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A Fuzzy Logic Approach for Pavement Section Classification

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Abstract: Section classification is one of the primary challenges in any successful pavement management system. Sections are normally classified based on their pavement condition index in order to categorise as “good”, “moderate” and “poor”. Conventionally, this has been done by comparing various pavement distress data against threshold values. However, borderline values between two categories have significant influence on the subsequent pavement maintenance and rehabilitation decision. This study is the first attempt to create a system based on fuzzy logic to estimate the pavement condition index (PCI). In this paper, section data classifications are conducted using a fuzzy inference system (FIS) to utilise multiple distress data such as cracking, patching, bleeding and ravelling to develop a membership function for each defect. A FIS rule based system was then used to develop a fuzzified pavement condition index (PCI) for section classification. The result showed good agreement with the conventional PCI based pavement classification system. The proposed system has the potential to realistically differentiate pavement sections, which would aid to have economical maintenance and rehabilitation decision.

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Key words*: Fuzzy Logic; Pavement classification; Pavement condition index; Pavement distress; Pavement management system.*

Introduction

Pavement condition assessment is an important element of the decision-making procedure of a pavement management system. It presents a quantitative measure for evaluating pavement section deterioration for a whole pavement network [1]. There are two purposes behind the assessment of pavement condition: to recognize maintenance and rehabilitation requirements and to monitor the pavement network conditions [2].

Pavement condition can be classified by a range of performance indicators such as the Pavement Condition Index (PCI), International Roughness Index (IRI), or the Present serviceability index (PSI) by utilizing various features of road surfaces. For highway pavements, these indicators usually comprise pavement surface deterioration, deflection, rut depth, roughness, and skid resistance [1]. Many agencies use conventional and statistical approaches for determining pavement performance indicators without considering uncertainty. Therefore, previous studies applied artificial intelligence techniques in the pavement performance determination.

For pavement classification, many techniques have been used over the years. Sagheer *et al.* established a knowledge-based system for pavement deterioration classification by using logic programming and Prolog language to diagnose distresses in flexible pavements [3]. Khurshid *et al.* developed an analytical methodology to find an optimal facility performance threshold for the pavement maintenance system based on cost effectiveness [4]. Terzi used data mining technique for modelling pavement serviceability index PSI for flexible pavement [5]. Mishalani and Gong found a methodology for assessing the contributions of the condition sampling–related advances to improve decision making [6]. The unified pavement distress index (UPDI) was calculated based on final membership functions to assess overall pavement distress conditions [7]. Eldin and Senouci develop a pavement condition rating index based on back-propagation neural network method for rigid pavement [8]. Terzi established an artificial neural network (ANN) model to determine a pavement serviceability index (PSI) [9].

Fuzzy logic based approaches have found their way into pavement condition modelling. In this regard, Shoukry *et al.* created universal pavement condition model that is able to combine the quantitative and qualitative data based on fuzzy logic. The output of this model is the fuzzy distress index (FDI) [10]. Fwa and Shanmugam developed a fuzzy logic-based system for pavement condition rating and maintenance-needs assessment [11]. Moreover, Bandara and Gunaratne suggested a new subjective pavement assessment methodology considering predominant distress types, severity and extent found in flexible pavements based on fuzzy set theory [12]. Arliansyah et al. developed a method based on fuzzy logic theory to calculate membership functions using linguistic terms based on expert`s opinion data for pavement condition assessment [13]. Golroo and Tighe proposed efficient pavement condition assessment methodology based on a fuzzy set approach for pervious concrete pavement structures (PCPSs) [14]. Furthermore, Koduru *et al.* suggested a methodology for categorising of four pavement distresses based on expert system and fuzzy logic to raise the consistency and reduce subjectivity [15]. Liu and Sun applied fuzzy optimisation BP neural network model (FOBPNN) as a management tool to evaluate the performance of expressway pavement [16]. A recent study by Sun and Gu developed a new approach to assess the pavement condition by integrating the advantages of analytical hierarchy process (AHP) and fuzzy logic theory [1].

In the work mentioned above, pavement condition assessment models were developed based on the fuzzy set theory, especially on the membership function concept, to deal with the subjectivity

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associated with expert judgment of distress extent and severity. Moreover, fuzzy set theory was used for ranking and finding the relative importance of different distress types on overall pavement condition performance. However, the previous researches have not developed a fuzzy inference system for pavement classification. Therefore, this study is the first attempt to estimate the pavement condition index (PCI) by using a fuzzy inference system.

