A FUZZY INFERENCE SYSTEM BASED ASPHALT SURFACE DETERIORATION PREDICTION MODEL DUE TO COMBINED INTERACTION OF DYNAMIC LOADING-WATER-PAVEMENT

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ABSTRACT

A Fuzzy Inference System (FIS) based deterioration prediction models has been developed in two stages. Firstly, experimental work was conducted to evaluate the performance of asphalt surfaces due to the combined action of water and dynamic loading. Then, a FIS model was developed using high dimensional inputs, such as three types of asphalt surfaces, three aggregate sizes, and two weather conditions (dry and wet), and repeated loading at two frequencies. The two outputs of the model, i.e., cracking and rutting, showed excellent agreements with the experimental measurement of cracking and rutting. The validation and sensitivity analysis were also conducted to evaluate the model performance and to evaluate the influence of each input parameters on distress prediction. The FIS models demonstrated the potential for further development as a routine prediction model to differentiate the performance of asphalt surfaces subjected to dynamic loading while submerged in water.

Key words: Deterioration prediction model, FIS, Wang & Mendel technique, fatigue cracking, rutting, fuzzy logic.

INTRODUCTION

Asphalt pavements are complicated physical structures that react in a complicated way to the impacts of the environmental and to the load-related variables (1). Water is one of the environmental variables behind asphalt surface damage. It is recognised that the water on the surface or water builds up in the pavement structure due to rainfall or poor drainage accelerates surface damage with repetitive traffic loading, which may subsequently occur in pavement surface layer spalling or loosening, leading to localised and structural damage (2-6). When traffic moves on the submerged pavement, the interaction of tire-water- pavement creates pore water pressure. Despite extensive studies conducted on water related material degradation in the last fifty years, research on the impact of water pressure on pavement performance caused by the dynamic action is still very limited.

To address this shortcoming, authors of this paper have developed a novel experimental method to measure water pressure under a pavement when pavement is subjected to flooding and trafficking at the same time (7, 8). The impact of load frequency, tires tread shape and thickness, and depths of surface water on pore water pressure in the pavement have been investigated in detail. The results showed that pore water pressure under the pavement depends on loading speed and shape and thickness of the tread. Water pressure increased significantly when high frequency loading is combined with square types of tread with deep tread depth when water trapped inside the groove.

Rutting, cracking and raveling are the three main distresses that can happen on asphalt surfaces when pavement is flooded with water and experiences repeated traffic loading. There are different standard laboratory tests available to assess and quantify these distresses. However, in the presence of water, these distresses can occur simultaneously. It is, therefore, essential to develop a test method that can simulate combined traffic-tire-water-pavement interaction in a controlled laboratory environment. To address this issue, the test developed by the authors to measure pore water pressure under a pavement has been used in a repeated load scenario. The combination of load magnitude, speed, tread characteristics and depth of surface water that create maximum pore water pressure, from Saeed et al (2018), were used (7, 8). By doing this, it was possible to quantify the type and amount of deterioration on different types of surfaces and compared to each other (9).

Once the deterioration has been quantified, it is important to develop a prediction model for evaluating the relative performance of different types of surfaces, which can be utilised to optimise the selection of asphalt surface suitable for specific loading and climatic conditions. A prediction model usually is done by learning from the past for which actual data is gathered and analysed to investigate the resulting pattern (10). There is a plethora of prediction models available in the literature, from simple deterministic linear regression model to a probabilistic Markov chain to artificial intelligence based (11-13). All these methods have their merits and short-comings. After a careful literature review, in this study, a Fuzzy Inference system (FIS) has been used (14). FIS modelling has excellent learning capabilities, requires less computational effort, suitable to deal with high dimensional problems and easier to implement (15). A brief overview of the method has been given in the modelling section of this paper.

OBJECTIVES

The primary objective of this study was to develop multi input models to predict deterioration of asphalt surfaces due to the combined action of repeated traffic loading with specific tire characteristics applied on submerged asphalt surfaces. The input parameters for this study were asphalt surface type, aggregate size and loading frequency. Three asphalt surfaces, namely, hot rolled asphalt (HRA), stone mastic asphalt (SMA) and porous asphalt (PA) were chosen as these are the most commonly used surfacing types. Each of these mixtures was produced with different sizes of aggregates to assess their impact on mixture performance and was tested in two environmental, dry and wet, and in two loading conditions, 5Hz and 10Hz, to simulate different loading speeds.

