Technical Paper

ISSN 1997-1400 Int. J. Pavement Res. Technol. 7(4):287-296

Unsupervised Artificial Neural Network for Efficient Mapping of Doweled Concrete Pavement Joints Condition

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Abstract: Concrete pavement joint evaluation involves a number of assessment criteria, such as deflection near the joint, load transfer efficiency of the dowels and severity of voids under the slab. Although there are well defined thresholds for each of these parameters, often there arises a situation where each of the considered parameters lends contradictory assessment that leads to a considerable subjectivity in the evaluation process. A Self-Organizing Map (SOM), an unsupervised learning procedure in artificial neural network, is utilised for the first time to map the joint condition of concrete pavements from Falling Weight Deflectometer (FWD) deflection bowls. A novel methodology is proposed for labelling the network, whereby pavement engineering expertise can be directly used in a SOM for consistent deflection data classification in joint evaluation. The effectiveness of the trained network is demonstrated by using joint assessment parameters; namely, load transfer efficiency (LTE), void intercepts and absolute deflection. The joints were classified as good, marginal or poor. For the three parameters based SOM classification, an accuracy of 65-70% was obtained; this improves to 87.5% when the SOM was trained with 2-parameters (LTE and absolute deflection). However, when the SOM was tested with the data classified as 'good', accuracy improves to around 90%. Therefore, a SOM can be a powerful supplementary tool for a consistent and non-subjective evaluation of concrete pavement joints.

DOI: 10.6135/ijprt.org.tw/2014.7(4).287

Key words: *Absolute deflection; Concrete pavement joints; Falling Weight Deflectometer (FWD), Load transfer efficiency (LTE); Self-organizing map (SOM); Void intercepts.*

Introduction

Joints are vital of controlling pavement cracks and movement in concrete pavement. Without joints, the majority of in-service concrete pavements would be damaged with cracks within a short period. The good performance of a "joint" in a jointed concrete pavement is dependent on both physical and environmental factors [1, 2]. Physical factors include the dowel bar, foundation and concrete properties (strength, aggregate interlock, and aggregate type). Temperature variation is the main environmental factor causing the expansion and contraction of the slab.

Despite good service history, jointed concrete pavement often suffers from poor performance of joints. A simple schematic diagram of the joint deterioration process is shown in Fig. 1. As shown in Fig. 1, the rainwater ingress through worn joint sealant reacts with dowel bars. Over a long period of time, and under repeated loading, the high stresses found at the top and bottom edge of a dowel bar erode the surrounding concrete causing 'oblonging' [3, 4]. This 'oblonging' creates multiple problems within the joint. The void spaces caused by the repetitive loading reduce the ability of the bar to adequately transfer load. If the load is not transferred by the bar, it is carried into the subgrade. In addition, it increases the stresses in the slab because of a reduction in the transfer of load from one slab to another. The void spaces also allow greater infiltration of water, increasing the rate of steel dowel corrosion, resulting volume increase and lose of strength over time. The corroded dowel may also bind the joint and prevent proper lateral movement caused by the freeze-thaw pavement expansion [5].

As traffic flows across a defective joint between two slabs, the dynamic loading is gradual on the approach slab and sudden on the leave slab, which results in an asymmetric load condition caused by the step in the pavement at the joint. This is shown graphically in Fig. 2. Asymmetric loading generally results in voids initially developing under the leave end of the slab and propagating towards the approach (i.e. in the opposite direction to traffic flow). Since the fundamental requirement of a slab is to spread the imposed wheel loads evenly throughout the foundation, any voiding, however small, has a detrimental effect on the performance of a pavement. When a void develops beneath a joint, slabs are more likely to crack due to fatigue and/or settlement.

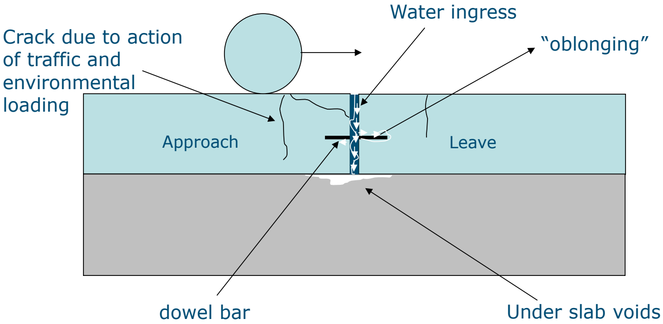

Fig. 1. Schematic Diagram of the Joint Failure Process.

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Note: Submitted November 17, 2013; Revised April 28, 2014; Accepted June 26, 2014.

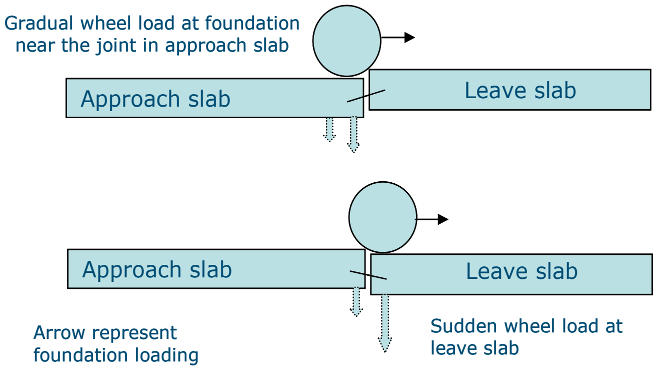

Fig. 2. Asymmetric Traffic Loading at Joints.

The structural conditions of joints are evaluated by means of the Falling Weight Deflectometer (FWD), by applying a load on one side, and then measuring the vertical deflection response on either side of the joint. These near joint deflections can be used to evaluate the load transfer efficiency (LTE), to estimate the size of the void under the slab and to assess the overall condition of the pavement near the joint. Once calculated, these parameters are then compared against threshold values so that engineers can assess the overall joint condition.