The objective of this study is to develop a simple and effective system that is able to deal with uncertain data and transfer the knowledge and experience to the less experienced engineers. This study proposes a fuzzy rule-based system for estimating pavement condition index (PCI) for pavement considering various distresses, severity and extent as input variable.

Pavement Condition Assessment

Many indices that combine the effects of all distresses found in pavement sections are being used by highway authorities for estimating maintenance need priorities for each section. Calculation procedures for different indices range from simple subjective condition assessment to mathematical equations [17]. The most common condition indices are present serviceability index (PSI), an evaluator used to describe the functional condition with respect to ride quality, and also Pavement condition index (PCI) which is another index commonly used to describe the extent and severity of distresses on a pavement section [10].

Conventional Pavement Condition Index (PCI) Classification Procedure

The pavement condition index (PCI) is a numerical rating of the pavement condition that ranges from 0 to 100, with 0 being the worst possible condition and 100 being the best possible condition as shown in Fig. 1. The procedure of calculation PCI for flexible pavement was adopted from [17] and is presented below;

Step1: Determine severity, and the extent of each distress type for a pavement section. The severity level is expressed by three fuzzy sets, namely, "low", "medium", and "high". Whereas, the extent is quantified by linear or square (metre) feet or number depending on the distress type.

Step2: Calculate pavement distress density by;

Density % $= \frac{\text{Distress area}}{\text{section area}} * 100$ (Distress extent is measured by square (metre) feet)

Density % $= \frac{\text{Distress length}}{\text{section area}} * 100$ (Distress extent is measured by linear (metre) feet)

Density % $= \frac{\text{number of potholes}}{\text{section area}} * 100$ (Distress extent is measured by number of potholes)

Step 3: Obtain deduct points (DP) from deducting value curves for each pavement distress type.

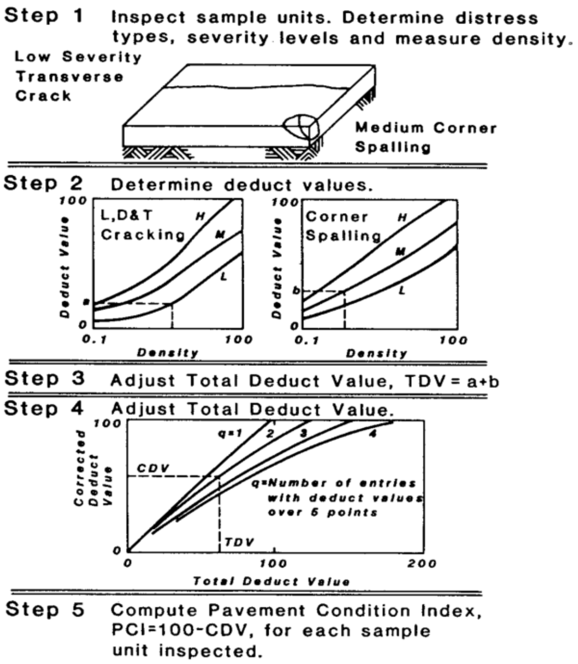
Step 4: Determine total deducted value (TDV) for all distresses of each section.

Step 5: Adjust total deduct value (TDV) by calculating corrected deduct value (CDV).

Step 6: Compute PCI for each section by subtracting (CDV) from 100.

Long Term Pavement Performance (LTPP) Database

One of the major pavement performance data for researchers is the Long Term Pavement Performance (LTPP) program that was created in the early 1980s by the Transportation Research Board of the National Research Council 1993 with the sponsorship of the Federal



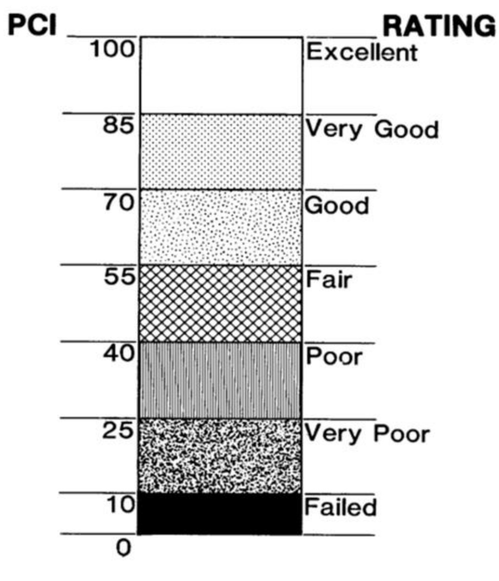


Fig. 1. PAVER System Procedure [17].