In the prediction models, both rutting and cracking were considered as the main distresses. After developing the model, validation exercise and sensitivity were carried out to evaluate the model accuracy and the influence of each parameter in asphalt performance.

This study consists of two main stages, in stage 1, brief description of the experimental study on different types of asphalt surfaces are presented. Detail explanation of stage 1 research was reported in (9). In stage 2, a brief overview of the FIS system followed by model generation from stage 1 experimental data, results in analysis, and model validations and finally key conclusions, are presented.

STAGE 1: ASPHALT DISTRESS MEASUREMENT DUE TO COMBINED ACTION OF TRAFFIC-WATER-PAVEMENT

Sample preparation and test set-up

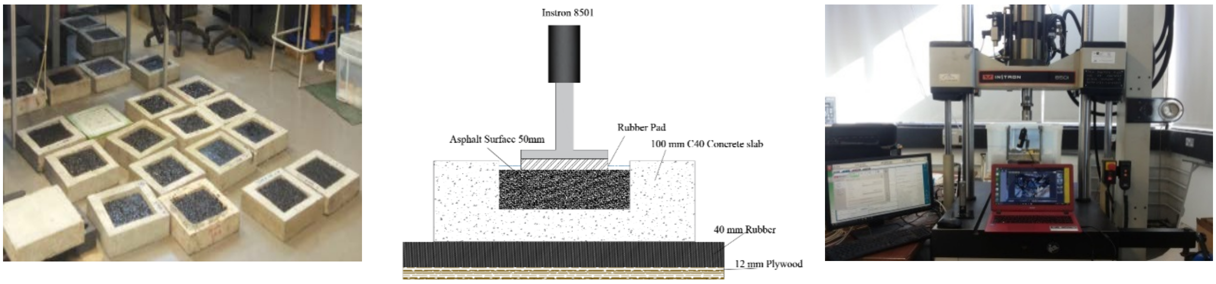
In total, 36 slabs (200mm×200mm×50mm) were manufactured using relevant BS EN standards. All compacted slabs were tested for bulk density as detailed in BS EN 12697-6: 2003(16). The actual percentage of air voids of each test specimen were calculated according to BS EN 12697-8: 2003 (17). The target void contents were 8-13% for the SMA; 4-6% for the HRA and >16% for the PA (18-20). Sample characteristics and mixture properties are given in Table **1**.

TABLE 1 Specimen characteristics and mixture properties

Mixture Type	Nominal maximum size (mm)	No of sample	Specimen Size (mm^3)	Void contents (%)		
				Max	Min	Std
HRA	10	6	200×200×50	7.81	5.97	0.736
	14	6	200×200×50	8.00	5.20	1.017
	6*	×	×	×	×	×
SMA	6	6	200×200×50	12.78	8.97	1.421
	10	6	200×200×50	13.63	10.36	1.371
	14	6	200×200×50	12.50	10.33	1.024
PA	14	6	200×200×50	20.89	18.00	1.315
	10**	×	×	×	×	×
	6**	×	×	×	×	×

*not common type of road surface.
** Not suitable of PA mixture design.

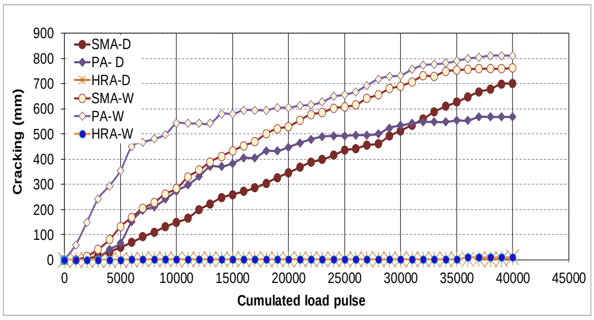
The experimental program consisted of designing a novel loading plate, and an INSTRON 8501 machine to apply dynamic loading. Details test set-up can be found in (9). A picture of the specimens, the schematic diagram of the loading arrangement and the test setup are presented in Figure 1. A 5kN sinusoidal load at a frequency 5Hz and 10Hz were applied for 20,000 to 40,000 load cycles to produce significant damage to the surface (9).



