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ADAPTIVE NEURO FUZZY INFERENCE SYSTEM FOR PREDICTING FLEXIBLE PAVEMENT DISTRESS IN TROPICAL REGIONS

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Abstract

The construction of asphalt pavement road networks is very costly for the government budget. A flexible pavement maintenance prediction is unavoidable to reduce government expenses and increase the service life span of pavements. This paper aims to predict flexible pavement maintenance in tropical regions using an Adaptive Neuro-Fuzzy Inference System (ANFIS) model. This research proposes Artificial Intelligent (AI) method with the statistical approach. Moreover, three ANFIS models with different membership functions were used to make predictions. The data from two types of flexible pavements, single distress and combined distress, were used to make predictions. Four parameters, i.e., severity, density, road function, and treatment technique, were used as inputs, while the target parameter is the pavement condition. To obtain the Fuzzy Inference System (FIS) for the three ANFIS models, three different structures, i.e. (3 3 3 3), (3 3 2 2) and (3 2 3 2) as well as three rules 81, 36 and 36, respectively, were used to train the models with 30 epochs. The ANFIS model's finding among the three has a regression square (R^2) of 0.934 and Root Mean Square Error (RMSE) of 0.565. Results show that the predictions made using ANFIS are accurate and closely approximate the target data.

Keywords: ANFIS, Combined distress, FIS, Flexible pavements, Tropical regions, Single distress.

1. Introduction

The pavement condition of road surfaces is essential for developing a country's economic, industrial, commercial, and entertainment sectors [1-3]. Road networks are the most widely used modes of transportation service in Malaysia and many other countries in the world [4]. The condition of pavements is complex and is determined by various factors, including axle/wheel loading configurations, types of materials, the thickness of the layers, and environmental conditions [5-7]. The severity level of distress varies based on the country, state, road category, or class, some factors on a maintenance level [8]. Furthermore, the maintenance strategies for flexible pavement and rehabilitation are two primary treatment techniques used to enhance the pavement condition. Hence, maintenance techniques work by retarding the pavement rate by repairing minor defects before increasing significant defects. Therefore, pavement maintenance and rehabilitation are expensive activities, and the available budget to manage the existing pavement infrastructure is limited. Managers require a prioritisation method to select the most appropriate maintenance options [9-11]. In general, a novice engineer's lack of experience to make the right decisions with the right treatments for asphalt pavement maintenance leads to failure results [12]. Additionally, when making decisions regarding complex engineering operations, inexperienced engineers depend on the methods and experiences passed down orally in their departments, not an acceptable decision-making method [13]. Pavement engineers and professional decision-makers in the highway sector have to deal with the challenges in rehabilitating flexible pavements to ensure that the pavements are in good condition and implementing significant enhancement that extends the service life of the pavements [14-17].

Several types of research implemented two commonly employed fuzzy inference systems (FIS) used in various related fields of civil engineering applications such as water, solid waste, and environmental [18-21]. However, the pavement condition is also required using artificial intelligence prediction. The majority of the studies focus on predicting pavement surface distress conditions without considering treatment technique solutions. Lou et al. [22] developed a neural network model for forecasting the conditions of cracked pavements. Shekharan [23] developed neural network models for predicting the conditions of five families of pavement: original flexible, overlaid flexible, composite, jointed, and continuously reinforced concrete pavements. Sun and Gu [24] proposed using the fuzzy logic theory and the Analytical Hierarchy Process (AHP) to assess pavement conditions and prioritise highway maintenance projects. Arliansyah et al. [25] described how a fuzzy set theory approach could assess pavement conditions in different situations.