Highway Administration and the American Association of State Highway and Transportation Officials [18]. The LTPP program monitors and collects pavement condition data on all active sites. The pavement performance data consists of seven modules: Inventory, Maintenance, Monitoring (Deflection, Distress, and Profile), Rehabilitation, Materials Testing, Traffic, and Climatic [19].

In this study, the LTPP data for monitoring module is chosen to build a fuzzy rule based system for pavement classification. The extracted data from monitoring module in 1999 were used for rules generation. Six distress types (alligator crack, block cracking, longitudinal and transverse crack, patching and pothole, bleeding, and ravelling), severity level and extent of each section were used to generate rules and then for the sections classification based on the PCI values. Initial analysis of the data showed that the majority of the pavements within the seventy one sections have very poor to fair PCI values when classified using the conventional chart based method (as shown in Fig. 1).

Fuzzy Rule-Based System

A fuzzy rule-based system is one of the most popular methods used in classification problems. Fuzzy inference is a method that interprets the values in the input vector and, based on user-defined rules, assigns values to the output vector. The advantages of this approach is knowledge representation in the form of *if–then* rules, the mechanism of reasoning in human understandable terms, the capacity of taking linguistic information from human experts and combining it with numerical information, and the ability of approximating complicated nonlinear functions with simpler models [20].

Fuzzy inference systems are also known as fuzzy-rule-based systems, fuzzy models, fuzzy associative memories (FAM), or fuzzy controllers when used as controllers. Basically a fuzzy inference system is composed of five functional blocks (see Fig. 2):

- a rule base containing a number of fuzzy *if-then* rules;
- a database which defines the membership functions of the fuzzy sets used in the fuzzy rules;
- a decision-making unit which performs the inference operations on the rules;
- a defuzzification interface which transforms the crisp inputs into degrees of match with linguistic values;
- a defuzzification interface which transforms the fuzzy results of the inference into a crisp output [21].

Model Formulation

Fig. 3 shows the flowchart of the proposed model developed for pavement sections classification using the Fuzzy interference system.

Initially, for building pavement classification model based on fuzzy inference system, the density of alligator crack, block cracking, longitudinal and transverse crack, patching and pothole, bleeding, and ravelling is used as FIS inputs and calculated PCI as output. The FISPro (Fuzzy Inference System Professional) version 3.4 is then employed to design a fuzzy inference system from the numerical data. This software is one of the many automatic learning methods created using the C++ language with a graphical Java interface. Nevertheless, it is not a "black box" system like other learning methods. It contains algorithms to make the reasoning rules easy to interpret, so that the user understands how the fuzzy system operates [22].

Membership Functions

The membership functions of inputs parameters are established by *k*-means clustering method using pavement date from 71 pavement sections in the LTTP database. The basic concept of *k*-means clustering method is to select randomly k initial cluster means, or centres. After many repetitions, these initial cluster means are updated in such a way that they represent the data clusters as much as possible. A brief description of the k-means clustering is presented below [23]:

1. Initialising C_i by randomly choosing C points from among all the data points.
2. Compute the membership matrix (U), where the element (u_{ii}) is 1 if the j^{th} data point x_i belongs to the group i and 0 otherwise.
3. Compute the fitness function by the following equation. Stop if the fitness function value is lower a certain threshold value.

$$J = \sum_{i=1}^{c} Ji = \sum_{i=1}^{c}\left(\sum_{k,x_k \in C_i} \|X_k - C_i\|^2\right) \qquad (1)$$

4. Update the cluster centres C_i and calculates the new U matrix.

Three triangular membership functions for density representing different severity levels (low, medium, and high) are created for each input. However, the seven triangular membership functions of output (PCI) are created manually based on deducted value curves as shown in Figs. 4 -10. In these Figures, the x-axis represents each input and also output, whereas the y-axis is a membership function between 0 and 1.

