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Modeling the Deduct Value of the Pavement Condition of Asphalt Pavement by Adaptive Neuro Fuzzy Inference System

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Abstract: The quality of roads directly impacts the services they provide. Different indices are used to determine the pavement condition. Based on these indices, the pavement management system provides an estimation of the future costs of roadways and the ways of optimizing them. One of the indices used in the specification of the pavement condition is the Pavement Condition Index (PCI). To determine the value of this index, considering the amount and the severity of each sample's distress, the deduct values should first be calculated based on the experimental charts. In this study, the researchers try to present a model based on the Adaptive Neuro Fuzzy Inference System (ANFIS) to determine the deduct value used to calculate the PCI.

Key words*: ANFIS, Deduct value, Distress, Pavement, PCI.*

Introduction

A pavement management system (PMS) aims to investigate road pavement conditions and present the best options for repair and maintenance, while considering price concerns [1, 2]. In order to assess the pavement condition, different indices have been introduced, such as International Roughness Index (IRI), Pavement Condition Index (PCI), Pavement Condition Rating (PCR), Pavement Serviceability Index (PSI), and Pavement Serviceability Ratio (PSR). Each of these indices, which concern different quantitative and qualitative characteristics of pavement conditions, presents a quantitative index that tests the general pavement condition [3].

Noting that the presented methods for the specification of the indices are experimental, some mathematical methods are also needed to assess the indices modeling. In each of the different methods of determining the pavement quality, researchers presented diverse methods of calculation, some of which led to easier mathematical functions for use in computer software. For instance, in a 2006 study done by Behbahani et al. on a fuzzy model, membership functions are presented to estimate the value of PCI index. The model presented for PCI values of more than 80 produces results very close to the real values of this index. For the lower PCI values, the difference between the values taken from this model and the real values is extremely increased [4]. Moreover, in 2006, Terzi presented a model based on mining with the aim of estimating the value of PSI [5]. In 2007, Terzi et al. estimated the value of PCR using Fuzzy methods [6]. In the same year, Terzi presented a model for PSR index using the neuro-fuzzy method [7]. In 2009, Golroo investigated the quality of pavements in cold weather, determining the Fussy index and comparing it with the existing indices [8].

Among the existing methods, PCI is one of the most useful methods, considering the comprehensive definition of all the distresses and their effects in the specification of the indices. The PCI developed by the United States Army Corps of engineers, is based on a visual survey of the pavement and a numerical value between 0 and 100 that defines 100 as representing an excellent pavement [9].

Calculated PCI index needs three parameters, which are the type of distress, the amount of distress, and the severity of distress. The value of this index is determined after the specification of the amount and the severity of each distress, based on the type of distress, and using the deduct value, which is estimated based on the charts and the experts' experiences [3]. The deduct value of each distress used to calculate PCI, using different experiences of the researchers regarding the impact of the types of these distresses, is determined and depicted as different graphs, based on the severity and the amount of each distress [3, 4].

In this study, the researchers try to present a model to estimate the deduct value of distresses used to calculate PCI, using the amount and the severity of the distresses along with the Adaptive Neuro Fuzzy Inference System (ANFIS).

Review of Fuzzy and Neuro-Fuzzy Methodology

"Fuzzy" means lacking clarity, and this fuzziness results from modeling the most similar human inference through a complex mathematical pattern. Basically what a fuzzy system does is convert human knowledge to mathematical formula. This important act is done with linguistic variables, "if-then" fuzzy rules, and mapping system (fuzzy engine). Fuzzy systems are based upon knowledge and rules [10]. The heart of a fuzzy system is a knowledge base that consists of the fuzzy "if-then" rules. Briefly, the starting point of making a fuzzy system is collecting a set of fuzzy "if-then" rules from the knowledge of experts or studying literature in the related field. The next step is combining these rules into their mathematical forms [11].