There are well defined thresholds for each of the parameters derived from FWD testing, to assess the joint performance. However, frequently there arises a situation where each of the considered parameters lends contradictory joint assessment that leads to considerable subjectivity. This paper treats the situation where decisions on joint performance have to be made by considering three assessment criteria. However, this method of assessment requires considerable engineering judgment and, as with most real-world measurements, Furthermore, when it comes to network level assessments, manual classification is monotonous and time consuming, generally, as the number of data points can easily run into thousands. This necessitates an automated, minimum human-intervention, hence better and consistent process to assess and classify overall joint condition. The procedure is generally known as self-organising maps a pattern classification technique (a brief description is given in the section **Self-Organizing Maps** below). For a given FWD data set, pattern classification techniques can be used to conclude whether that joint is in a good condition or not.

Research Objectives

In this paper, FWD deflection data, collected from sections of concrete roads in the UK, are used to calculate the absolute deflections near the joints, voids near the slab joint and load transfer between two adjacent slabs. Traditionally, concrete joint classification is performed by calculating some and/or all of these parameters and then comparing them against respective threshold values to categorize each joint as good, marginal or poor. The assessment of joints by this method can lead to subjective and inconsistent decisions. This paper advocates supplementing this practice with the aid of self-organising maps (SOMs). SOMs is a type of neural networks, essentially provide a methodology and means by which high dimensional data can be easily classified and visualized [6]. A SOM has the added advantage of capturing expert engineering assessment in its node labeling process. By using experts' classifications for labeling, the nodes of the trained SOM as good, marginal or poor, it is argued here that their knowledge of joint classification can be captured numerically and used for a non-subjective, accurate and automated joint classification process. This paper attempts to explore the use of SOMs in classifying pavement condition data collected from the FWD deflection testing. A brief outline of the SOM based data clustering, and a comparison of the automated and manual classification of data for joint condition is also presented.

Joint Evaluation Parameters

Researchers have developed different parameters to evaluate dowel bar condition and/or estimation of under slab voids from the deflection data. As part of this study, the following three most widely accepted parameters are considered.

- **Absolute deflection (D)** under the loading plate to evaluate general pavement condition near the joint. Although absolute deflection provides an indication of overall pavement condition, the deflection value is generally low because of the high flexural rigidity of the concrete pavement. As a result, absolute deflection may not give true representation of the joint condition if the deflection is very low.
- **Load transfer efficiency (LTE)** across the slab to estimate the performance of a dowel bar as a load transfer device. The LTE measured using a FWD can be defined by the following equation.

$$\text{Joint load transfer (\%)} = (d_{\text{unloaded}} / d_{\text{loaded}}) * 100 \qquad (1)$$

where,

d_{unloaded}: deflection of the unloaded slab 50mm from the joint

d_{loaded}: deflection of the loaded slab 50mm from the joint

- **Void intercept (VI)** near joints to estimate possible under slab void. Where traffic flows in one direction, voids generally develop on the leave side of the joints and propagate against the flow of traffic towards the approach side. Researcher's developed different techniques utilising FWD deflection parameters to estimate the size of the voids [7-9]. To determine void intercept values, at least three tests should carried out at each position with different load levels. Voids underneath the joint will be closed as the pavement is loaded. Increasing the applied load will further increase the closure of the void resulting in deflections that will not increase proportionally with the load level. In theory, in a no-load condition the corresponding pavement deflection should also be zero. However, for voided foundations where deflections may not increase proportionally with load, a linear regression analysis may not intercept the origin of a load versus a deflection plot. The point at which the linear regression line intercepts the y-axis (positive or negative) is known as the void intercept (Fig. 3). The magnitude of the intercept increases as the size of the void present beneath the slab increases. It is important to note that detecting voids in this manner should be treated cautiously as factors like test temperature and dowel misalignment could have significant influence on the results.

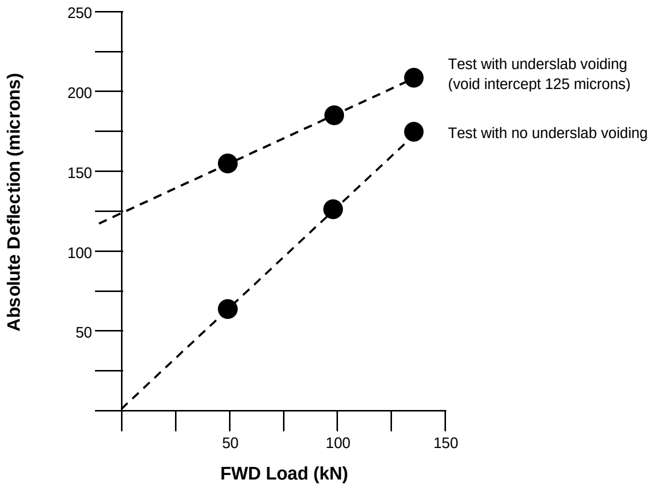

Fig. 3. Graph Showing Void Intercepts Analysis.

Self-Organizing Map (SOM)

Traditionally, pattern classification from a data set has been performed using statistical methods. However, the introduction of intelligent computational models (also generically known as artificial intelligence methods), such as neural networks and fuzzy logic, has resulted in high data processing speed, good learning and adapting abilities (for the classification system), efficient data storage and management and thereby reduce computing resources for pattern classification [10]. As these intelligent data modelling methodologies require far less information than conventional statistical method, compact computing resources are sufficient. Since real life engineering decisions are made in ambiguous environments that require a very high level of human expertise that must remain consistent, the application of soft computing can be an attractive option for engineering practice. In the last two decades, SOMs have been extensively used in image analysis/classification and speech recognition [11, 12]. In recent years, SOMs have found their way into some areas of civil engineering, e.g. water resources [13] and geology [14]. However, a literature search suggests that SOM has not been explored yet to categorize/classify pavement joint condition evaluation.