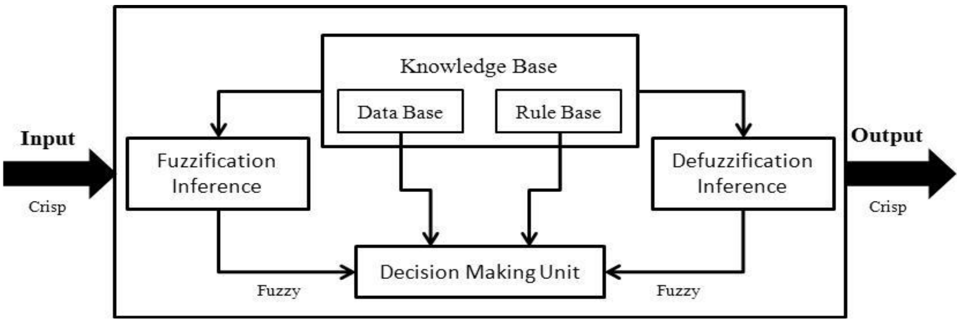


Fig. 2. Fuzzy Inference System Structure [8].

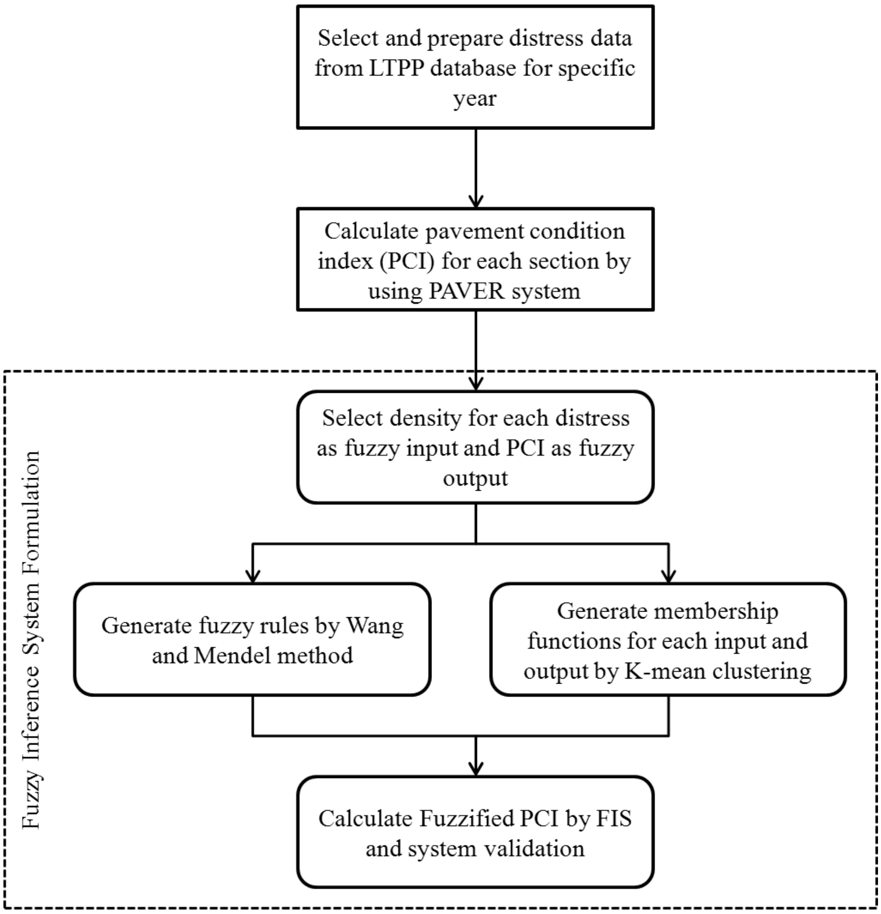


Fig. 3. Flow Chart of Pavement Classification Model Based on Fuzzy Inference System (FIS).

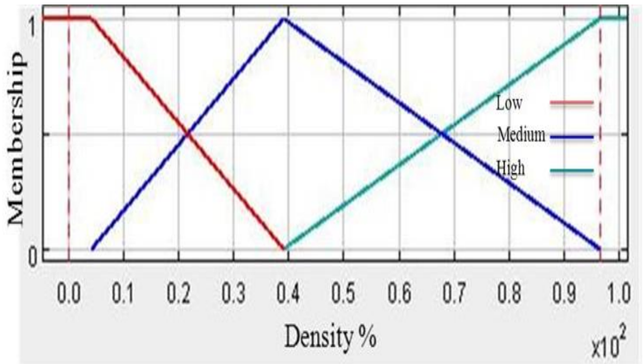


Fig. 4. Membership Functions for Alligator Crack.