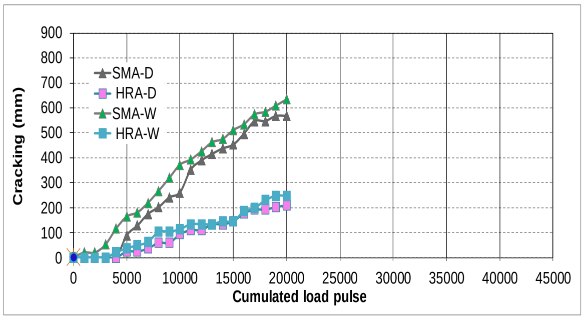
Specimens ready for testing   Test setup   Distress measurement setup

FIGURE 1 Experimental works (stage 1)

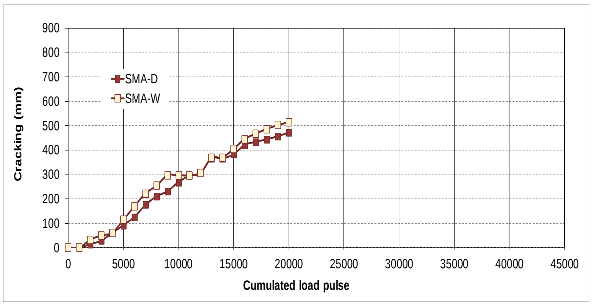
For each mixture type, three specimens were tested in dry condition and three in wet condition. The asphalt surface was immersed with 1-2mm water, and this depth was constantly maintained by regular feeding of water throughout the duration of the test. Specimens tested in wet condition went through overnight conditioning in water at room temperature to ensure saturation before testing. The distresses were measured at every 1000 cycles by a microscope, digital images and grid system to ensure the consistency in measuring. The result of cumulative cracking and rutting, both measured in mm, of asphalt specimens, is given in Figure 2.



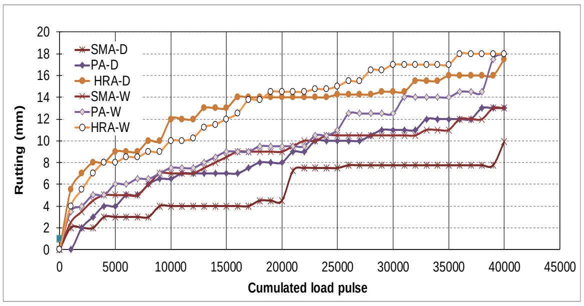
a. Cumulative cracking for 14mm SMA, PA and HRA



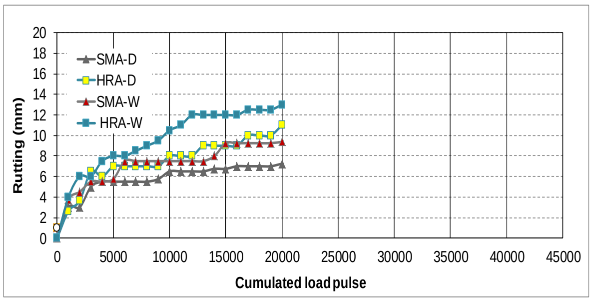
b. Commutative cracking for 10mm SMA and HRA



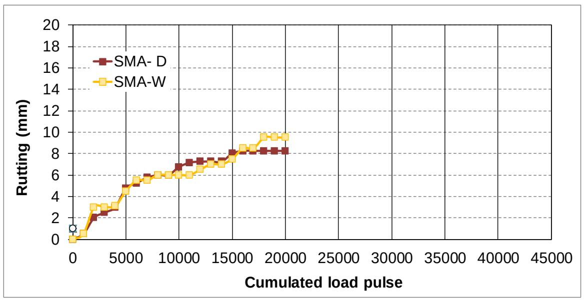
c. Commutative cracking for 6mm SMA



d. Cumulative rutting of SMA, PA and HRA14 mm



e. Cumulative rutting of SMA and HRA10 mm



f. cumulative rutting of SMA 6 mm

FIGURE 2 Cumulative of average cracking and cumulative maximum Rutting

The results showed that depending on the kind of asphalt surfaces, the presence of water accelerates cracking, rutting and other distresses such as raveling. The cracking propensity was found severe in highly open graded mixtures then the gap graded hot rolled asphalt (Figures 2a). Compared to dry condition measurement, the appearance of surface crack was around seven times faster in porous asphalt tested in wet conditions. It is interesting to note that while porous asphalt is designed to drain water within open voids, the continuous presence of water on the surface water combined with loading can significantly reduce their load-bearing capacity. It is consequently essential proper drainage for adequate performance of open graded mixtures reducing the probability of pore water build up in the clogged voids.