Fuzzy systems use fuzzy sets with the aim of converting input variables to output variables [12]. These systems are beneficial especially in adding human experiences and verbal data to the model. For this purpose, variables of the model are expressed with

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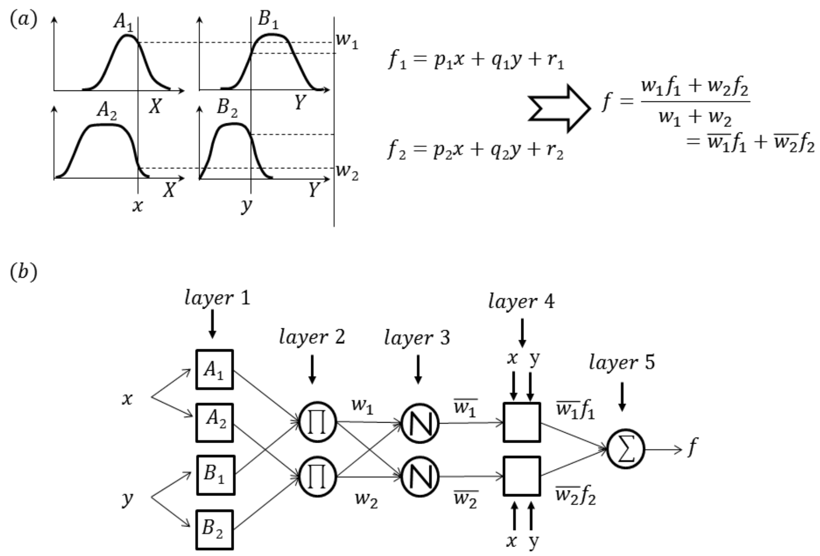

Fig. 1. Structure of ANFIS (a) Fuzzy Inference System (b) Equivalent ANFIS [16].

fuzzy sub-sets. For the inference under consideration, fuzzy set operations are used. These operations are obtained by generalizing classical set operations. Fuzzy logic is one of the methods used in handling the uncertainties in the model or the data. Fuzzy inference systems are based on fuzzy rules, which are called fuzzy "if-then" rules. In some resources, instead of fuzzy inference systems, terms such as fuzzy model, fuzzy associative memory, and fuzzy logic controller are also used [13]. Fuzzy "if-then" rules, which are the fundamentals of fuzzy inference systems, consist of anterior and posterior portions. Input variables, which cause the result and the logical relationships between them, are present in the anterior portion, whereas result variables that appear according to these input variables are located in posterior portion. Generally, this fuzzy rule is as given below:

$Rule$: $if\ A$(Condition) then B (result)

Here, A represents the conditions that are defined by input variables in the anterior portion, while B represents the output value in posterior portion.

Various models are proposed for fuzzy inference systems in application [14]. While these numerous models resemble each other from a general process sequence and methodology point of view, they differ in terms of structures of membership functions in posterior portions. Fuzzy inference systems are categorized in three different groups according to these differences in posterior portions. These are the Mamdani, Tsukamoto, and Sugeno type inference systems. Of these, the Sugeno type inference system is most advantageous due to the ease of parameter optimization [15].

In the Sugeno type, Fuzzy inference system (FIS) output variable in the posterior portion is a linear function of the input variable, or it has a membership function in the form of a constant function. The Sugeno type inference systems, parameters of which are optimized, are called Adaptive Network FIS (ANFIS). Two fuzzy ruled Sugeno type FIS are shown in Fig. 1 [13].

In optimization of ANFIS parameters, various methods such as backward spreading, least squares estimation, Kalman filter, or hybrid learning algorithms, which consist of combination of multiple mathematical optimization methods, can be used [16].

Review of Genetic Algorithm

Genetic Algorithm (GA) is an evolutionary computing technique that, in principal, mimics the mechanism of natural selection process. According to Goldberg (1989), GA differs from the classical, calculus-based optimization techniques in the following ways: (I) instead of using a point-to-point search method, as in the traditional optimization techniques, GA simultaneously searches from a population of points, known as chromosomes, to explore the solution space; (II) GA uses probabilistic transition rules (for its operators) as a guide to search the solution space with likely improvement; (III) GA can work with continuous and discrete parameters, differentiable and non-differentiable functions, uni-modal and multi-modal functions, as well as convex and non-convex feasible regions [17, 18].