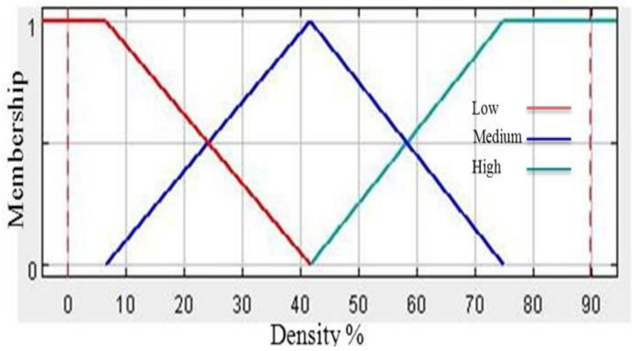


Fig. 6. Membership Functions for Longitudinal and Transverse Crack.

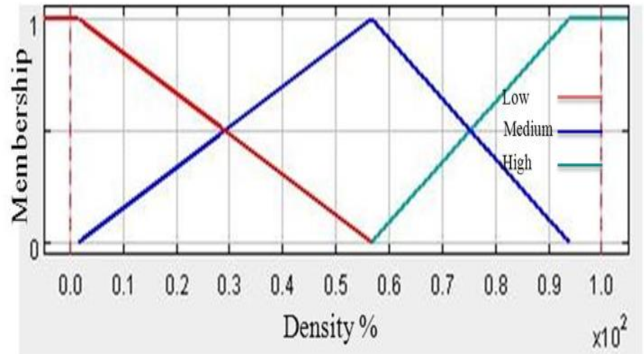


Fig. 5. Membership Functions for Block Crack.

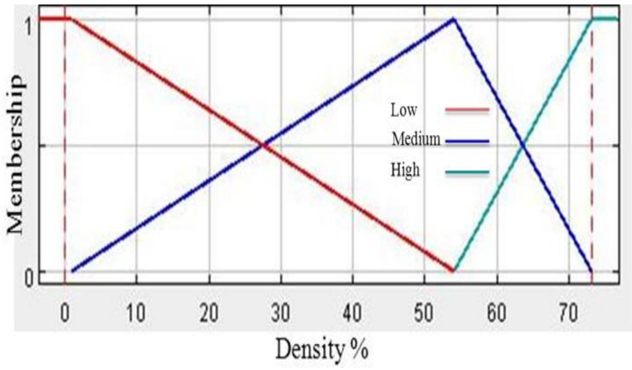


Fig. 7. Membership Functions for Patch and Pothole.

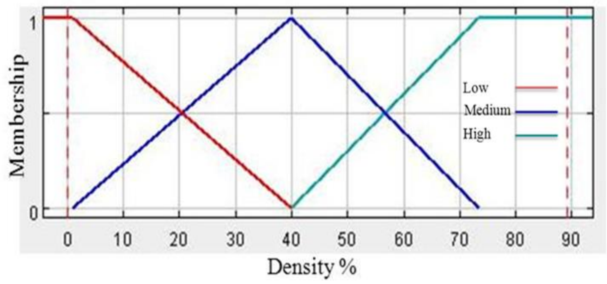


Fig. 8. Membership Functions for Bleeding.

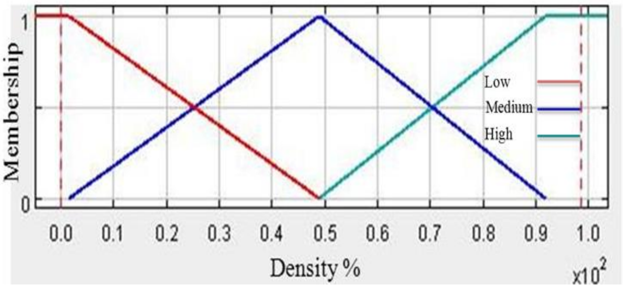


Fig. 9. Membership Functions for Ravelling.

