vs. PSR
PSI
PSR

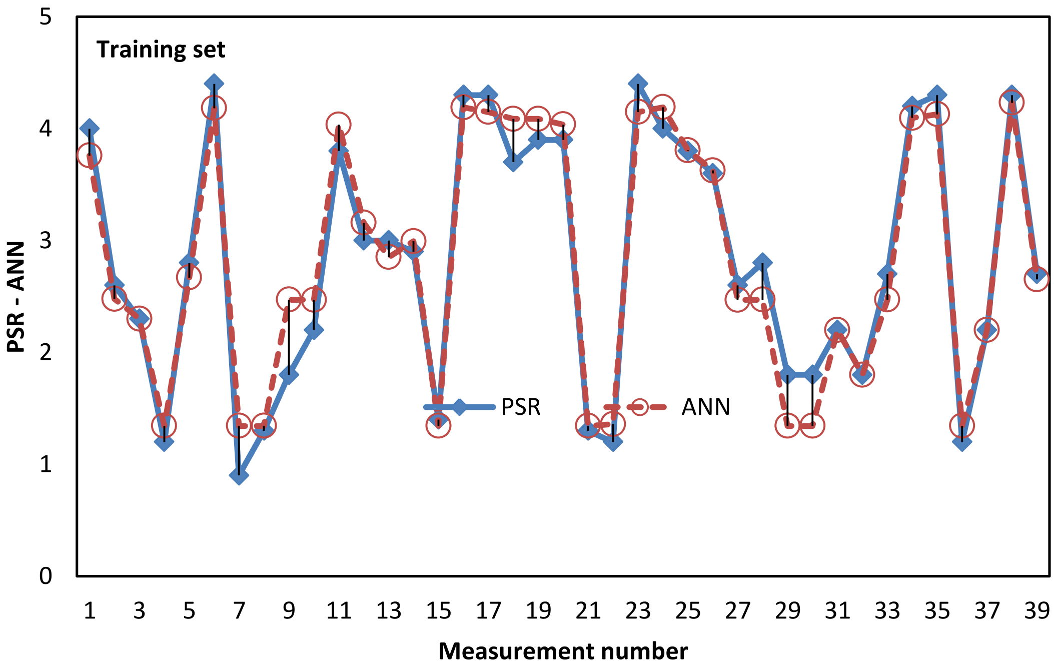
(a)


Training set
PSR
PSI
PSR - PSI
Measurement number

(b)