Abbreviations

The abbreviations used in this paper are as follow:
W: the recommended weight for each kind of distress
D: the density of each distress
S: the severity of each distress
CDV: the deduct value that is calculated from the main pavement condition index procedure
FCDV: the deduct value calculated from the ANFIS model

ANFIS modeling

In order to construct the ANFIS model, three variables are used as inputs. These variables are severity, percentage of density, and weight of each distress. Severity is divided to three levels—high, medium, and low—according to the PCI main method [3]. This variable is defined to the model as three values respectively: 3, 2 and 1 for each severity levels. To calculate the percentage of density, the quantity of each distress type at each severity level by the total area of the sample unit is divided, and then multiplied by 100 to obtain the percentage of density per sample unit for each distress

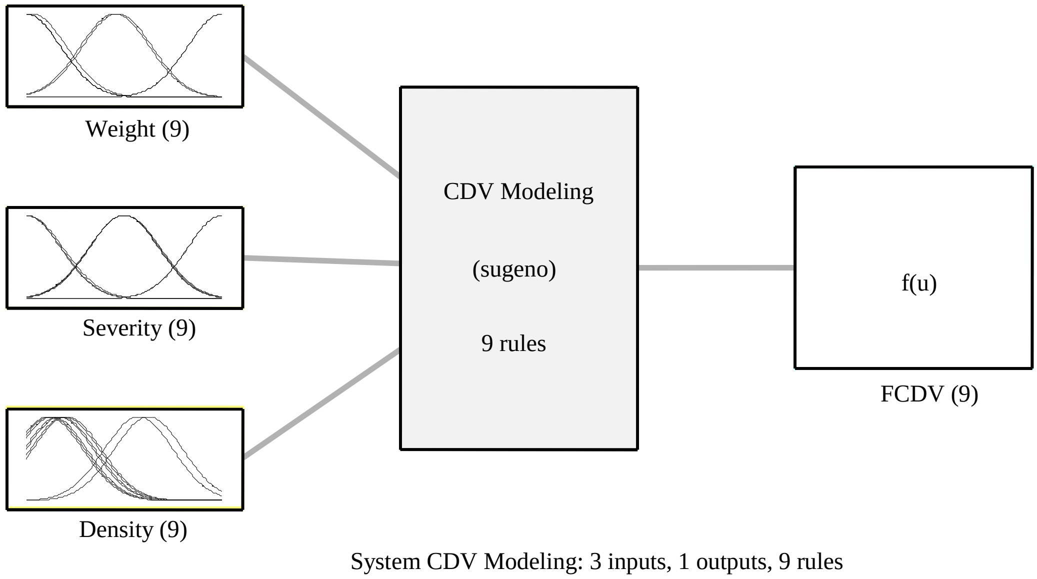

Fig. 2. Schematic Chart of ANFIS Model.

Fig. 3. The Case Study Area in Shahid Chamran University.

type and severity [3]. The third variable in the ANFIS model is the weight of each distress. This variable is considered because of the different effects of each kind of distress on the quality of highway pavement. Thus, for each kind of distress, a value is selected as weight of the distress effects on the pavement quality. The output of the ANFIS model is the modeled deduct value that is called FCDV. The ANFIS model is based on Sugeno-type fuzzy inference system structure using subtractive clustering that is analyzed with the ANFIS toolbox in MATLAB software. To generate the ANFIS model, range of influence, squash factor, accept ratio, and reject ratio were set to be 0.5, 1.25, 0.5 and 0.15, respectively. The schematic chart of the ANFIS model is shown in Fig. 2.

To train the ANFIS model, about 355 distresses are evaluated. The area that has been considered as case study, as shown in Fig. 3, is located in three streets in the campus of Shahid Chamran University. Each distress has a code that indicates the kind of distress. For each distress, density and severity are calculated. Some samples of the collected data are shown in Table 1.

Determining the Weight of Distresses Using Genetic Algorithm

In order to find the best weights of each distress used in the ANFIS model as input variable, a simple genetic algorithm is developed. The core of optimization is to establish a mathematic function to find the least squares of error between CDV and FCDV that is shown in Eq. (1), in which *n* is the number of evaluated distresses. As follows, the characteristics of the proposed model are described along with a brief review on the applied GA:

Table 1. Some Samples of Calculated Data From the Case Study.