Morova et al. [26] developed an ANFIS model for predicting Present Serviceability Ratio (PSR), one of the critical parameters used in designing rigid pavements. Tabatabaei et al. [27] used an ANFIS model to determine the deduct values used to calculate the pavement condition index. Due to the factors causing deterioration of asphalt pavements, which subsequently reduce the pavement service life, this research aims to evaluate the deterioration of pavements by using ANFIS prediction in order to help decision-makers to reduce the maintenance expense of flexible pavements, reduce pavement failure, and identify the problems before initiating maintenance and rehabilitation works. In summary, the main goals of this research are to predict pavement condition by using three ANFIS models with different structures. As well as assess the outcomes by comparing all ANFIS models and provide a sound recommendation regarding the ANFIS structure, which would best predict the pavement condition.

2. Data

The information on flexible pavement distress for the present study was gathered from several sources that provide comprehensive information on flexible pavement maintenance, pavement maintenance manuals, reports, books, and journal articles, as presented in Table 1.

Table 1 Reference used for developing the criteria for coding.

No.	Title	Type	Year	Publisher
1	Code of Practice for Crack Sealing and Joint Repair Systems for Road Surfaces	Code	2013	ADEPT
2	Material Design Construction Maintenance and Testing of Pavement	Publication	2009	ASCE
3	Guide to Road Maintenance Solutions	Report	2012	BPB
4	Road Maintenance Techniques	Report	2010	CC
5	Pavement Maintenance	Manual	2006	CLRP
6	A Technical Guide to Their Causes, Identification and Repair	Project	2010	CSIR
7	Pavement Maintenance Plan	Manual	2014	CVPW
8	The Maintenance of Paved Roads in Malaysia	Manual	1998	DFID
9	Pavement Distress Identification	Manual	2011	DOT
10	Economic Evaluation of Pavement Maintenance	Report	2002	DRI

Two groups of flexible pavement distress are single and combined distresses. Flexible pavement single distress is further classified into transverse cracking, longitudinal cracking, block cracking, alligator cracking, bleeding, ravelling, polishing, delimitation, shoving and corrugation, rutting, distortion, patching deterioration, and pothole. Flexible pavement combined distress is further classified into transverse cracking and alligator cracking, ravelling and potholes, rutting and alligator cracking, and alligator cracking, potholes, and rutting. Table 2 shows the criteria for the maintenance of patch deterioration as an example of the data used.

Table. 2. Criteria for the maintenance of patching deterioration (categorical data).

Evaluation		Road	Treatments	Pavement
Severity	Density	Functional	Techniques	Condition
Low	Rare	Minor	Cold mix patching	Corrective
Low	Rare	Major	Cold mix patching	Corrective
Medium	intermittent	Minor	Cold mix patching	Corrective
Medium	intermittent	Major	Cold mix patching	Corrective
Medium	Frequent	Minor	Cold mix patching	Corrective
High	Frequent	Major	Cold mix patching	Corrective
High	Extensive	Minor	Cold mix patching	Corrective
High	Extensive	Major	Cold mix patching	Corrective

Patching is conducted on pavements where the original pavement has been replaced or wrapped with a new material to treat the existing pavement. A patch is considered a failure regardless of how well it is carried out. Skin patching is a patch of the entire width of the lane. Patching is carried out on previously localised pavement deterioration that has been removed and patched with utility cuts. Various strategies and treatments can be implemented based on the severity and density of patching deterioration. The patches' corrective action with only one method can be removed from the pavement's surface on either structural or non-structural overlay.