Fuzzy Rule Generation

The major challenge in FIS is the generation of the rules. In high-dimensional problems, it is very difficult to generate every possible rule with respect to all antecedent combinations. The

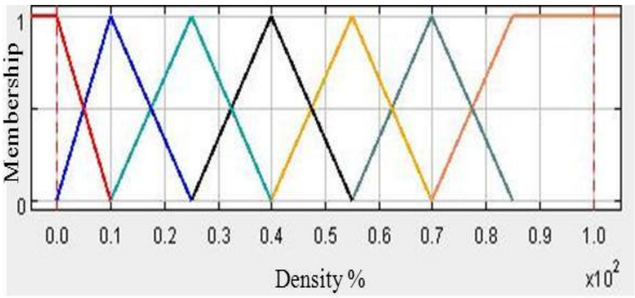


Fig. 10. Membership Functions for Pavement Condition Index (PCI).

number of rules of a complete rule set is equal to

$$\prod_{i=1}^{n} m_i$$

where m is the number of membership functions for input *i* and *n* is the number of inputs.

The fuzzy rules are generated either from an expert knowledge or numerical data [24]. The generated rules of the classification model described in this work are difficult and complex because they consist of six inputs to one output. Therefore, the FISPro programme is employed to overcome this problem. The fuzzy rules are generated based on Wang & Mendel method. This method needs predefined fuzzy membership functions for each input and output. It can automatically generate rules from data. It starts by generating one rule for each data pair of the training set. The i^{th} pair one is written as, if X_1 is $A^i{}_1$ and X_2 is $A^i{}_2$ . . .and X_p is $A^i{}_p$ then Y is C^i.

Table 1. If then Rules Generated by Fuzzy Inference System (FIS).

Rule No.	Input Rule - *if "Alligator Cracking" is … and "Block Cracking" is …*						Output Rule - *Then "PCI" is…*
	Distress type						
	Alligator Cracking	Block Cracking	Longitudinal & Transverse Cracking	Patching & Pothole	Bleeding	Ravelling	
1	Low	Low	Low	Low	Low	Medium	Very Good
2	Medium	Medium	Medium	Low	Low	Low	Very Poor
3	Low	Low	Low	High	Low	Low	Fair
4	High	Low	Low	Low	Low	Low	Poor
5	Low	Low	Low	Low	Low	High	Poor
6	Low	Low	Low	Medium	Low	Low	Good
7	Medium	Medium	Low	Low	Low	Low	Very Poor
8	Low	Low	Low	Low	Medium	Low	Good
9	Low	Low	Medium	Low	Medium	Low	Poor
10	Low	High	Low	Low	Low	Low	Fair
11	Low	Low	Medium	Low	Low	Low	Poor
12	Low	Low	High	Low	Low	Low	Poor
13	Low	Low	Low	Low	Medium	High	Poor
14	Medium	Low	High	Low	High	Low	Very Poor
15	Low	Low	High	Low	High	Low	Poor
16	Medium	Low	Low	Low	High	Low	Poor
17	Low	Medium	High	Low	Low	Low	Fair
18	Low	Medium	Low	Low	Low	Low	Fair
19	Low	Low	Medium	Low	Low	Medium	Poor
20	Low	Low	Medium	Low	Low	High	Poor
21	Medium	Low	Medium	Low	Low	Low	Poor
22	Low	Low	Low	Low	Low	Low	Excellent

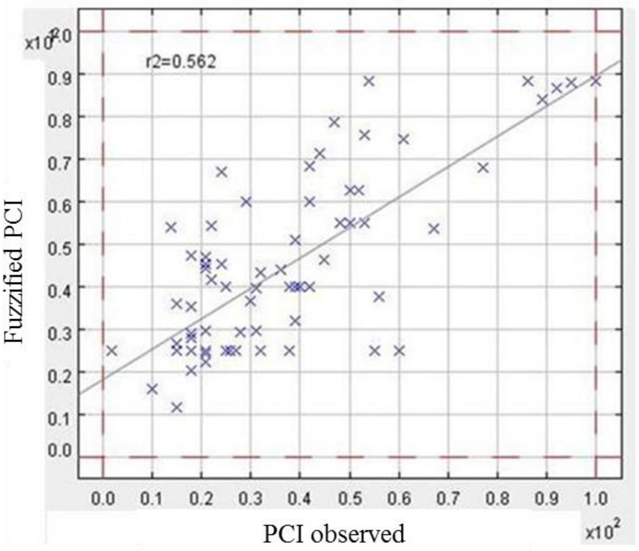


Fig. 11. The Performance of Fuzzy Logic Based Pavement Classification Index.