Artificial neural networks (ANNs) are inspired by biological nervous systems and present a very effective non-algorithmic, numerical approach to information processing [15]. ANNs have been used in a variety of situations ranging from intelligent control of machines [10], weather forecasting [16], cell identification in biology [17], financial fraud detection [18] to pavement and geotechnical engineering [19, 20]. A number of network models have been proposed. Multilayer perceptions, radial basis function networks, Kohonen self-organizing maps (or simply self-organizing maps), and the Hopfield network are some of them. The networks are generally trained by any one of the three different procedures: supervised learning, unsupervised learning and reinforcement learning.

Multilayer perceptrons (commonly used neural network) are ubiquitously used nowadays that there is a real danger in identifying any given type of neural network as a multilayer perceptron, which has commonly come to be known as neural network. In reality, there are a number of distinct types of neural networks, both by the way of network architectures and algorithms used. Hence, it is very important to recognise the differences between SOMs and multilayer perceptrons. Briefly, SOMs are trained by an unsupervised learning procedure as opposed to the supervised learning procedure conducted in the widely used, multi-layer perceptron neural networks. For a detailed description on the difference between these methodologies, readers are directed to Jang et al. [15].

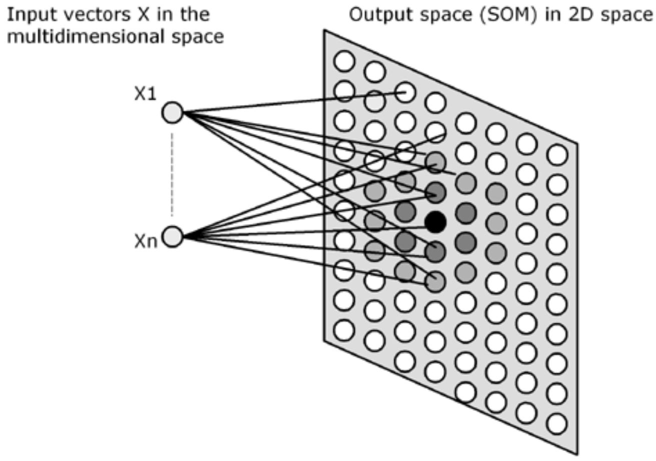

Fig. 4. A two-dimensional SOM with 100 Nodes in a 10x10 Grid [19].

SOM; architecture and Algorithm

A simple SOM network is shown in Fig. 4. Each node (i.e. neuron) has a weight vector, where the number of weights is equal to the number of features in the input. For example, for the case shown in Fig. 4, since the input vector is n-dimensional given by $\mathbf{x}=\{x_1, x_2, \ldots, x_n\}$, which indicates there are n features in this classification problem, each of the 100 nodes will have n number of weights vectors collectively denoted as $\mathbf{w}$; node i will have a weight vector $\mathbf{w_i}=\{w_{i1}, w_{i2}, \ldots, w_{in}\}$. Whenever a new input (of n dimensions) is presented during the training stage, all the neurons in the network compete with each other and the one with the closest weights wins. For each input $\mathbf{x}$ (t) winning neuron c is determined by the following relationship:

$$|\mathbf{x}(t)-\mathbf{w}_c| = \min\{|\mathbf{x}(t)-\mathbf{w}_i|\} \tag{2}$$

where, $|\mathbf{x}(t)-\mathbf{w}_i| = \{\sum_{j=1}^{n} (x_j-w_{ij})\}^{1/2}$

i.e. the best neuron is selected such that the Euclidian distance between the weights of a neuron and the input $\mathbf{x}(t)$ is minimum.

The winning neuron and its neighbourhood neurons are updated for their weights, in such a way that the weights are brought closer to the input. The neighbourhood $N_c(t)$ includes all the units inside a certain distance from the best matching unit c. Hence, the training process is expressed as,

$$\mathbf{w}_i(t+1) = \begin{cases} \mathbf{w}_i(t)+\alpha(t)\{\mathbf{x}(t)-\mathbf{w}_i(t)\} & \text{if } i \in N_c(t) \\ \mathbf{w}_i(t) & \text{if } i \notin N_c(t) \end{cases}$$

where, α (t) is the learning rate (0 < α (t) < 1)

The neighbourhood $N_c(t)$ for weight updating starts at a large value and gradually shrinks as the number of training inputs presented to the network increases. Towards the end of the training there will not be any neighbourhood at all, hence only the weights of the winning neuron get updated. Similarly, α (t) is decreased monotonously to zero during training. When the training phase is completed, each node will be representing a set of the input data that have similar characteristics; hence, the overall network will represent all of the input data in a discrete manner. At this point an expert of the classification procedure will decide which of the nodes belong to which clusters, based on their trained weights. When a new input is given to the network for classification, the neuron, which has the closest weights, wins and the data is assigned the class label of that neuron.

SOM: Convergence

The training phase of SOM can be very slow. Batch versions of the SOM training rule are designed to update network weights only after all training data have been presented to it in contrary to updating the weights after the supply of each data [21]. A time varying learning rate has also been used to improve the speed of convergence during training, for example an exponential decay with time.

For the problem of joint classification training data is usually static. Hence the training data set, in an ideal situation, is supposed to cover all possible variations/ combinations possible in real-world data, training is expected to be a one-off process. Hence converge time is not of utmost importance here and the general training algorithm outlined in the SOM: architecture and algorithm section can be used without any alterations.