3. Adaptive Neuro-Fuzzy Interface System (ANFIS)

Jang [28] is the first researcher to recommend the ANFIS method and has successfully applied it to several problems. Zadeh and Kacprztk [29] were the first researchers to proposed using Fuzzy Logic (FL) to solve complex systems. Since then, it has been widely used and strongly recommended to solve problems in different fields [30]. ANFIS recognises problems by integrating fuzzy rules and Artificial Neural Network [31]. Many researchers have used ANFIS methods to model sophisticated systems [32-36]. The prediction methods of soft computing have been used to solve complex highway pavement engineering problems during the past decade. For instance, they have been used to solve complex non-linear problems [37-40]. ANFIS serves as a basis for making a set of fuzzy 'if-then rules with proper membership functions to build the required input-output pairs. Here, the membership functions are tuned to the input-output data to ensure that the best performance is achieved. Generally, ANFIS utilises an initial fuzzy inference system (FIS) and tunes it with a backpropagation algorithm based on the gathered input-output data. The benefits of using ANFIS over the common estimation methods are: (i) ANFIS is an excellent approach for generating complicated and non-linear relationships between input and output data; (ii) ANFIS does not require many precise data; (iii) it can understand and adaptation capability quickly [36, 41, 42], and (iv) the most crucial advantage of ANFIS models is that they are universal approximations with the ability to obtain interpretable If-Then rules [43]. MF is an essential factor that influences prediction accuracy [44]. FIS is a valuable tool for emulating non-linear behaviours using fuzzy logic and fuzzy linguistic rules [45]. Inference methods for fuzzy rule-based systems were developed in this study, such as Sugeno [43]. FIS is also a fuzzy-rule-based system, fuzzy expert system, fuzzy modelling, fuzzy associative memory, fuzzy logic controller, and simply (and ambiguously) fuzzy system. These systems combine information, techniques, and methodologies from different sources [46]. They have human-like expertise in a particular domain and can adapt themselves and perform better in a changing environment. In ANFIS, neural networks identify patterns and facilitate adaptation to environments [47]. FIS integrates human knowledge and performs interfacing and decision-making.

Structure of ANFIS

The general structure of ANFIS comprises three conceptual parts; (i) a rule base which includes a selection of fuzzy rules, (ii) a database that defines the membership functions applied in the fuzzy rules, (iii) and a reasoning mechanism that performs the suggested method based on the rules and provided facts to obtain an acceptable output or conclusion [48, 49]. The purpose of ANFIS is to determine a model that can relate initial values with predicted values properly. For this purpose, five layers are required to structure the ANFIS architecture, as shown in Fig. 1. This includes (i) the input layer, which is used to map the input properties for input membership functions, (ii) the fuzzification layer where the input membership function is a set of Takagi Sugeno Kang type of fuzzy if-then rules, (iii) the fuzzy-rule evaluation layers which are the rules for a set of output properties and output membership functions, and (iv) the defuzzification layer, which is an output membership function for a single-value output or decision related to the output. ANFIS has an input layer, an output layer, and hidden layers consisting of function and fuzzy rules [30, 49]. The present research has four ANFIS rules:

Rule 1: if x1 is A1, x2 is B1, x3 is C1 and x4 is D1,
then f1 = p1x1 + q1x2 + k1x3 + l1x4 + r1
Rule 2: if x1 is A2, x2 is B2, x3 is C2 and x4 is D2,
then f2 = p2x1 + q2x2 + k2x3 + l2x4 + r2
Rule 3: if x1 is A3, x2 is B3, x3 is C3 and x4 is D3,
then f3 = p3x1 + q3x2 + k3x3 + l3x4 + r3
Rule 4: if x1 is A4, x2 is B4, x3 is C4 and x4 is D4,
then f4 = p4x1 + q4x2 + k4x3 + l4x4 + r4

The general rule is

fi = pix1 + qix2 + kix3 + lix4 + RI, i = 1,2,3,4

where x1, x2, x3, and x4 are fuzzy sets Ai, Bi, Ci, and Di, respectively, which represent the inputs severity, density, road function, and treatment technique. p, q, k, and l are the model parameters computed throughout the training process.

4. Method

4.1. Preparation of data for prediction

In the present study, data preparation consists of representing flexible pavement distress: (i) evaluation, (ii) road function, (iii) treatment technique and (iv) pavement condition. Flexible pavement evaluation is based on severity and density. Severity is further classified into low, medium and high, while density is further classified into rare, intermittent, frequent and extensive. The road function is classified as minor and major. Some researchers have categorised maintenance treatments and methods as crack sealing, crack filling, clean and seal, coarse and seal, burn seal, crack routing and sealing, thin hot mix overlay, chip seals, micro-surfacing, cold in-place recycling, spray injection patching, fog seals, cold mix patching, milling and hot mix overlay and scrub seals [50]. Pavement conditions are classified as a corrective, preventive, emergency, thin overlay, micro-surfacing, cold mix patching, and milling and hot mix overlay. The distress shown by flexible pavements is categorised into surface defects, surface deformation, cracking, and patching and potholes [51]. Based on these criteria, a total of 279 and 80 data were used for training and testing the three ANFIS models, respectively.