Code of Distress	Name of Distress	Severity	Amount of Distress	Density	CDV (According to PCI Main Method)
1	Alligator Cracking	2	13.45	6.97	23
1	Alligator Cracking	1	44.8	10.30	34
1	Alligator Cracking	3	6.5	11.82	39
6	Shoving	3	2	4.70	15.5
10	Longitudinal and Transverse Cracking	1	18.5	1.06	3.5
⋮	⋮	⋮	⋮	⋮	⋮

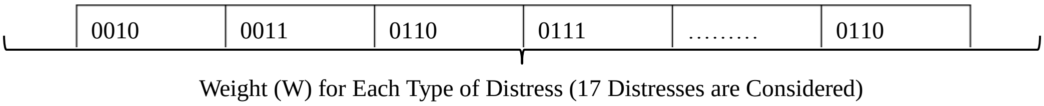

Fig. 4. Schematic View of Binary Chromosome.

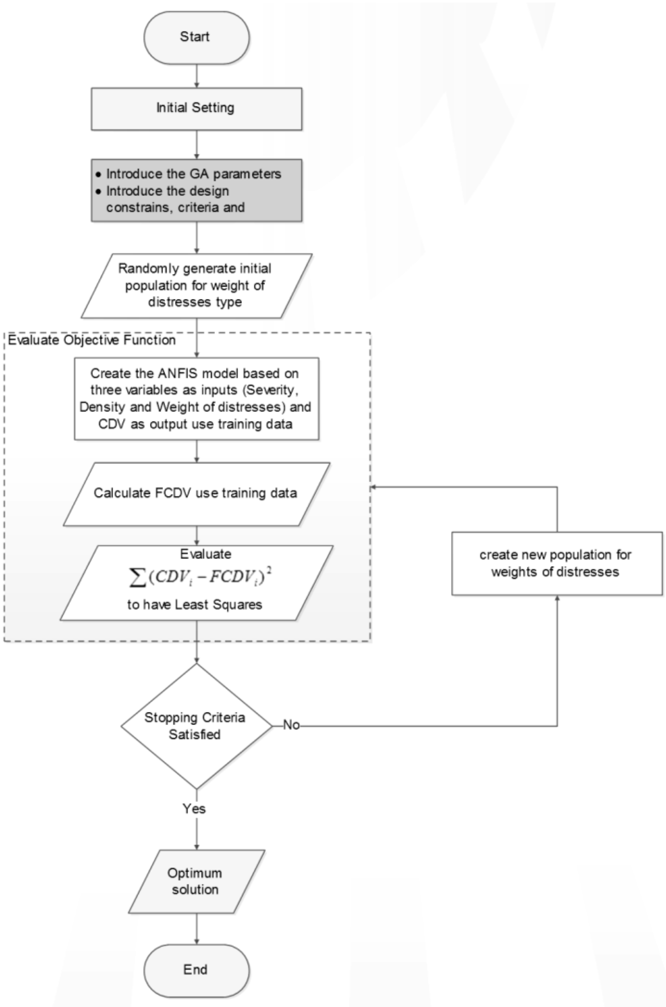

Fig. 5. Schematic Flowchart.

Chromosomes:

In GA terminology, a chromosome is a vector of variables to be optimized. In binary GA, real decision variables are encoded with binary 0-1 values (bits). Each chromosome represents a design alternative which can be potentially feasible or not. In this problem, the variables are weight of each type of distress to minimize the least squares between CDV and FCDV (Eq. (1)). So, a design chromosome is consisting of $17 \times N_b$ genes (0-1 values), in which N_b is considered as binary bits to represent each parameters in weights as shown in Fig. 4.