SOM: Clustering and Classifying

SOM is a topology preserving transformation that clusters similar patterns together. Upon the completion of training, nodes are left with trained weights. No cluster boundaries exist as yet. It is now important to identify the nodes that represent a given pattern and define them as members of a single cluster. Cluster boundaries can be determined in an automatic manner. The unified distance matrix (U-matrix) is one such method by which cluster boundaries can be determined and visualized. The U-matrix contains a geometrical approximation of the node weight distribution in the SOM [21]. For each neuron in the SOM, the U–matrix denotes the distance to the neighbouring neurons b considering their weight vectors. Large values in the U-matrix signify cluster boundaries. The cluster boundary visualization is usually provided by a colour scheme denoting distances.

The SOM can be used for data classification as in the current research. This paper proposes to capture human knowledge hence an expert/ experts will be considering all network nodes individually and assign them classes. This labelling process essentially identifies classes and thereby defines class boundaries. The SOM, once labelled, can be used to classify new data.

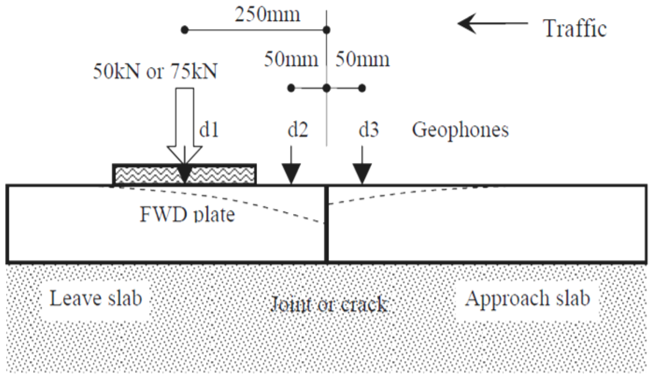

Fig. 5. FWD Testing for Joint Testing (DMRB, 2008).

SOM: Applications

The SOM has been extensively used for clustering as well as a classifier in a variety of applications ranging from biology to machine control. The SOM is superior to many other techniques owing to its advanced visualization capabilities, especially for large-dimensional data.

Data Collection

The FWD data for this study were collected from sections of concrete roads in the UK which experience heavy traffic. Cores were extracted at regular intervals to determine their thickness, assessing the internal condition of the material and their compressive strength. The thickness of the pavement was found to be fairly uniform between 250 mm to 300 mm with an unbound base. The slabs were approximately 3 m to 5 m long and jointed with dowel bars. The test setup as recommended in the HD 29/08 of the Design Manual for Roads and Bridges (DMRB) for concrete pavement joint testing is shown in Fig. 5 [22]. In order to calculate the load transfer efficiency, the d_{200} geophone was positioned around 50 mm from the joint of loaded slab whereas d_{300} geophone was positioned 50 mm from the joint of unloaded slab. The ratio of d_{300}/d_{200} was used to calculate the LTE. At each location, four loads, one bedding load and three at 700 kPa, 1000 kPa and 1300 kPa were applied. The pavement temperatures were recorded at the surface and at 100mm from the surface and it was fairly consistent between 8°C -12°C throughout the test duration.

It should be noted that the load transfer measurement is one of the most time-consuming parts of deflection testing although the testing could be conducted in a comparatively efficient manner with a trained operator. It requires the operator to carefully position the load plate and sensors across the joint, using either cameras mounted under the FWD or with the help of an assistant. The testing was limited to the approach side of the slabs only as testing on both the approach and leave sides would significantly increase overall testing time.

Results

Table 1. Threshold Limits for Condition Parameters.

Parameters	Good	Marginal	Poor
Load Transfer Efficiency (LTE) (%)	>75%	50-75%	<50%
Void Intercepts (VI) (µm)[a]	<25	25-50	>50
Absolute Deflection (D) (µm)	<200	201-225	>225

Note: a: AASHTO [24]

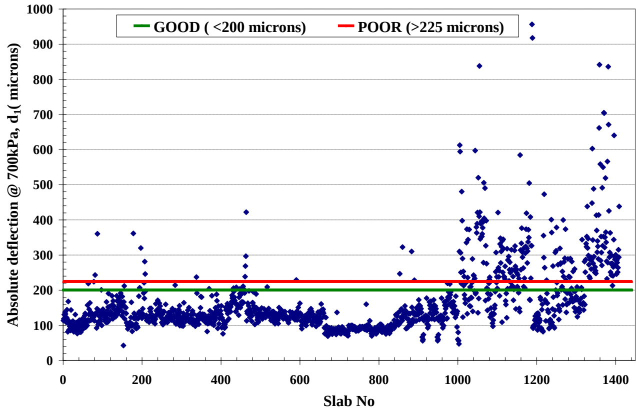

Fig. 6. The Normalised Deflection at the Centre of Loading Plate.

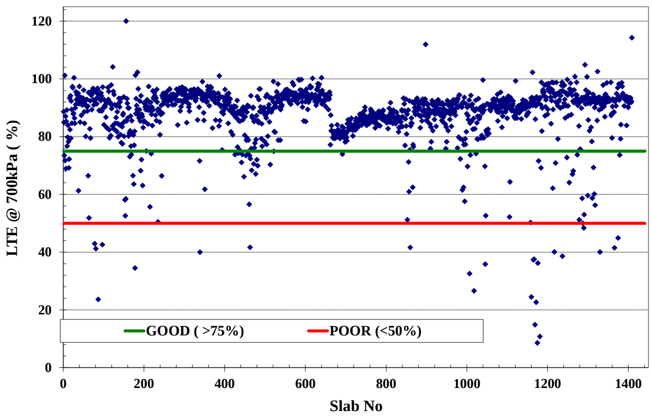

Fig. 7. Load Transfer Efficiency for All Joints @ 700 kPa.