All tested SMA mixtures showed good rutting resistance compared to porous and hot rolled mixtures (Figures 2d-2f), although their cracking resistance was significantly decreased in the presence of water. Besides, while both 10mm and 14mm HRA presented the best performance regarding resistance to cracking, the rutting was significantly higher compared to the other two mixtures. However, at the end of 40,000 pulses, the porous asphalt showed significant rutting (Figure 2d). The best performance was observed in 10mm SMA. When compared the impact of aggregate size, the gradation seemed to have more impact on load-bearing capacity than the size of aggregates. Air voids do not appear to influence wet condition performance. For instance, notwithstanding similar void contents in SMA 14 and SMA 10, SMA 10 (Figures 2a-2f) was not very sensitive to wet conditions as it was in SMA14. It appeared that aggregate nominal size may influence wet condition performance.

STAGE 2: DETERIORATION PREDICTION MODEL BY FIS

Fuzzy interface system (FIS) is one of the most popular methods used in classification and prediction problems (21). Fuzzy inference is a technique that interprets the values in the input vector and, based on user-defined rules, assigns values to the output vector (22). Dehzangi et al., (2007) stated the benefits of this method that is represented by the knowledge in the form of *If-Then* rules, interpreting the mechanism of logic in human-understandable terms. Fuzzy logic has advantages over other computational techniques as it can take linguistic information from human experts and combines it with numerical data. In addition, it can approximate complex nonlinear functions with simpler models (23).

Fuzzy based model is developed in two main steps, generation of membership functions and fuzzy rules. A short description of each of these steps is given below.

Membership functions generation

Within the fuzzy approach, the fuzzy set *A* of universe *X* is determined by the function $\mu_A(x)$, named the membership function of set *A* (24).

$$\mu_A: \times \rightarrow [0, 1]$$

Where $\mu_A(x) = 1$ if x is totally in A; $\mu_A(x) = 0$ if x is not in A; $0 < \mu_A(x) < 1$ if x is partly in A. in this research, the membership functions of inputs variables are generated by data clustering method.

Data clustering

Numerical data clustering is the foundation of various modelling and classification algorithms to evaluate their performance (25). It separates the data set into many data subsets, such that the similarity within a subset is higher than between the subsets. A similarity among elements of input vectors is an essential feature to achieve data clustering (26). The most common clustering method, one has been used in this study, is *k*-means clustering. The fundamental thought of this clustering technique is to choose *k* initial cluster means, or centres randomly. After many repetitions, certain initial cluster means are updated in such a way that they represent the data clusters as much as possible (27). A limitation of the *k*-means clustering algorithm is that the number of clusters is fixed; after *k* is chosen, there will always be *k* cluster means or centres *(21)*. The *k*-means algorithm can avoid this difficulty by eliminating the excess clusters. A cluster center may be removed if it does not have enough samples it is likely to prevent this problem by picking a large enough *k* *(26)*. The steps for *k*-mean clustering technique are as follows;

i. Initialise C_i by randomly choosing C points from among all the data points.
ii. Compute the membership matrix (U), where the element (u_{ij}) is 1 if the j^{th} data point x_j belongs to the group i and 0 oppositely.
iii. Compute the fitness function by using the following equation. Stop if the fitness function value is lower than a certain threshold value:

$$J = \sum_{i=1}^{c} = Ji = \sum_{i=1}^{c}(\sum k, x_k \in c_i \| x_k - c_i \|^2)$$

Update the cluster center C_i and calculate the new matrix (*U*). The *k*-means clustering algorithm is iterative. Accordingly, it is hard to forecast its convergence to the best solution *(21)*.

Fuzzy rules

A rule containing several fuzzy *If-Then* rules (28), and they are 1) a database which defines the membership functions in the fuzzy sets used in the fuzzy rules; 2) a decision-making unit which performs the inference operations on the rules; 3) fuzzification interface which transforms the crisp inputs into degrees of a match with linguistic values; 4) defuzzification interfaces which transform the fuzzy results of the inference into a crisp output.
The number of rules of a complete rule set is equal to

$$\Pi_i^n = 1^{m_i}$$

Where *m* is the number of membership functions for input *i*, and *n* is the number of inputs

