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Schlotjes, Megan; Burrow, Michael; Evdorides, Haralampos; Henning, Theuns

DOI:
10.1680/tran.12.00084

Transport
Volume 168 Issue TR3

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ice | proceedings

Proceedings of the Institution of Civil Engineers
Transport 168 June 2015 Issue TR3
Pages 212–222 http://dx.doi.org/10.1680/tran.12.00084
Paper 1200084
Received 12/11/2012 Accepted 03/01/2014
Published online 10/03/2014
Keywords: maintenance & inspection/pavement design/risk & probability analysis

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Using support vector machines to predict the probability of pavement failure

Megan R. Schlotjes BE(Hons)
Joint PhD student, Department of Civil and Environmental Engineering, University of Auckland, Auckland, New Zealand and University of Birmingham, Edgbaston, UK

Michael P. N. Burrow MA, PhD
School of Civil Engineering, University of Birmingham, Edgbaston, UK

Harry T. Evdorides PhD
School of Civil Engineering, University of Birmingham, Edgbaston, UK

Theunis F. P. Henning PhD
Department of Civil and Environmental Engineering, Faculty of Engineering, University of Auckland, Auckland, New Zealand

This paper presents a method to predict the probability of structural failure of road pavements using information contained in road data sets. Expert knowledge was used to develop failure charts to identify the potential factors that may contribute towards pavement failure. A computational technique (a support vector machine) was built to use this information to determine, from the data sets, the probability of failure of individual road sections. With this prediction comes an indication of the predominant failure types, the causes of structural failure and the risk profile of a road network. The usefulness of the approach was demonstrated on a data set taken from the New Zealand long-term pavement performance study of state highways. Analysis of the data set showed that the network was in good condition, but a small number of pavement sections with a high likelihood of failure were identified. Furthermore, the application of the failure paths examined the three predominant failure types occurring on the network and identified their possible causes. Rutting appears to be significantly influenced by the road pavement strength, fatigue cracking seems to be affected notably by the environment (i.e. water ingress) and shear failure is caused primarily by the combination of traffic, pavement composition and strength. In addition, it was confirmed that measured functional pavement condition alone is not a good identifier of failure and that the inclusion of a parameter related to strength, such as pavement deflection, is essential.

Notation

b	bias for the SVM model, defined by the research data (no units)
F_{N}	number of predicted false negatives
F_{P}	number of predicted false positives
N_{Total}	total number of predictions
N_1	total number of predicted non-failures
N_2	total number of predicted failures
N_3	total number of actual non-failures
N_4	total number of actual failures
P_{Actual}	actual failure probabilities, from the research data set (binary output)
P_{Failure}	overall failure probability, predicted by the trained SVM model
$P_{\mathrm{Predicted}}$	predicted probabilities
$P(A)$	predicted probability of failure for failure type A
$P(B)$	predicted probability of failure for failure type B
$P(N)$	predicted probability of failure for failure type N
T_{N}	number of predicted true negatives
T_{P}	number of predicted true positives
$\boldsymbol{w}$	weight vector for the SVM model, defined by the research data (no units)
$\boldsymbol{x}_1$, $\boldsymbol{x}_2$	closest points (vectors) to the decision boundary in the SVM model
γ	margin from the SVM decision boundary to the closest point, namely the support vectors
2γ	SVM margin calculated in the machine learning task

1. Introduction

Road asset managers with limited road maintenance budgets are faced with the challenging task of prioritising maintenance expenditure on road networks thereby ensuring that the structural integrity of the network is preserved over time (Robinson *et al.*, 1998). Once a failed road pavement has been identified, asset managers need to select the most appropriate maintenance treatment. However, without a comprehensive understanding of pavement failure, inappropriate maintenance is often carried out. At present, a combination of available data, such as traffic, road inventory and condition, is used together with pavement deterioration models to estimate future network condition and to evaluate the maintenance requirements on a road network.

Predicting structural road pavement failure is a challenging task because of the complex interaction between the factors that contribute towards failure, the different modes or mechanisms by which a road may fail, the availability, quality and variability of data, and the inherent uncertainty of the behaviour of road pavements (Reigle, 2000). There are models that focus on singular or multiple types of failure (e.g. cracking or rutting) and systems with diagnostic capabilities have been reported (Henning, 2008). The formulation of such models requires a thorough understanding of the complexities of pavement failure, which can in turn assist in the selection of appropriate model variables (Isa *et al.*, 2005). While a number of researchers have developed approaches for infrastructure systems that utilise an understanding of failure types (Evdorides, 1994; Xiao *et al.*, 2011), this practice is not widely used in the road sector, arguably because of the unavailability of data of appropriate quantity and quality and computational techniques that are accessible to the practising engineer.