Conventional Classification

Approximately 1,409 deflection bowls were analysed. The threshold limits for each parameter were set according to the guidance given in both the AASHTO (American Association of State Highway and Transportation Officials) and HD 30/08 in DMRB [23] and are shown in Table 1. According to the AASHTO [24], the void intercept values greater than 50 µm (0.002 inch) at the theoretical zero are considered to be typical of a situation where voids are expected. However, for this investigation, a lower value 25 µm were adopted. This was chosen from the practical experience gained by the authors from the heavily trafficked concrete pavement in UK road network.

Figs. 6, 7, and 8 present the absolute deflection, LTE and VI results for all joints. The results show considerable variations in joint condition along the road. It can be seen that the absolute deflection is generally variable, and the majority of the joints have

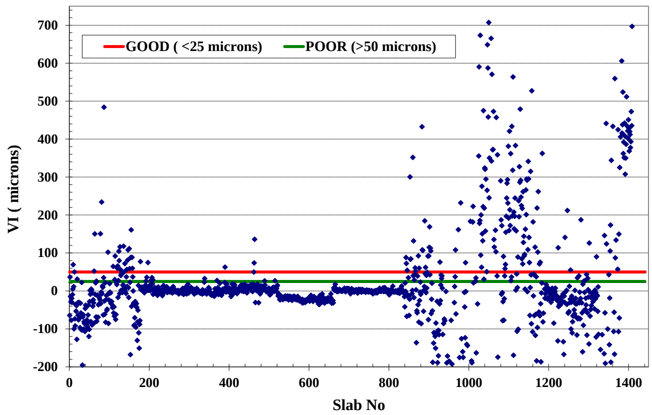

Fig. 8. Void Intercepts (VI) Efficiency for All Joints.

values less than 200 µm indicating overall good pavement condition near the joint. The results indicate that the lower the deflection of the concrete near joint, the more efficient the joint system for load transfers. The LTE is also generally variable but most of them were greater than 75%, indicating a good dowel condition to transfer the load. Although, the VI also follows a similar trend, significant numbers of joint between slabs 1,000-1,400, show intercepts greater than 50 µm, possibly indicating the presence of under slab voids. It can also be seen that negative void intercepts are calculated for significant numbers of joints. This is due the steep slope of the straight light caused by the large increase in deflection at 1000kPa and 1300kPa loading. This is likely to be the combined effect of oblonging of dowels and under slab voiding (weak foundation). A negative intercept would result from a stress-softening in support system.

A plot of the LTE against VI is given in Fig. 9 to visualize whether there is any relationship between under slab voids and dowel condition. It can be seen that despite good load transfer between joints, the VI is greater than 50 µm in a significant number of cases indicating a potential foundation problem due to the deterioration of the granular base. In addition, the results also show a large number of joints with some form of problems showing ‘good’ LTE with ‘low’ to ‘marginal’ void intercepts. Similarly, the plot of absolute deflection against VI intercepts as shown in Fig. 10, highlight that a significant number of joints have potential foundation problems (high void intercepts despite) despite good quality concrete (low deflection near the joint). This information can be used by engineers to identify joint locations with existing and/or developing defects. However, the whole process requires considerable engineering judgment, which is subjective and may lead to poor decision-making on the quality of a given joint.

SOM-based Classification: Configuration and Training

The same data was used to train in a SOM to develop an expert system for a consistent decision-making. However, the distribution of the obtained data was not ideal for training an artificial neural network, as there is only a small percentage of data that could indicate a ‘poor’ joint. The majority of the data corresponds to a good joint condition. In an ideal situation, there must be approximately equal number of samples representing each categorization scenario (i.e. clusters); any decision can result in a

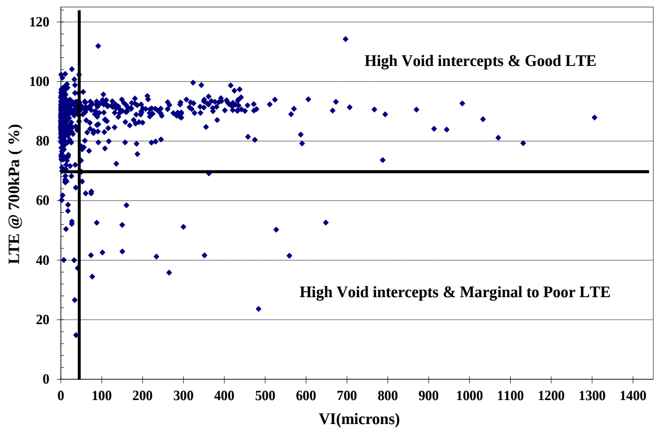

Fig. 9. Load Transfer Efficiency and Void Intercepts for All Joints.

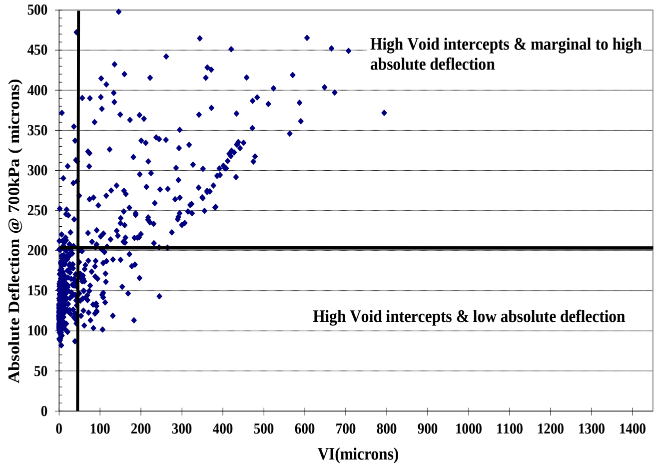

Fig. 10. Absolute Deflection Near Joints and Void Intercepts for All Joints.

joint being classified as good, marginal, or poor. It is important to note that as the test position were kept as constant as practically possible in the field, the temperature was relatively constant during the test, and the slab dimensions were similar in all tested sections, no adjusted was felt necessary during SOM analysis.