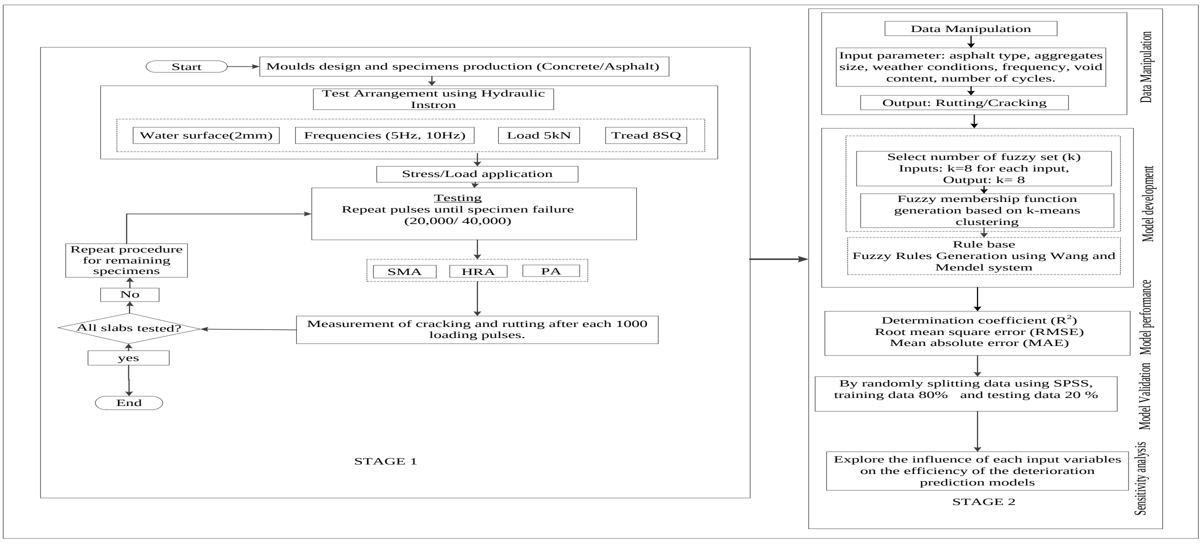
The fuzzy rules are generated either from skilful experience or numerical data (29). In this study, the widely used Wang & Mendel technique was adopted to create fuzzy rules mechanically from numerical data (30). This method needs predefined fuzzy membership functions for each input and output (21, 31). It begins by performing one rule for each data pair of the training set The ith pair rule is as follow:

$$\text{IF } x_1 \text{ IS } A_1^i \text{ AND } x_2 \text{ is } A_2^i \ldots \text{ AND } x_p \text{ THEN } y \text{ is } C^i$$

The fuzzy sets A_1^i are those for which the degree of match of X_j^i is maximum for each input variable j from pair i. The fuzzy set Ci is the one for which the degree of match of the observed output, y, is maximum (32).

DETERIORATION PREDICTION MODEL

Figure 3 shows the flowchart of different stages in the damage prediction model. A short description of each of these stages is given below.



Note: 8SQ refers to 8mm deep square tread

FIGURE 3 Flowchart for prediction model development.

Data Manipulation

For building a pavement deterioration, the three asphalt types, three aggregate sizes, two weather conditions, one load and two frequencies were used as FIS inputs, and a measured cracking and rutting were defined as the FIS output. Cracking and rutting were used as an output parameter in the first model and the second model respectively. It was assumed that the void content remains constant even after the progressive damage of the asphalt surfaces during testing.

The severity level of each distress type, as shown in Table **2**, was determined by using the Distress Identification Manual for the Long-Term Pavement Performance Program (33). All linguistic data information was then converted to the numerical numbers. For example, each mixture was given a numerical identification number, such as HRA=1, SMA=2, PA=3, and for aggregate size, 14 was for a large stone, 10 for medium size stone and 6 for small size stone. The dry condition was referred to as "0" while the wet condition was given number "1".

Membership function

The membership functions of input variables were generated by *k*-means clustering using Fuzzy Inference System Professional (FisPro) software (34). As both rutting and cracking occur in asphalt surface simultaneously, the membership functions for inputs variables of both rutting and cracking in the deterioration model were kept the same. For each parameter type, three triangular membership functions representing the range of variability (low, medium, and high), as shown in Table **2**, were generated. The seven triangular membership functions of output were generated manually. The membership functions are shown in Figure 4.