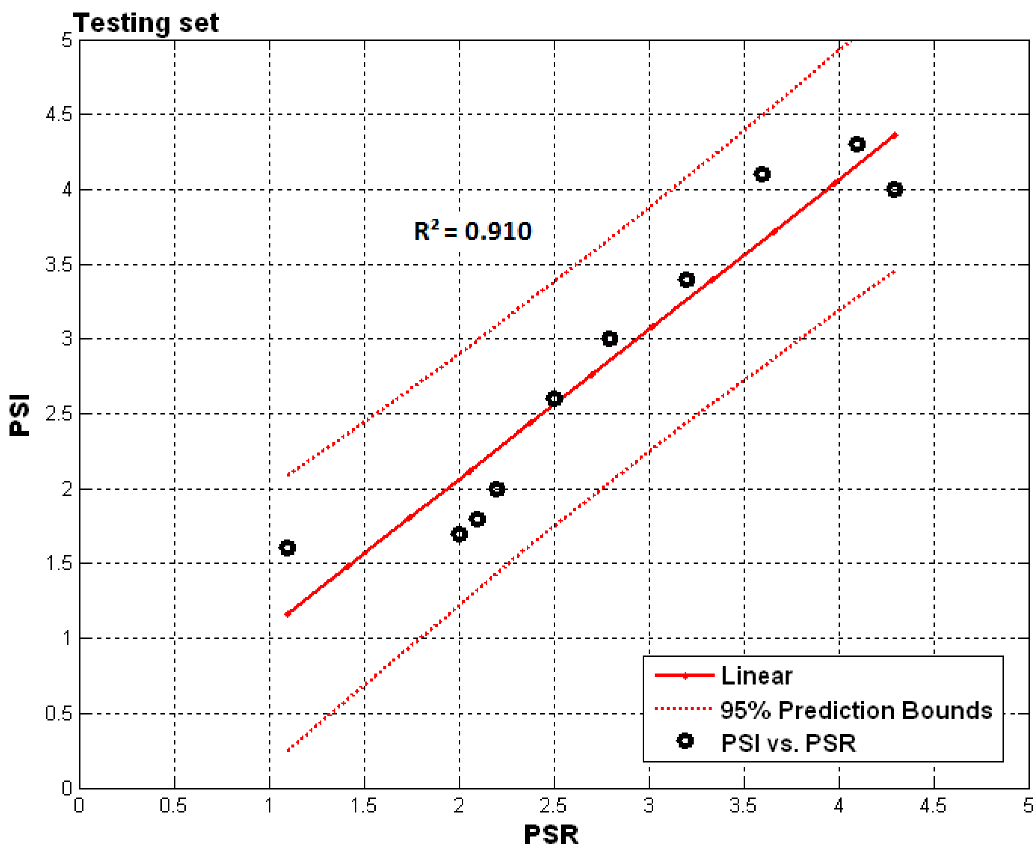


(c)

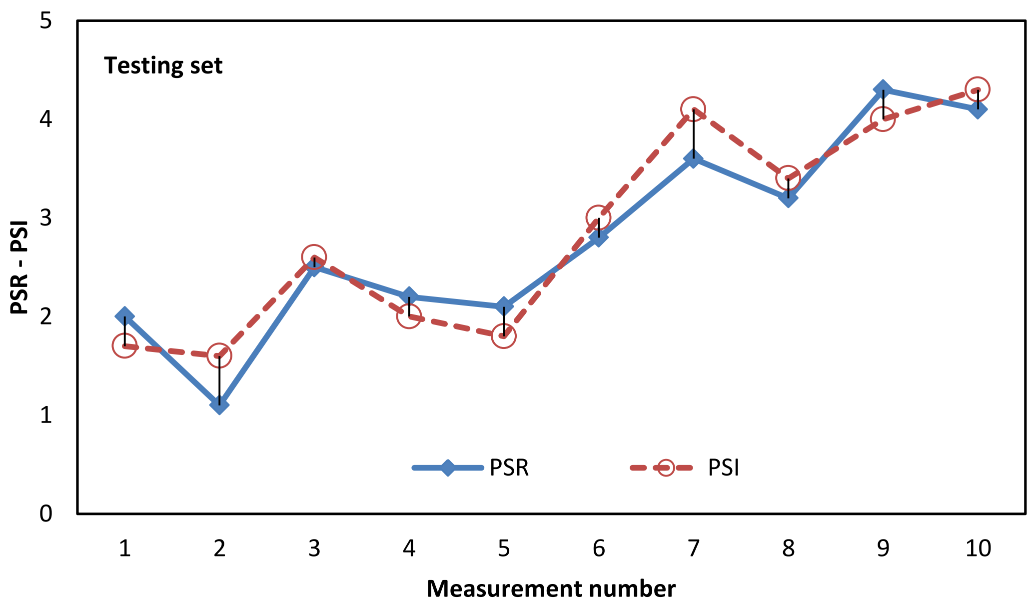


(d)