4.2. ANFIS Models

The ANFIS prediction model cannot handle categorical variables, and therefore, the variables have to be represented as numerical values. In this study, all categorical data were represented as numerical values for the training and testing of the three ANFIS models. For example, the low, medium, and high variables are described as 1, 2, and 3. Table 3 is the numerical value's representation of Table 2. The ANFIS model was used to produce output based on specific inputs. The mapping provides a basis from which decisions are made, and models are discerned. Four parameters, i.e., severity, density, road function, and treatment technique, were used as inputs to make the predictions, while the target parameter is pavement condition. Three ANFIS models with varying structures were used to make predictions. The number of membership functions (MFs) utilised for each input of the three models were (3 3 3 3), (3 3 2 2) and (3 2 3 2). The Sugeno fuzzy model was chosen for obtaining the fuzzy inference system (FIS). Linear output, as well as 81, 36 and 36 rules, were used to generate FIS. For the FIS training, 30 epochs and hybrid optimisation methods were considered zero error tolerance [52]. The MATLAB software was used to train the ANFIS model.

Table. 3. Criteria for the maintenance of patch deterioration (numerical data).

Evaluation		Road	Treatments	Pavement
Severity	**Density**	**Functional**	**Techniques**	**Condition**
1	4	8	23	14
1	4	9	23	14
2	5	8	23	14
2	5	9	23	14
2	6	8	23	14
3	6	9	23	14
3	7	8	23	14
3	7	9	23	14

5. Results and Discussion

The data used in this study were obtained through knowledge acquisition (KA) in the work of [53]. Three ANFIS models with membership function's structure (3 3 3 3), (3 3 2 2) and (3 2 3 2) successfully predicted flexible pavement distress by using 279 training data, 30 epoch and (81, 36, 36) rules. Figure 2 shows the training data used for flexible pavement conditions. The horizontal axis in Fig. 2 represents the data used for training (279 data), while the vertical axis shows the target pavement condition. As an example of the result of the model structure, Fig. 1 shows the first ANFIS model structure with membership functions (3 3 3 3). It consists of four inputs (severity, density, road function, and treatment technique), with each input having three membership function (inputmf), 81 rules obtained from three membership functions for the four inputs, membership functions for the output (outputmf) and lastly, the output (pavement condition).

The MF type used for ANFIS prediction is the triangular shape (trimf), which is the most straightforward and Sugeno output membership functions. Figure 3 shows the Adaptive Neuro-Fuzzy Inference System for pavement condition inputs, the method used for prediction, and the output. For the input, severity is indicated by red and yellow, it shows that the FIS type is Sugeno system, the inference method (AND) is (prod), the inference method (OR) is (probor), the defuzzification is (wtaver), the name is (severity), the type is (input) and the data range is (1 to 3) which represent low, medium and high. After making the prediction, 80 data were used to test all three ANFIS models.

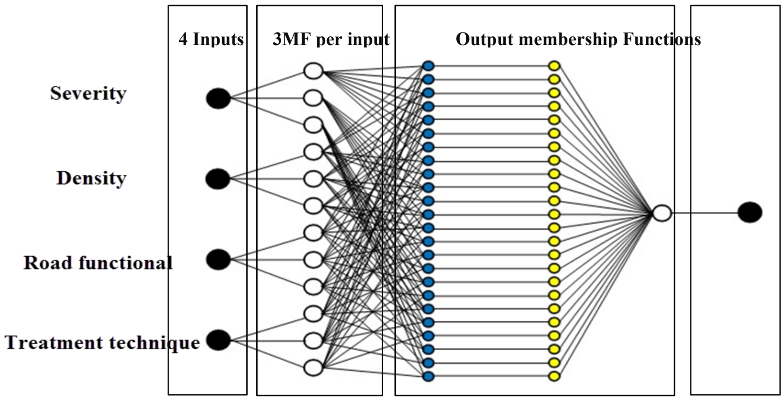

Fig. 1. ANFIS model structure for flexible pavement condition.