TABLE 2a Criteria used to evaluate the severity levels of cracking

Mixture ID	Severity level Low	Severity level Medium	Severity level High
	70 mm to 100mm with a few connecting cracks	100mm to 150mm with interconnected cracks	> 150mm interconnected cracking forming a complete pattern and pieces move with loading
HRA10-D	9320	10236	14664
HRA10-W	7180	7820	15096
HRA14-D	40,000*	-	-
HRA14-W	40,000*	-	-
SMA6-D	4350	5120	6420
SMA6-W	4313	4780	5640
SMA10-D	4785	5192	6448
SMA10-W	3290	3712	4576
SMA14-D	6037	7360	10001
SMA14-W	3732	4344	5420
PA14-D	5025	5400	5960
PA14-W	1110	1432	2000

TABLE 2 b Criteria used to evaluate the severity levels of rutting

Mixture ID	DMRB criteria Low Severity <6mm; 6mm< Medium <11mm; High severity>11mm			
	@ 20,000 load cycles		@ 40,000load cycles	
	Measured rutting (mm)	Severity level	Measured rutting (mm)	Severity level
HRA10_D	11.4	H	-	-
HRA10_W	13.2	H	-	-
HRA14_D	14.3	H	14.5	H
HRA14_W	17.5	H	18	H
SMA6_D	8.3	M	-	-
SMA6_W	9.5	M	-	-
SMA10_D	7.5	M	-	-
SMA10_W	9.4	M	-	-
SMA14_D	4.5	M	9.9	M
SMA14_W	9.0	M	13	H
PA14_D	8.2	M	13	H
PA14_W	9.5	M	18	H

* The cracks length in HRA14 mixture was 10 mm for both cases with the number of load pulse 40,000