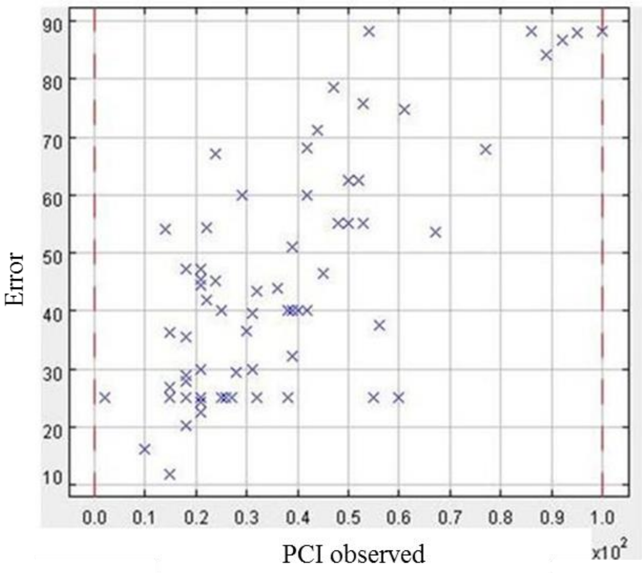


Fig. 12. Error of Fuzzy Pavement Classification System.

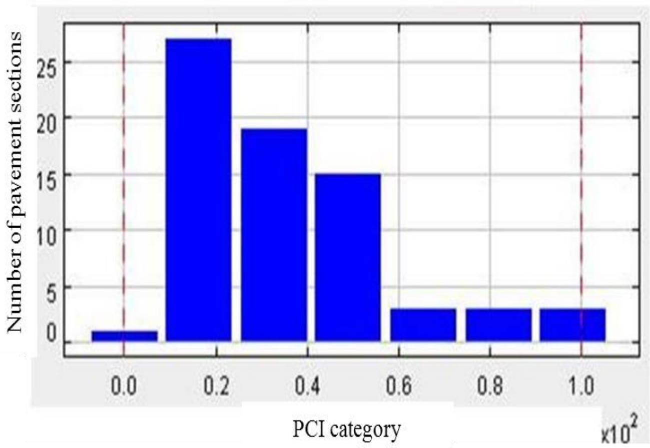


Fig. 13. Pavement Distress Data for Each PCI Category.

The fuzzy sets A^i_j are those for which the degree of matching X^i_j is maximum for each input variable *j* from pair *i*. The fuzzy set C^i is the one for which the degree of matching the observed output, Y^i, is maximum [22].

Results

The generated rules for each distress type and overall PCI value are given in Table 1.

After generating membership functions and rules, the system is tested by calculating the performance of the fuzzy pavement classification. The relation between observed PCI and calculated PCI from is presented in Fig. 11 which shows correlation of 56%. To understand the level of error for each PCI category, the error levels are plotted in Fig. 122. It can be seen that the errors in the “excellent”, “very good”, “very poor”, and “fail” class of PCI are low compared to the “medium classes”. This is because most raw data used in this study were either poor or good quality. An improvement can be achieved if more data of medium quality are used in the membership classifications. As well, there is not enough mix between distress data. For example, as presented in Fig. 13, the distress data for each PCI class derived from the FIS showed, within the seventy one sections used in this study, the number of sections with very poor to fair PCI categories are disproportionately higher than the sections with either good or excellent PCI category.

Summary and Conclusions:

A fuzzy interference system (FIS) was used to develop a fuzzified pavement condition index (PCI) in classification purpose for flexible pavement. Compared to the conventional crisp (pass and fail) approach, this system has the potential to deal with the uncertain and high dimensional distress data. Membership functions were developed for six commonly used pavement distresses (alligator crack, block cracking, longitudinal and transverse crack, patching and pothole, bleeding, and ravelling), extracted from seventy one section in the Long-Term Pavement Performance (LTTP) database. Triangular and semi-triangular shapes were used for membership function for each distress type. These membership functions were then utilised in a fuzzy interference system (FIS) to generate rules for categories of section classification.

The results showed an overall 56% correlation between the fuzzified based PCI and the conventional PCI. This level of correlation was achieved despite the majority of the sections were in the poor to fair category. To improve the correlation, further research is underway to develop the model with a good spread of poor to excellent sections by using extra pavement sections data or change the shape of membership functions. Overall, this method showed considerable promise to generate rules with the less amount of time especially when high dimensional distress data are needed for section classification.

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