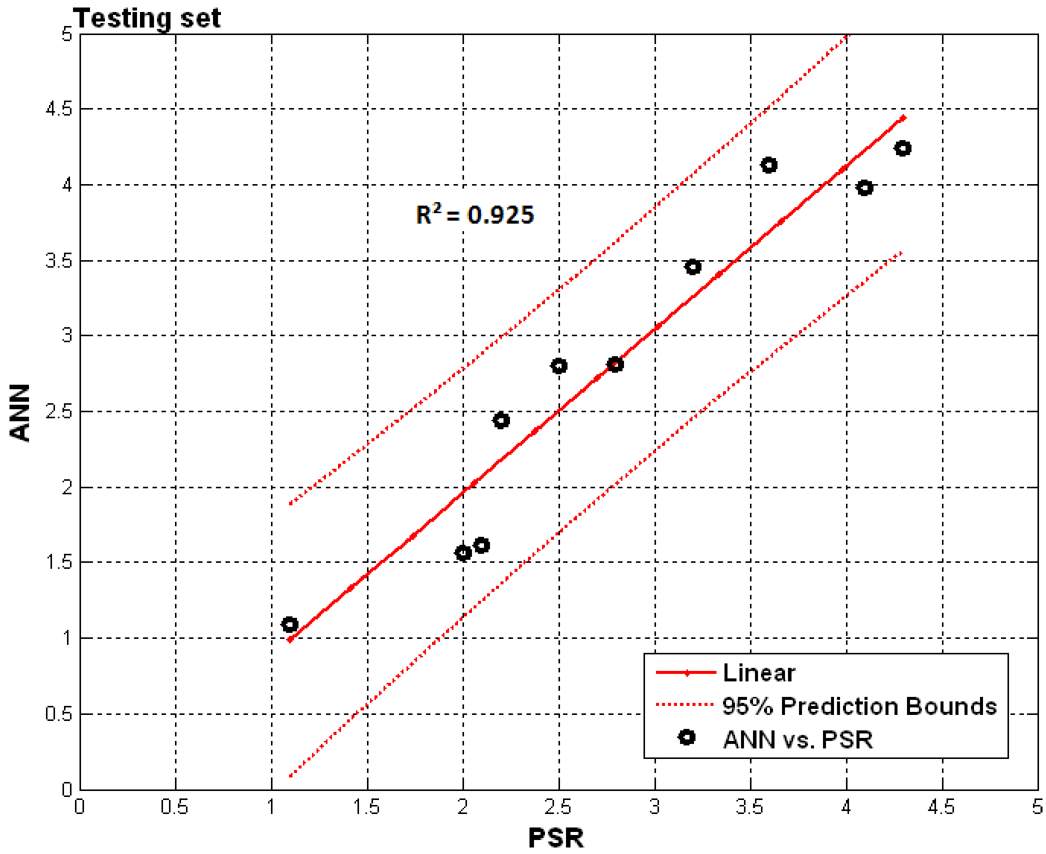
Figure 6 (a), (b), (c), (d). Comparison of the ANN and PSI with target data (PSR) for the training set