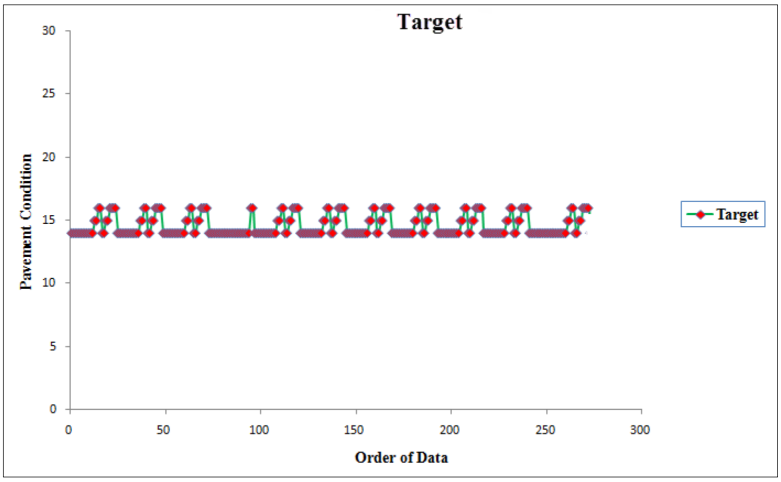

Fig. 2. Training data for flexible pavement condition.

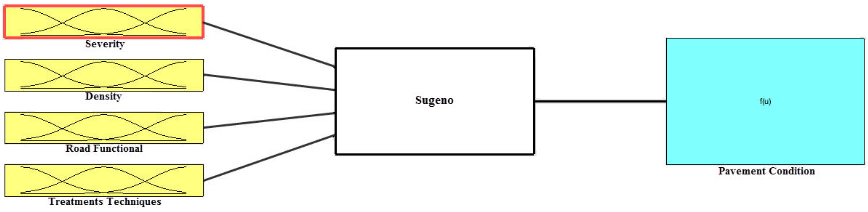

Fig. 3. Adaptive neuro-fuzzy inference system for pavement condition.

Figure 4 shows the plot of the predicted values and the target data. The ANFIS prediction is represented in red, and the target values are represented in blue. Figure 4 shows that the predicted and target values of pavement condition almost overlap due to the high accuracy of regression square (R^2) of 0.934 and root mean square error (RMSE) of 0.565, which are shown in Fig. 5. 80 data sets were chosen to test the validity of the best ANFIS prediction model for pavement condition. As shown in Fig. 6, the test data's error measure shows a high accuracy value due to the regression square (R^2) of 0.911, which indicates an excellent performance for the tested ANFIS model for pavement condition. The ANFIS models were able to determine the relationship between the four input variables and pavement conditions. This result proves that the predictions made by the ANFIS model are accurate and approximate the target data.

If (Severity is in1mf1) and (Density is in2mf1) and (Road-Functional is in3mf1) and (Treatments-Techniques is in4mf1), then (Pavement-Condition is out1mf1) (1)