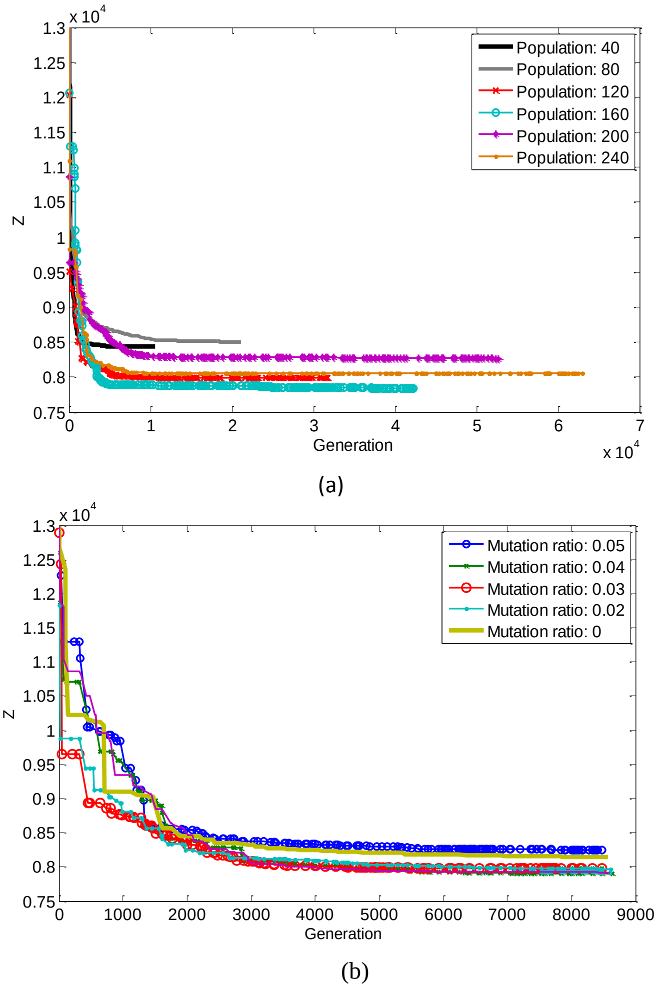

Fig. 6. (a)Sensitivity Analysis for Population Size (Mutation Ration = 0.02), (b) Sensitivity Analysis for Mutation Ratio (Population Size = 160).

Table 2. The Weight of Each Distress Optimized by Genetic Algorithm.

Distress Code	Kind Of Distress	Optimized Weight
1	Alligator Cracking	68.25
2	Asphalt Bleeding	89.24
3	Block Cracking	60.36
4	Bumps and Sags	65.31
5	Corrugation	77.32
6	Shoving	88.78
7	Edge Cracking	59.42
8	Reflection Cracking	78.70
9	Lane/Shoulder Drop Off	60.20
10	Longitudinal and Transverse Cracking	88.99
11	Pothole	92.19
12	Rutting	76.01
13	Depression	76.41
14	Slippage Cracking	81.11
15	Swell	76.85
16	Weathering/Raveling	78.74
17	Polished	78.84

chromosomes, which are randomly generated in the beginning. The chromosomes evolve through successive iterations, namely generations in GA [1]. Deciding about the population size, N_{pop}, is greatly dependent on the problem size and its mathematical specification. However, some preliminary sensitivity analysis and the user experiences on Gas are quite substantial in this regard. Herein, the initial population is randomly generated as a binary matrix with N_{pop} rows and $17 \times N_b$ columns.

In the genetic model, the weights are considered between 0 and 100 (Eq. (3)). In each generation of the genetic algorithm, some random data will be considered as weight of each distress. According to these weights, an ANFIS model will be generated based on data training. Then FCDV will be calculated by using three input variables that are extracted from data training. The least squared of error between CDV and FCDV is the objective function. Fig. 5 shows the flowchart of this modeling. For more information, this part of the model is also developed by MATLAB software and the whole process take about 24 minutes for computations using a personal PC with a Intel Core2 Duo @2.40GHz CPU and 1.00GB of RAM.

$$Z = \sum_{i=1}^{n} (CDV_i - FCDV_i)^2 \quad (1)$$

$$FCDV = \textit{the output of generated ANFIS model with}(S\_i,D\_i\ ,W\_i\ )\ \textit{as inputs} \quad (2)$$

$$0 \le W_i \le 100 \quad (3)$$

Results

In the simple GA used herein, the uniform crossover method is adopted and considered. A brief sensitivity analysis was done for