This paper describes a computational methodology that quantifies the probability of structural failure of road pavement sections and identifies the most likely contributing factors. This is achieved using fault trees, developed using expert opinion, to identify the combination of factors that could contribute to failures. A computational technique, known as a support vector machine (SVM), automates the process by examining possible failure paths in a given set of data associated with a road pavement to classify whether the scrutinised road pavement is sound or has failed, and to assign a probability of failure according to the potential failure paths identified from the fault tree analysis.

Accordingly, this paper presents

- the theoretical framework used for the diagnosis of the cause of failure and the probability of failure
- the development and testing of the methodology using data from New Zealand
- a discussion of the usefulness of the methodology developed.

2. Pavement performance modelling

A number of approaches have been adopted to predict road pavement performance, of which the probabilistic approach is becoming increasingly popular due to the stochastic nature of the variables measured on the road networks. This approach recognises that much of the data collected on road networks is highly variable (Martin, 2008). Methods used to this end include logistic regression, basic linear and non-linear models, Bayesian probabilities, genetic algorithms and kernel-based learning methods (Caruana and Niculescu-Mizil, 2006; Henning, 2008; Martin, 2008; Park *et al.*, 2008). In other fields such as medical diagnostics and other engineering disciplines, neural networks, SVMs, fuzzy logic and analytical hierarchy processes have been used successfully to calculate risk probabilities (Pal, 2006; Tu, 1996; Volinsky *et al.*, 1997).

The success of a particular modelling technique depends greatly on the appropriateness of the model for the situation at hand and its performance can be enhanced by understanding the underlying causes of failure (Isa *et al.*, 2005). Two such widely employed techniques are failure mode and effect analysis (FMEA) and fault tree analysis (FTA) (Patev *et al.*, 2005; Seyed-Hosseini *et al.*, 2006). FMEA is an analytical tool for reliability analysis that can be used to identify possible failure causes in order to minimise, or eliminate, failure in systems. By using a weighted ranking system, each failure is assigned a risk number that represents the overall impact of failure. The causes of failure can be graphically represented using FTA, which further enables concurrently occurring failure factors to be included in the modelling process (Patev *et al.*, 2005). With this approach, the failure paths can be established from the breakdown of the critical paths.

3. Theoretical framework

3.1 Conceptual design

In order to determine the probability of road pavement failure from road data sets, the approach adopted used expert knowledge to identify the predominant types of failure on a road network and the associated foremost factors that contribute towards failure. Subsequently, a computational technique was identified and developed to analyse road pavement data sets containing these factors. The developed technique is capable of determining the probability of failure for each of the failure types and identifying the most probable combination of factors that contribute to the failure. The probabilities of failure for each failure type were considered together to determine the overall failure probability of a pavement section. The overall approach thus consisted of two main parts – fault charts to diagnose the cause of failure and a computational model to calculate the probability of failure.

3.1.1 Fault charts

Fault, or failure, charts were built by canvassing the views of a panel of experts in conjunction with a preliminary analysis of road networks. Initially, the predominant failure types, or mechanisms occurring on the road network, were identified and, for each type, the expert panel identified fundamental groups of factors that contribute to the failure. These were then broken down further into associated sub-factors and used by the panel of experts to develop a fault chart for each failure type. These charts can then be used to identify the underlying causes of failure and the interactions between factors associated with failure and the failure modes. Three such charts, which focus on the predominant mechanisms associated with structural failure occurring on New Zealand road networks, are shown in Figures 1 to 3. The charts are presented in such a way that the causes contributing to the failure are sequential. For example, a surface with poor pavement results in deformation of the pavement layer(s) and subsequent rutting failure (Figure 1).