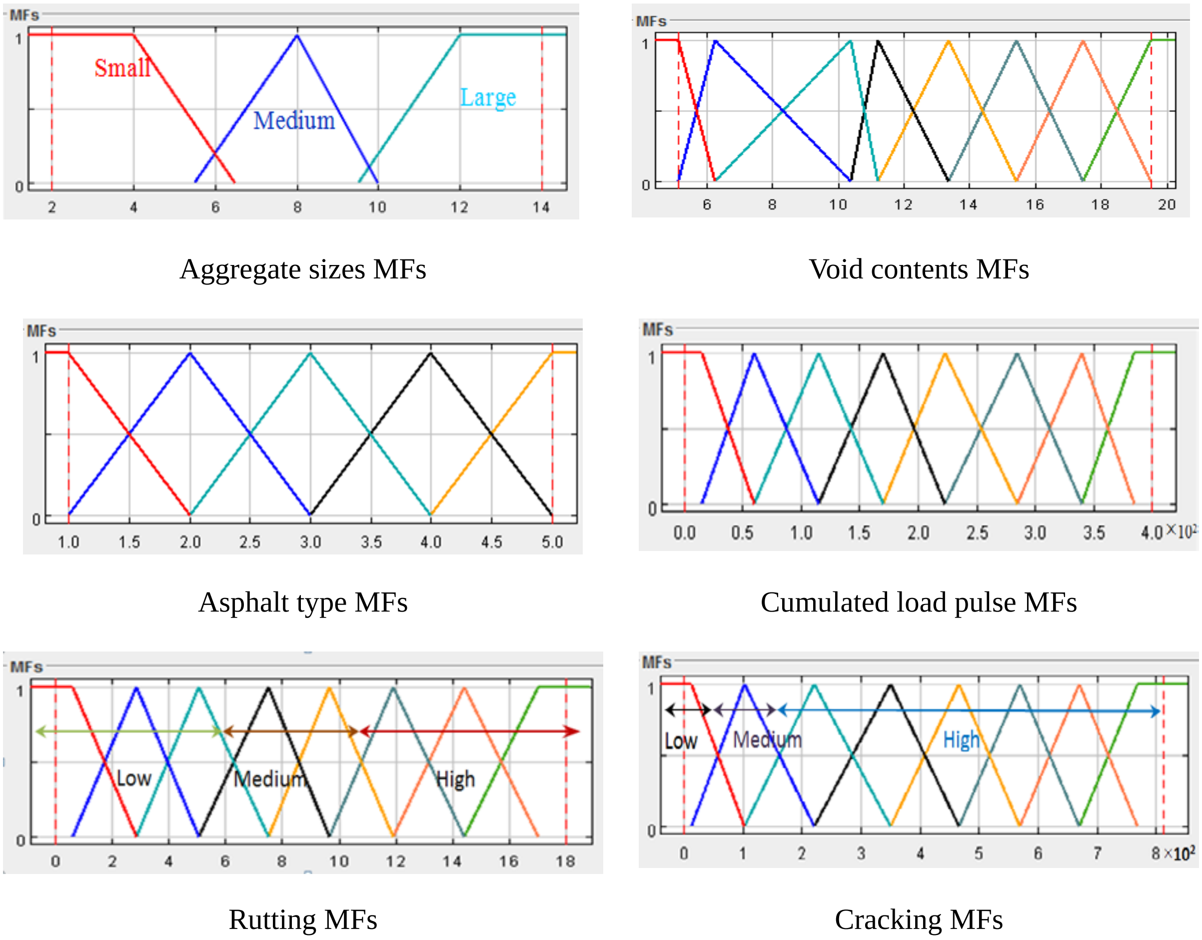


FIGURE 4 Membership functions for model developement

Fuzzy Rule

The FisPro software was used for automatic generation of fuzzy rules from the numerical data. The generation of fuzzy rules of the deterioration model reported in this study was challenging and complicated as it consisted of six inputs and one output for each model. To overcome the problem of generation of the fuzzy rules and membership functions with a high-dimensional problem, the membership functions of inputs parameters were created based on the k-means clustering technique in (FisPro) software (21). FisPro offers the possibility to generate fuzzy inference systems and to use them for reasoning purposes, especially for simulating a physical or biological system (31). In total 158 rules were created for each model using the logic given in the fuzzy inference system section of this paper. A typical example is given in the following Table **3**.

TABLE 3 Fuzzy If-Then rules generated by cracking (selected)

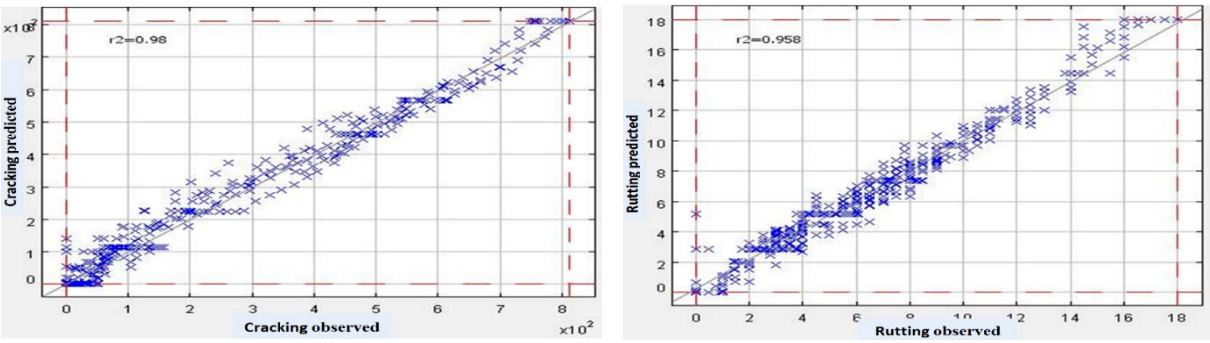
Rules	Input Rule - If “Type if Asphalt ” is … and “Size if Aggregate” is …						Output Rule- The Cracking Severity Level is …
	Asphalt Type	Aggregate Size	Weather	Frequency	Void Content	No of Cycles	
1	SMA	Large	Dry	5Hz	Medium	0-6000	Low
2	PA	Large	Dry	5Hz	Very high	0-6000	Low
3	HRA	Medium	Dry	5Hz	Medium	0-6000	Low
4	HRA	Large	Dry	5Hz	Medium	0-6000	Low
,							
,							
157	HRA	Large	Wet	5Hz	Medium	34000-40000	Low
158	SMA	Medium	Wet	10 Hz	High	34000-40000	High

RESULTS AND DISCUSSION

As mentioned earlier, two separate deterioration models for cracking and rutting were developed. For each model, six input variables (asphalt type, aggregate sizes, weather conditions, frequencies, void contents and cycles numbers) were used to generate output for rutting and cracking. The results are given below.

Pavement Deteriorations (Rutting and Cracking)

Figure 5a and Figure 5b show model correlation for rutting and cracking respectively. It can be seen that a correlation of approximately 95.8% was achieved between measured and predicted rutting and 98% correlation between measured and predicted cracking. This indicates a very good accuracy of both models.