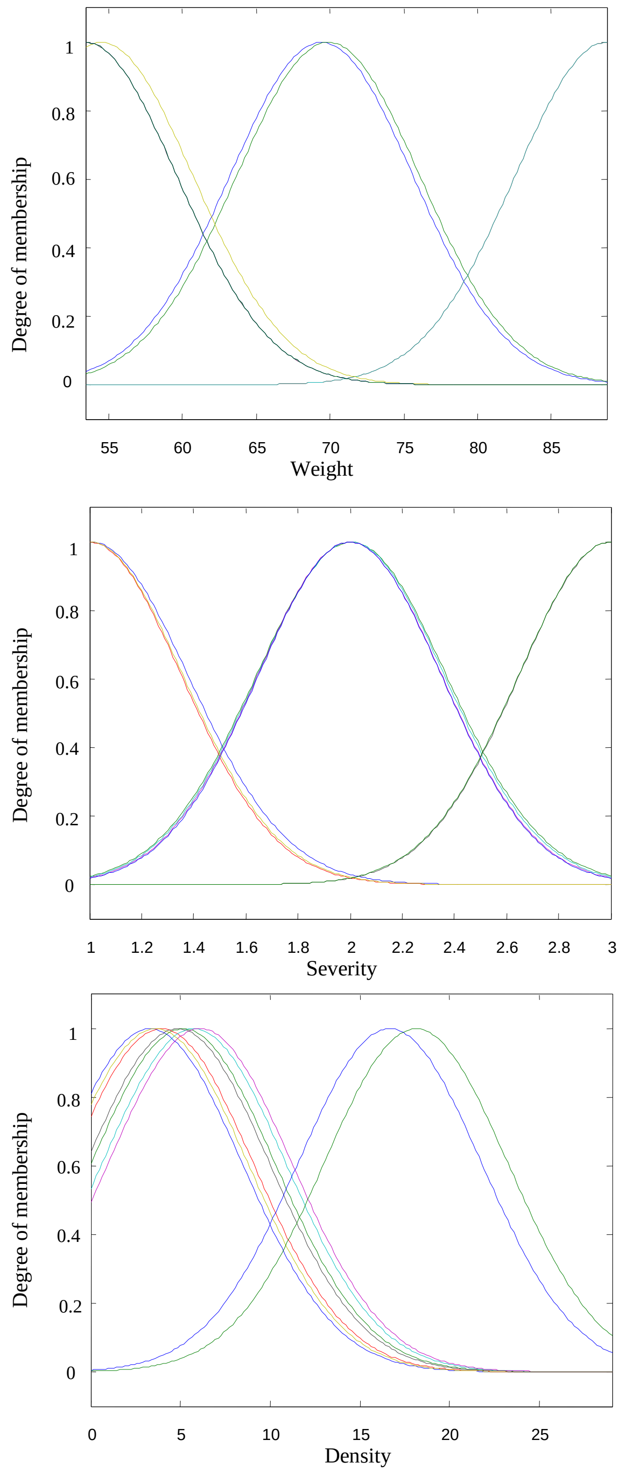

Fig. 7. Membership Functions.

population size and mutation ratio. Figs. 6 (a) and (b) demonstrate some sample runs after the sensitivity analysis, respectively, for the population size and mutation ratio. These figures obtain the minimum of the objective function at generation duration. According to this sensitivity analysis, the population size and mutation were set to be 160 and 0.03.