Presenting the network with equal data distribution representing the three classes will ensure that the network is presented with almost all the possible data combinations during its training phase. Out of the 1,409 samples, 24 representing each of the three possible clusters were retained for testing and the remaining 1,385 were used to train the network. The values of D, LTE and VI and their respective threshold values are denoted by 1 for 'good' conditions, by 2 for 'marginal' conditions, and 3 for 'poor' conditions for various parameters including that of overall joint condition, throughout this paper.

The overall condition of each joint was assessed in two ways- by evaluating the average of all three individual parameters and by considering the worst-case condition of all three parameters.

It should also be noted that although the deflection bowl will have discontinuity at joints, this discontinuity would be low for a good joint and high for defective joints. The whole deflection bowl therefore can provide a good indication of the overall condition of the pavement and foundation. However, the manual assessment part involved the use of only seven deflection parameters, d_{-300}, d_{-200} or d_{300}, $d_{200,}$ (depending on the testing position), for the calculation of LTE at 700 kPa, d_1 at 700 kPa for absolute deflection, and d_1 at 700 kPa, 1000 kPa and 1300 kPa loading for the estimation of VI. For SOM based classification, the whole deflection bowl (i.e. all 9 deflections) must be used together with d_1's for the loadings of 1000 kPa and 1300 kPa (i.e. 11 parameters, in total) for a superior performance of the network. However, principal component analysis on the data of 1409 deflection bowls using Matlab® suggests that there is a negligible variation in the variables d_{600}, d_{900}, d_{1200} and d_{1800}, when the whole dataset is considered (less than 1% variation). For a detailed treatment on principal component analysis and its implications on data classification, refer to a standard text such as Jang et al. [15]. Hence, the effect of these four variables on joint classification is ignored and only the other seven inputs are supplied to the SOM.

For a given dataset, the number of SOM nodes is used as $5\sqrt{n}$, where n is number of data instances in the dataset (SOM toolbox [25]). As there are 1385 data points (joints) for training, the network must have, according to the above formula, 186 nodes. For a rectangular network configuration (which is the most commonly used type) the ratio of the rectangle's side lengths are given by the ratio between the first two largest eigenvalues of the dataset. The two largest eigenvalues are found to be 83,602 and 18,865 (all eigenvalues of the dataset can be found through principal component analysis on it). Hence, the ratio is 4.29. The closest configuration that matches the values of the total number of nodes and the aspect ratio is 7 x 28 (196 nodes). A network created using the C++ programming language is trained with the 1,385 data. At the end of the training phase each of the 196 nodes will have seven weight values representing each of the seven inputs.

Trained-SOM: Capturing Expert Knowledge

The trained network must now be taken through a very important labelling process. At this point, each node of the trained network has weights representing all 7 deflection values in that order. By considering the weights each node in the trained network, the labelling process must identify every node as, for example, good or bad. The labelling of the node is crucial as this determines how the future joint data that will be supplied to the network for classification is going to be used. The labelling process allows the data to be treated in a flexible and 'soft' manner rather than the rigid threshold value based joint classification (in the form of equations implemented through Microsoft Excel spreadsheets). The novelty in this line of research, hence in joint data classification, comes from this flexibility and self-organizing map (and unsupervised learning) is a unique structural paradigm that facilitates this.

This paper proposes a new direction whereby total emphasis is placed on expert's knowledge of joint deflection data than on inequality relationships that has been in use until now. The proposition here is that pavement experts from academic, industry and government organisations utilize their experience to label a set of representative network covering various pavement, foundation and weather condition scenarios. Since the network is proposed to be trained with a large amount of joint condition data, this labeling process, once performed captures the knowledge of the experts numerically. The labeled network is now embedded with the knowledge that has been acquired by the experts through years and years of experience. Hence the classification of all future data will not only be classified accurately, it will also be a consistent and non-subjective process. This form of knowledge capture is novel and unique for the transportation industry and is the main thrust of this paper.

This form of knowledge capture is planned as a future extension of this research. In the absence of such a knowledge capture process, the classification effectiveness/accuracy of the self-organizing map, trained in this research, must be verified in one way or another. Hence, it is planned here to label the trained network using the established method of conventional classification that this paper recommends to be replaced, and then to test it with the some new data that has also been categorized with the same method of data interpretation. In this regard, the next section labels the trained SOM with the knowledge from the conventional way of classification. Then the SOM was tested with the 24 data samples retained for testing and compared against the categorization performed by the traditional data interpretation. It must be stated again that this process is ONLY performed to test the classification effectiveness of the network, and hence is NOT a method this paper advocates.

Based on the node weights at the end of training, the linguistic values (i.e. 1-good, 2-marginal, or 3-poor) of D, VI, and LTE are calculated for each node of the SOM (the calculations are performed as specified in the section **Joint Evaluation** above). Then each node is identified as good (1), marginal (2) or poor (3), based on the average of the linguistic values for D, VI, and LTE, as shown in Fig. 11. In addition, worst case based on the poor category for the linguistic values of D, VI, and LTE is also considered for node labelling. The corresponding node labelling is depicted in Fig. 12.