Testing set
$R^2 = 0.910$
PSI
PSR
Linear
95% Prediction Bounds
PSI vs. PSR

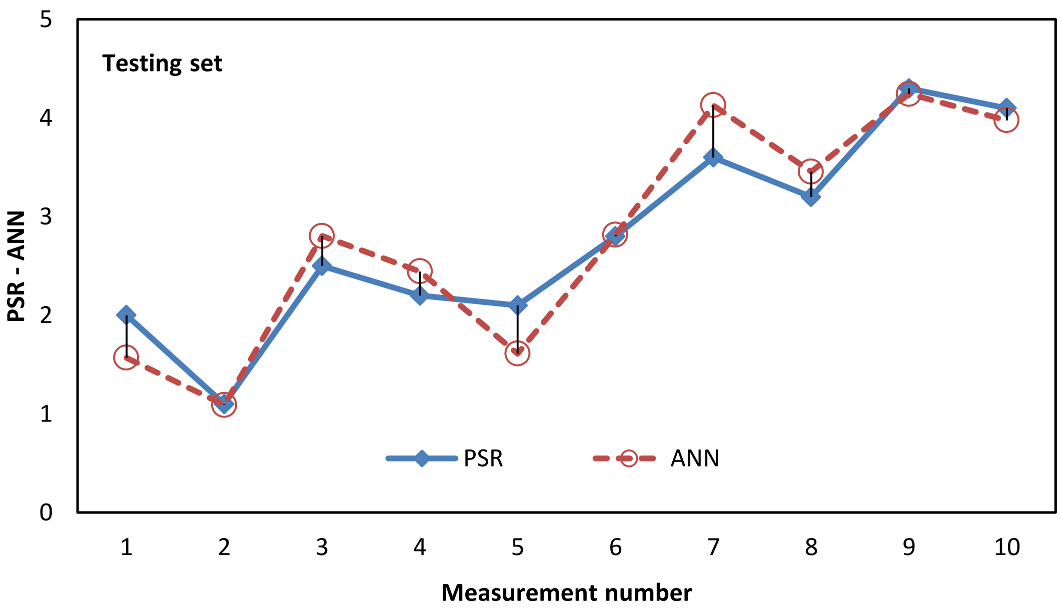
(a)


Testing set
PSR - PSI
Measurement number
PSR
PSI

(b)



(c)



(d)

Figure 7 (a), (b), (c), (d). Comparison of the ANN and PSI with target data (PSR) for the testing set

5. CONCLUSIONS

A pavement performance prediction is one of the most important components of the pavement management system. An accurate estimate directly affects the success of all the pavement management systems.

In this paper, an ANN model has been developed for the pavement serviceability ratio (PSR) determined on the surface of rigid pavements. The ANN model estimates better results than PSI for the AASHO panel data of the PSR.

This new model can help to estimate rigid pavement performance predictions for pavement management systems. However, it should be noted that artificial intelligence techniques developed directly from measured data and the validity of the data for accuracy and repeatability directly affect the success of the model.

6. REFERENCES

[1]. Kırbaş. U., and Gursoy, M., Developing the basics of pavement management system in Beşiktaş district and evaluation of the selected sections. *Scientific Research and Essays.* Vol. 5(8), Available online at http://www.academicjournals.org/SRE,18 April, 2010, pp. 806-812.

[2]. Hudson, W. R., F. N. Finn, B. F. McCullough, K. Nair, and B. A. Vallerga. Systems Approach to Pavement Design, Systems Formulation, Performance Definition, and Materials Characterization. Final Report, NCHRP Project 1-10, TRB, National Research Council Washington, D.C., March 1968.

[3]. Finn, F. N., C. Saraf, R. Kulkarni, K. Nair, W. Smith, and A. Abdullah. Development of Pavement Structural Subsystems. Final Report, NCHRP Project 1-10B. Washington,D.C., Feb. 1977.

[4]. Haas, R. A Guide to Pavement Management. Good Roads Association, Canada, 1977.

[5]. Karan MA, Haas R, Walker T. Illustration of pavement management: from data inventory to priority analysis. Transport Res Rec 1981, 814:22–8.

[6]. Hugo, F., W. J. Scholtz, M. Sinclair, and P. C. Curtayne. Management of Pavement Rehabilitation. Elsevier Science Publishers B.V., North-Holland, 1989.

[7]. AASHTO. AASHTO Guidelines for Pavement Management Systems. AASHTO, Washington, D.C., 1990.

[8]. Lee, H., and W. R. Hudson. Reorganizing the PMS Concept. In Proceedings of PMSNorth American Conference on Managing Highways, Ontario, Canada, 1985, pp. 59–80.

[9]. Haas R, Hudson WR, Zaniewski J. Modern pavement management systems. USA: Krieger Publishing Company; 1994.

[10]. Shahin, M.Y. Pavement Management for Airports, Roads, and Parking Lots. Second Edition, Springer Science, New York, 2005.

[11]. Rada GR, Perl J, Witczak W. Integrated model for project-level management of flexible pavements. J Transport Eng 1985;112(4): 381–99.