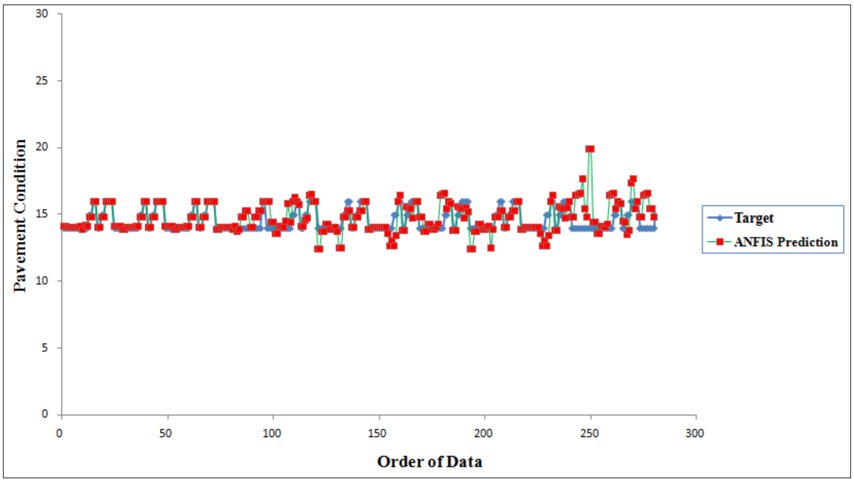

Fig. 4. Target and ANFIS prediction data for flexible pavement condition.

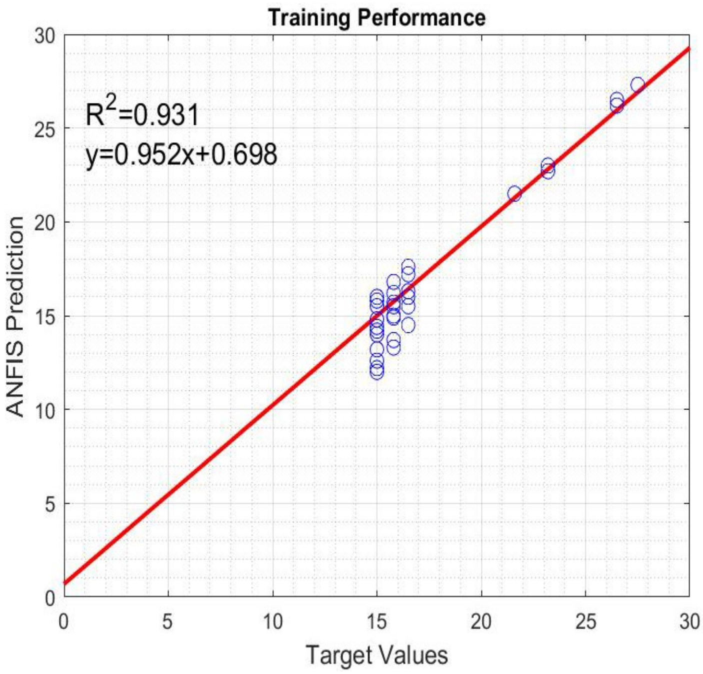

Fig. 5. Training performance of ANFIS model.

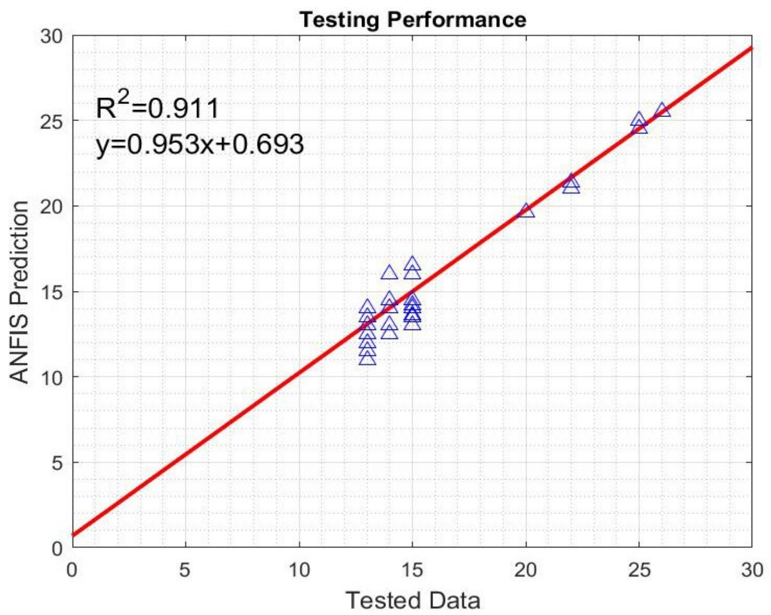

Fig. 6. Testing performance of the ANFIS model.