The test data of 24 samples was then supplied to the two-labelled SOMs for classification. The data of a given joint were fed to the trained SOM. By considering all of its nodes, the SOM identified the node that was closest to the data The identified node was then used, with the aid of either Fig. 11 or Fig. 12, to label the data (thereby the joint condition) as good, average or poor. In addition, the 24 samples were also classified manually. Both the average-based and worst case condition-based classifications are performed manually. The results of classification (both manual and SOM-based) are given in Figs. 13 and 14 respectively.

Performance Comparison: 2- Parameter Based Classification (LTE and Absolute Deflection)

The performance comparison was done by checking the accuracy of the SOM based classification from the following formula

$$\text{Classification accuracy of the SOM (\%)} = (N_C / N_T) * 100 \qquad (4)$$

where, N_C = Number of data points correctly classified by the SOM, N_T = Total number of data points classified by the SOM
With reference to Fig. 13, a classification accuracy of 71% is

1	1	1	1	1	1	1	1	1	1	1	1	1	2	1	1	1	1	1	1	1	1	2	2	3	2	2	2
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	1	2	2	1	1	1	2	2	2	1	1
1	1	1	1	1	1	1	1	1	1	1	1	2	2	2	2	2	3	1	1	1	1	2	1	1	1	2	2
1	1	1	1	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2	2	2	2	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2	2	2	2	1	1	1	1

Fig. 11. Trained Network –based on the Three Category (LTE, VI and D) Average Ranking.

1	1	1	2	3	3	1	1	1	1	1	2	2	3	1	1	1	1	1	1	2	3	3	3	3	3	3	3
1	1	1	3	3	2	1	1	1	1	1	1	3	2	2	1	1	1	1	1	2	3	3	3	3	3	3	3
1	1	1	2	1	1	1	1	1	1	1	1	1	1	2	1	3	2	3	3	1	3	3	3	3	3	3	3
1	1	1	1	1	1	1	1	1	1	1	1	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
1	1	1	1	1	1	1	1	1	1	1	2	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
1	1	1	1	1	1	1	1	1	1	1	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
1	1	1	1	1	1	1	1	1	1	1	1	3	3	3	3	3	3	3	3	3	3	3	3	3	1	3	1

Fig. 12. Trained network – based on the Three Category (LTE, VI and D) Worst Ranking.

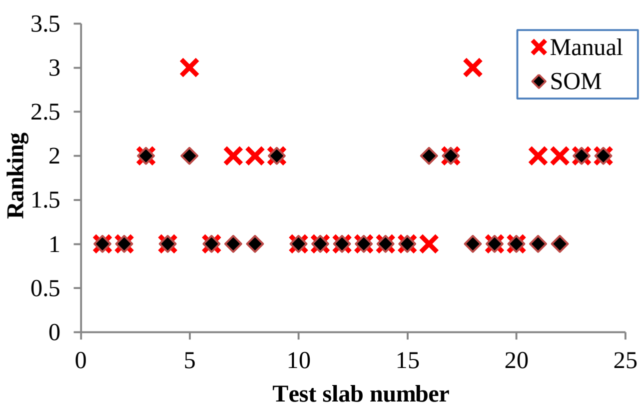

Fig. 13. Manual vs. SOM- overall Classifications Based on Average for the 24 Test Slabs.

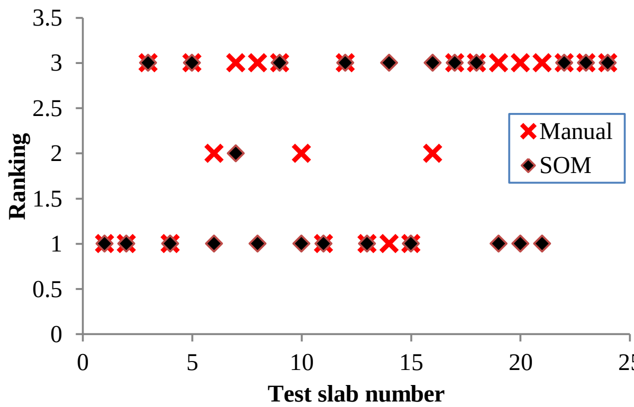

Fig. 14. Manual vs. SOM- overall Classifications Based on Worst-case Condition for the 24 Test Slabs.

obtained using SOM when the average of all individual joint conditions parameters is considered. According to Fig. 14, 62.5% of the data are correctly classified by the trained SOM for worst-case condition. The 30-35% classification error found must be chiefly attributed to the lack of data concerning bad joints. SOMs and neural networks in general, are numerical models that respond to the data supplied to them during the training phase. Although approximately equal number of data for each joint condition (good/ marginal/ poor) are used to test the performance of the trained SOM (24 datasets are handpicked such), it is noted that the training set of 1385 samples does not have enough representation of all the three possible joint conditions. Hence, the SOM has not been shown enough 'evidence' of possible data combinations during its training phase, making it to respond poorly to previously un-encountered/scarcely encountered data patterns.

As reported earlier in the results section, the SOM is presented with adequate numbers of joint data that correspond to a good joint condition (denoted by the linguistic variable 1). This is reflected in the classification results presented in Figs. 13 and 14. According to Fig. 13, out of the 13 samples classified manually as good (refer to the bottom row marked with 'X's) only sample number 16 has been wrongly classified as marginal by the SOM. This reflects a classification accuracy of 92.3% from the SOM. A similar analogy for Fig. 14 results in an accuracy of 85.7% (6 out of 7 data) for the condition named good. Therefore, it is strongly believed if the SOM is presented with more data that correspond to the joint conditions of marginal and poor, the overall classification accuracy will increase.