[12]. Tavakoli A, Lapin ML, Ludwig F. PMSC: pavement management system for small communities. J Transport Eng 1992;118(2): 270–81.

[13]. Bandara N, Gunartne M. Current and future pavement maintenance prioritization based on rapid visual condition evaluation. J Transport Eng 2001;127(2):116–23.

[14]. Shoukry S, Martinelli DR, Reigle JA. Universal pavement distress evaluator based on fuzzy sets. Transport Res Rec 1997;1592:180–6.

[15]. Saraf CL. Pavement condition rating system. Federal Highway Administration, Report No. FHWA/OH-99/004. 1998.

[16]. Fwa TF, Sinha KC. Routine maintenance and pavement performance. J Transport Eng 1985;112(4):329–45.

[17]. Madanat S, Prozzi JA, Han M. Effect of performance model accuracy on optimal pavement design. Comput-Aided Civ Inf Eng 2002;17:22–30.

[18]. Colorni A, Dorigo F, Maffioli F, Maniezzo V, Righini G, Trubian M. Heuristics from nature for hard combinatorial optimization problems. Int Trans Oper Res 1996;3(1):1–21.

[19]. Emiroğlu, M., Beycioğlu, A., Yildiz, S., “Anfis and Statistical Based Approach to Prediction the Peak Pressure Load of Concrete Pipes Including Glass Fiber”, Expert Systems with Applications (2011), doi:10.1016/j.eswa.2011.08.149.

[20]. Attoh-Okine, N.O., (1995). "Using Adaptive Neural Networks to identify Significant Variables in Pavement Performance Prediction", Intelligent Engineering Systems through Artificial Neural Networks, ASME Press Series, Vol 5, pp. 803-808,

[21]. Tutumluer, E. & R. W. Meier, (1996). Attempt at resilient modulus modeling using artifcial neural networks, Transportation Research Record, 1560, TRB, Washington, DC.

[22]. Tiğdemir, M., Karaşahin, M., & Sen, Z. (2002). Investigation of fatigue behaviour of asphalt concrete pavements with fuzzy logic approach. International Journal Fatigue, 24(8), 903–910.

[23]. Kalyoncuoglu, S. F., & Tıgdemir, M. (2004). An alternative approach for modelling and simulation of traffic data: Artificial neural networks. Simulation Modeling Practice and Theory, 12(5), 351–362.

[24]. Terzi, S. (2007). Modeling the pavement serviceability ratio of flexible highway pavements by artificial neural networks. Construction & Building Materials, 21, 590–593.

[25]. Ayata, T., Çam, E., Yıldız, O. (2007). Adaptive neuro-fuzzy inference systems (ANFIS) application to investigate potential use of natural ventilation in new building designs in Turkey.Energy Conversion and Management 48, 1472–1479.

[26]. Saltan, M., & Terzi, S. (2008). Modeling deflection basin using artificial neural networks with cross validation technique in backcalculating flexible pavement layer moduli. Advances in Engineering Software, 39(7), 588–592

[27]. Taşdemir, Y. (2009). Artificial neural networks for predicting low temperature performancea of modified asphalt mixtures Indian journal of engineering & Materials Sciences Vol. 16, August, 2009 pp 237-244.

[28]. Topçu I.B, Sarıdemir M (2008) Prediction of compressive strength of concrete containing fly ash using artificial neural network and fuzzy logic. Comput Mater Sci 41(3):305–311.

[29]. Alasha'ary, H., Moghtaderi, B., Page, A., Sugo, H. (2009). A neuro–fuzzy model for prediction of the indoor temperature in typical Australian residential buildings. Energy and Buildings 41, 703–710.

[30]. Subaşı, S. (2009). Prediction of mechanical properties of cement containing class C fly ash by using artificial neural network and regression technique. Scientific Research and Essays, 4(4), 289–297.