Comparison ANFIS models'

Table 4 shows a comparison between all ANFIS models' models. The assessment is done with regards to statistical results methods. R^2, MSE and RMSE were measured for all models choosing the training dataset. From the outcome in Table 4, in accordance with the model improvement choosing training dataset, it may be discovered that the ANFIS models show high R^2 and with good MAE together and RMSE values. In particular, each present model R^2 more significant than 0.9. The Coefficient of Determination (R^2) and Root Mean Square Error (RMSE) were used as performance criteria to evaluate all ANFIS models' efficiency. Table 4 shows the R^2 and RMSE for all models. The table shows that ANFIS models with membership function structure (3 3 3 3) can predict pavement condition with high accuracy in comparison to the other models.

The prediction for the best ANFIS model is shown in Fig. 7, where the vertical axis shows the values of ANFIS prediction while the horizontal axis shows the number of data. In addition, MAE and RMSE are less than 10%. Moreover, the output of match statistics of the ANFIS models. It is essential to point out that the statistical assessments for the training dataset recommend that ANN and RSM models predict pavement condition with good precision. Overall, the evaluation outcome provides proof that each model can precisely predict the treatment/techniques for the pavement.

Table 4. R^2 and RMSE for all ANFIS models.

ANFIS Model	MFs Structure	Rules	R^2 (Training)	R^2 (Testing)	RMSE (Training)	RMSE (Testing)
1	(3 3 3 3)	81	0.934	0.921	0.565	0.568
2	(3 3 2 2)	36	0.910	0.909	0.610	0.611
3	(3 2 3 2)	36	0.925	0.911	0.592	0.571

Fig. 7. ANFIS prediction for flexible pavement condition.

6. Conclusions

In the present study, an effort has been made to predict pavement maintenance using ANFIS to choose the best pavement condition for flexible pavement distress. Identifying pavement distress is a complex process that requires in-depth knowledge and experience to deal with all related factors. Hence, developing a programmed model to overcome the problems in this field is of crucial importance. Three ANFIS models with different structures were used to predict flexible pavement distress based on 279 different criteria. Various vital parameters such as severity, density, road function, and treatment technique were used as the input parameters, while the output parameter is pavement condition. A total of 81, 36 and 36 rules were used to construct the fuzzy inference system (FIS) for the three ANFIS models. Besides, 30 epochs and hybrid optimisation methods were used to train the FIS. The ANFIS model was tested to determine the accuracy of the prediction. Results show a good prediction precision. It has also been indicated with the facilitating of ANFIS, which can be developed many inputs produced with one output. Based on the result obtained from this study, research shows that the ANFIS model is a better modelling tool for predicting pavement treatment techniques. Finally, this study has shown that flexible pavement distress can be effectively predicted using the ANFIS model.

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Abbreviations

ADEPT	Association of Directors of Environment Planning and Transport
AHP	Analytical Hierarchy Process
ANFIS	Adaptive Neuro-Fuzzy Inference System
ASCE	American Society of Civil Engineers
BPB	Guide to Road Maintenance Solutions
CC	Cold Chon
CLRP	Cornell Local Roads Program

CSIR	Technical Guide to Their Causes, Identification and Repair
CVPW	City of Ventura Public Works
DFID	Department for International Development
DOT	Department of Transportation, Minnesota
DRI	Danish Road Institute
FIS	Fuzzy Inference System
FL	Fuzzy Logic
inputmf	Input Membership Function
KA	Knowledge Acquisition
MF	Membership Function
outputmf	Output Membership Function
PSR	Present Serviceability Ratio
R^2	Regression Square
RMSE	Root Mean Square Error

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