A significant number of VI showed negative intercepts (Fig. 8), and it was felt that the categorization of VI may have influenced the accuracy of the SOM. In order to compare the effects of the void intercept on the classification performance, two SOMs (for both the average and worst-case scenarios) were also trained by considering two parameters, LTE, and absolute deflection, D. A similar procedure was followed whereby the networks were trained with 1385 joint data and their performances were tested with the 24 joint data. The trained network configurations with their classes are shown in Figs. 15 and 16. It can be seen that the exclusion of VI has removed the majority of incongruence in the data, and hence enhanced the performance of SOM classification.

The trained networks were then tested with the test set of 24 FWD data. The classification results from the two SOMs were compared against the manual classification results for the 24 data sets. Figs. 17 and 18 depict the performance comparison for the cases of average and worst-condition respectively.

For both the categories (i.e. average and worst-case), a classification accuracy of 87.5% was obtained. This accuracy is far superior to the classification accuracies of 71% and 62.5% obtained for the SOMs trained with data that included VI. This emphasizes the need to further scrutinize the role of VI on joint condition evaluation if conventional classification technique is followed.

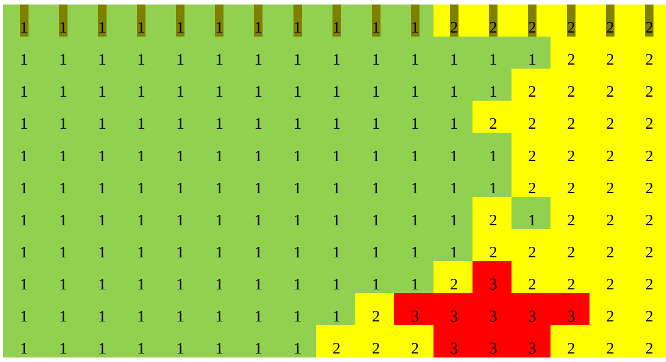

Fig. 15. Trained Network – based on the Two-category Average Ranking.

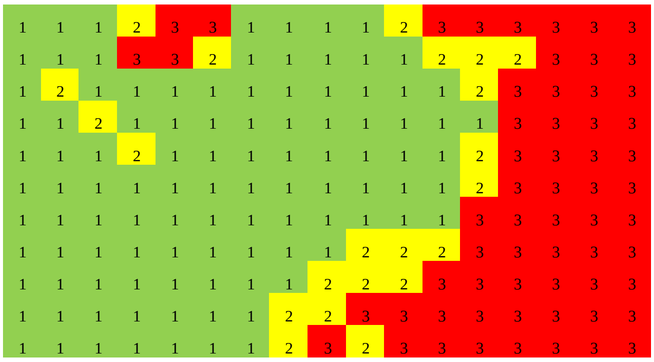

Fig. 16. Trained Network –poor Category of Any of the 3-parameter Based Ranking (LTE, VI and D).

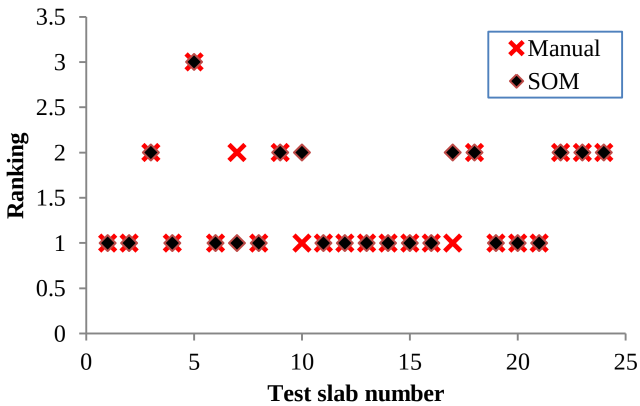

Fig. 17. Manual vs. SOM Classifications- LTE & D Based on Average for the 24 Test Slabs.

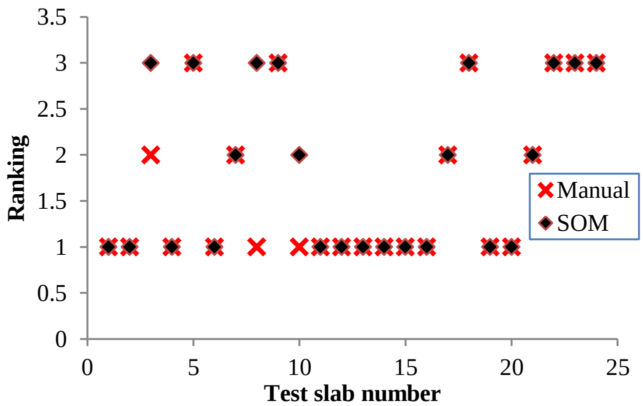

Fig. 18. Manual vs. SOM Classifications LTE & D Based on Worst-case for the 24 Test Slabs.

Conclusions

In this paper, for the first time SOM has been evaluated as a potential method for automated data classification as part of concrete pavement joints condition assessment using multiple parameters such as load transfer efficiency, void intercepts and absolute deflections. The paper also proposes a novel methodology whereby expert knowledge capture can be performed by the neural network paradigm used. To demonstrate the ability of the trained SOM in classifying joint data consistently and accurately, in the absence of an expert-based process, the network was labelled with conventional data differentiation method. Overall, accuracy in the region of 65-70% has been achieved by the automated SOM-based classification. This accuracy is obtained despite presenting the SOM with joint condition data predominantly classified as ‘good’. When the SOM is tested with the data of the class ‘good’, the SOM classification accuracy improves to around 90%. Based on these results, the use of SOM for joint condition classification appears to be very promising. Furthermore, two parameter-based classifications (LTE and D) showed the overall accuracy improved to 87.5%, highlighting the successful nature of the automated classification procedure obtained with SOM. These accuracy values show that the trained network has good potential for data classification. A process to use joint classification experts’ knowledge in labeling the SOM is planned as a future activity.

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