[31]. Saffarzadeh, M., & Heidaripanah, A. (2009). Transaction A: Civil Engineering Vol. 16, No. 1, pp. 98-105, Sharif University of Technology, February Effeect of Asphalt Content on the Marshall Stability of Asphalt Concrete Using Artificial Neural Networks.

[32]. Özgan, E. (2011). "Artificial Neural Network Based Modelling of the Marshall Stability of Asphalt Concrete", "Ercan Özgan", Expert Systems With Applications, 38, 6025-6030.

[33]. Yilmaz, M. Kok, . B. V. Sengoz, B.. Sengur, A Avci E. "Investigation of complex modulus of base and EVA modified bitumen with Adaptive-Network-Based Fuzzy Inference System" Expert Systems with Applications, 10.1016/j.eswa.2010.07.088.(In Press), Available online 3 August 2010.

[34]. Saltan, M., Terzi, S., & Küçüksille E. U. (2011). Backcalculation of pavement layer moduli and Poisson's ratio using data mining Expert Systems with Applications 38, 2600–2608.

[35]. Mirzahosseini, M. R., Aghaeifar, A., Alavi, A. H., Gandomi, A. H., Seyednour, R. (2011). Permanent deformation analysis of asphalt mixtures using soft computing techniques Expert Systems with Applications 38, 6081–6100.

[36]. Moazami, D., Behbahani H., Muniandy, R. (2011). Pavement rehabilitation and maintenance prioritization of urban roads using fuzzy logic. Expert Systems with Applications 38, 12869–12879.

[37]. Tapkın, S., Çevik, A., Uşar, Ü. (2011). Prediction of Marshall test results for polypropylene modified dense bituminous mixtures using neural Networks. Expert Systems with Applications 37, 4660–4670

[38]. Huhtala, M, J. Pihlajamaaki and V. Miettinen. "The Effects of Wide Based Tires on Pavements." Proceedings, Third International Symposium on Heavy Vehicle Weights and Dimensions. Queen's College Cambridge, United Kingdom. 1992. pp. 233-242.

[39]. Garber, Nicholas J., and Lester A. Houl: Traffic and Highway Engineering, West, Publishing, Company, New York, 1998.

[40]. Rouillard, V., Sek, M., and Perry, T.: Analysis and Simulation of Road Profiles, Journal of Transportation Engineering, Washington, D.C, USA, May/June 1996, 241-245.

[41]. AASHO Road Test. "The AASHO Road, Test Report 5, Pavement Research", By the Highway Research Board Of The NAS-NRC Division Of The Engineering And Industrial Research, Special Report 61E, No: 954, National Academy Of Sciences-National Research Council Washington DC, 1962.

[42]. Delatte, N. Concrete Pavement Design, Construction, And Performance, British Library Cataloguing in Publication Data, 2008, New York, USA, 2008.

[43]. Awasthi G., Singh T. and Das A., 2003, "On Pavement Roughness Indices" CV, Vol. 84, pp. 33 – 37

[44]. Öztürk, F., 2006, "1986 AASHTO Design Method of Fuzzy Logic Technique and Modeling of Flexible Road Pavements", Suleyman Demirel University Institute of Science in Civil Engineering Master of Science Thesis, Isparta.

[45]. Topçu, İ. B., Sarıdemir, M. (2008). Prediction of rubberized concrete properties using artificial neural network and fuzzy logic Construction and Building Materials 22, 532–540
[46]. Saltan M, Terzi S. Back calculation of pavement layer parameters using artificial neural networks. Indian J Eng and Mater Sci 2004;11:38–42.
[47]. Şencan A, Kalogirou A. S, "A new approach using artificial neural networks for determination of the thermodynamic properties. Energy Conversion and Management "46 (2005) 2405–2418.
[48]. Demuth H, Beale M. Neural network toolbox, user guide, Version 4. Natick: The MathWorks Inc.; 2001.