The performance of a fuzzy inference system-based cracking

b) The performance of a fuzzy inference system based on rutting

FIGURE 5 The performance of a fuzzy inference system

Table **4** shows the coefficient of determination together with the root mean square error (RMSE) and mean absolute error (MAE) to determine the level of agreement of the rutting and cracking values in the two data sets. The error levels are less than one for rutting, but high in the cracking. This is because the measurement of rutting was only up to 20mm and it was concentrated in confined areas under the loading. On the other hand, cracking was distributed across the slab and measured up to 800mm after the test which would create some variability. Despite this, high correlations in both cases indicate good model accuracy.

TABLE 4 :Model performance of asphalt deteriorations

Deteriorations Types	R^2 (%)	RMSE	MAE
Rutting	95.8	0.995	0.686
Cracking	98	27.45	19.808

Model Validation

The entire data set used to develop the prediction model were randomly split into training data (around 80%) and testing data (around 20%). The training data were used to generate the prediction models while the testing data were used to validate the models. The data for both models were split by using SSPS software(35). SPSS can automatise this selection process without requiring multiple steps. The process to split training data and testing data have been repeated to run models five times for both cracking and rutting to ensure all data were included.

The estimated root mean square errors (RMSE) for the models were used to compare their efficiency in prediction. Results for cracking and rutting are given in Tables **5a** and **5b** respectively.

TABLE 5a The validation of model performance for cracking

Model No	Training data 80% of all data			Testing data 20% of all data		
	R^2 (%)	RMSE	MAE	R^2 (%)	RMSE	MAE
1	97.9	30.174	22.129	97.9	34.356	24.994
2	98.1	30.305	21.96	98.3	27.891	21.146
3	97.9	31.513	22.537	98.2	29.834	22.614
4	98.2	29.919	22.152	97.7	30.315	21.324
5	98.3	28.093	20.819	98.2	28.417	21.678

TABLE 5b The validation of model performance for rutting

Model No	Training data 80% of all data			Testing data 20% of all data		
	R^2 (%)	RMSE	MAE	R^2 (%)	RMSE	MAE
1	95.8	0.882	0.601	95.4	0.846	0.588
2	85.4	2.808	2.293	96.4	0.721	0.55
3	96.9	0.726	0.54	95.7	0.842	0.61
4	96.2	0.795	0.587	96.8	0.7	0.581
5	88.1	1.457	0.971	95.6	0.878	0.641

The model developed for cracking has better accuracy (R^2= 97.9 to 98.3) than the rutting model (R^2= 85.1 to 96.9). Despite this difference, both models have shown very good agreement with the measured data.

Sensitivity analysis

To study the influence of each input variable in the performance of the asphalt surface, a sensitivity analysis was conducted to explore the influence of each input variables on the efficiency of the deterioration prediction models. For instance, the sensitivity investigation was conducted by generating the FIS model by respecting the effect of individual input and inactive effects of other inputs.

The correlation between the fuzzified and each input variable are shown in Table **6**. It can be seen clearly that the determination coefficients for asphalt type, aggregate size, weather conditions, frequency, void contents and the number of cycles were 15.1, 3.7, 10.8, 27.7, 0.1 and 28.6 for rutting and 0.1, 1, 10.1, 27.1, 39.4 and 7.4 for cracking. It was noticed that for this data set, the influence of void contents is significantly higher than that of other parameters on cracking; and in rutting number of cycles has a higher impact. In addition, as these variables are related to each other, the combined impact will be higher.

TABLE 6 Sensitivity level for each input variable

Input Variable	Deterioration model	
	Rutting	Cracking
	R^2 (%)	R^2 (%)
Asphalt Type	15.1	0.1
Aggregate Size	3.7	1
Weather Conditions	10.8	10.1
Frequency	27.4	27.1
Void Contents	0.1	39.4
Number of Cycles	28.6	7.4

CONCLUSION AND RECOMMENDATIONS

Multi input fuzzy-based deterioration prediction models have been developed to evaluate the combined interaction of traffic loading and water on asphalt surfaces. The prediction accuracy of the model was approximately 99% with the experimentally measured distresses such as cracking and rutting. The accuracy of rutting prediction model was marginally better than cracking prediction model. This was due to the spread of distresses on the tested specimens. The validation of the models also accurately predicted both distresses from a randomly selected dataset.

The sensitivity analysis to evaluate the influence of each variable on the model performance showed that irrespective of mixture type, mixture parameters (aggregate size, void contents), traffic parameters (loading frequency) and environmental factors (wet condition) have an impact on either cracking or on rutting or on both. Further development could be extended to implement this model on independent dataset experiences similar traffic and environmental loading.

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