The optimized weights for each kind of distress, calculated from

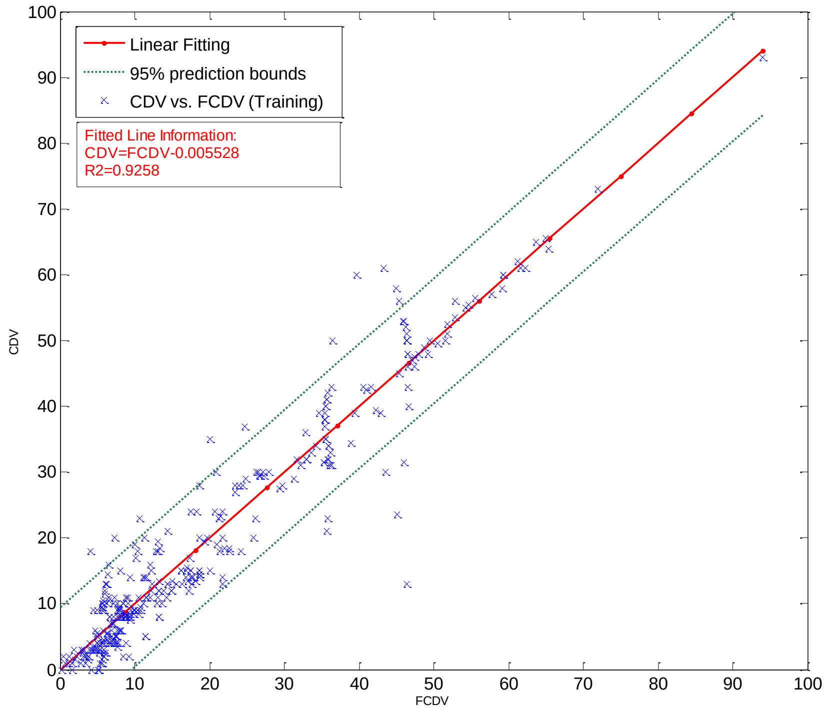

Fig. 8. Scatter Diagram for CDV vs. FCDV and Fitting Line Use Training Data.

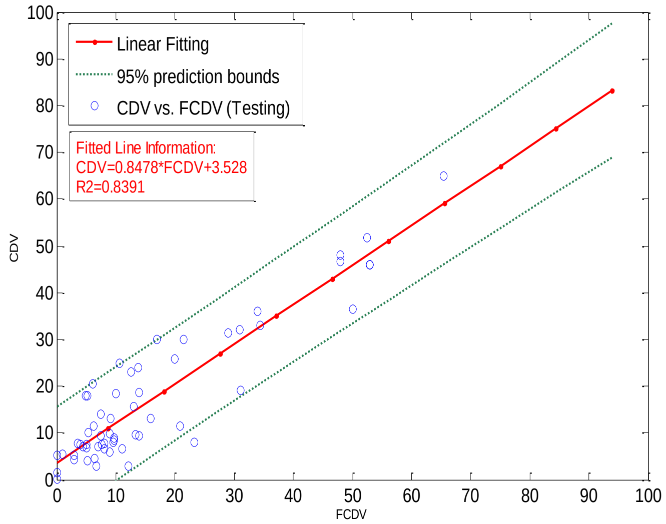

Fig. 9. Scatter Diagram for CDV vs. FCDV and Fitting Line Use Testing Data.

genetic algorithm, are shown in Table 2. For example, the maximum of the calculated weight is 92.19 that are related to potholes. As it was mentioned, the weight of each kind of distress shows how much the quality of pavement is affected. Due to the PCI main method, it is quite evident that potholes have the most effect on quality of pavement, and the weights determined in the model also show this.

After determining the best weights of each type of distress, the final ANFIS model was developed. The membership functions of this model are shown in Fig. 7 for three input variables. According to training data, the scatter diagram based on CDV vs. FCDV is displayed in Fig. 8. As this diagram shows, the R^2 value for fitted line is 0.9258, which is an acceptable value.

To control the model, the severity and density of 60 new distresses was evaluated. These distresses were sampled from the introduced case study. Fig. 9 illustrates CDV vs. FCDV for testing data. As can be seen, the R^2 value for testing data is 0.8391. Accordingly, it seems that this model has a good capacity to model deduct value of each distress type at each severity.

Conclusion

This paper introduces an ANFIS model to determine deduct values (CDV) used to calculate pavement condition index (PCI). This model has three variables as inputs, including severity and density on the distress and the weight of effect of each kind of distress on the quality of pavements. Severity and density are determined in field for each distress. In this paper, the weights of each kind of distress are proposed that were determined using a genetic algorithm based on some evaluated distresses.

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