3.1.2 Computational model

In order to determine the probability of failure of road pavements it was necessary to select an appropriate computational technique that could make use of the data corresponding to the failure types identified by the panel of experts. A number of methods were examined for this purpose, including logistic regression, neural

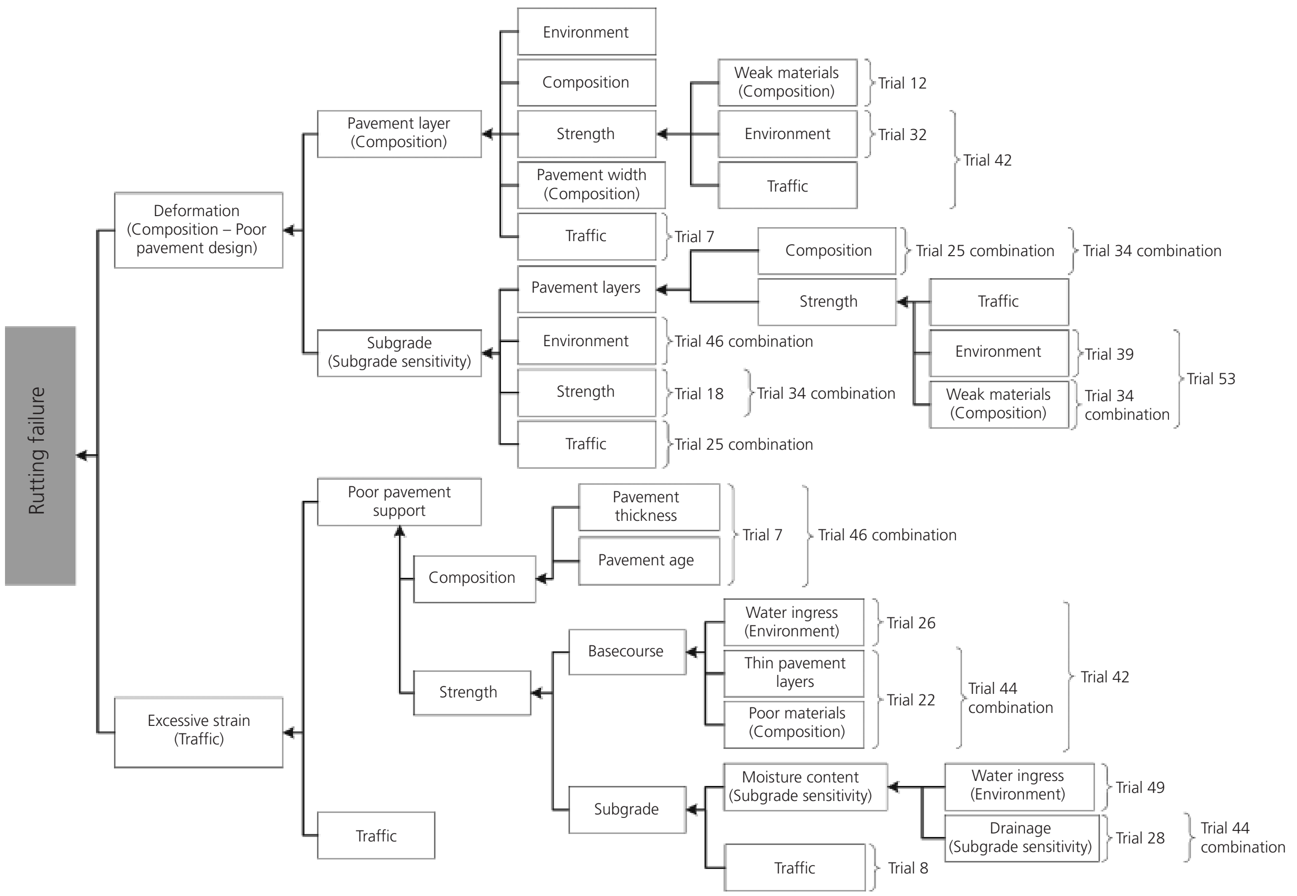

Figure 1. Rutting failure chart with the associated causes of failure identified in the methodology

networks, SVMs, probability trees and random forests (Caruana and Niculescu-Mizil, 2006; Chandra *et al.*, 2009). Following an extensive sensitivity analysis using road data from the New Zealand state highway (SH) long-term pavement performance (LTPP) programme, an SVM technique was chosen for the task in hand (Schlotjes *et al.*, 2012). An SVM is a supervised computational learning model with an associated training algorithm that can be used, for a given set of input data, to assign a probability to two possible categories to which the set of input data may belong (Van Looy *et al.*, 2007). Previous studies have employed SVMs in pavement engineering to, for example, estimate the pavement serviceability ratio and detect pavement cracking (Hu *et al.*, 2010; Yan *et al.*, 2011). The SVM training algorithm uses input training data to build a model that can assign probabilities to new input data sets. In this work, the input data sets consisted of road network information corresponding to the data types as identified by the panel of experts.

The SVM technique transforms typically non-linear data, or data difficult to separate with steadfast decision boundaries, using various kernel functions. Once transformed, the data can be easily separated such that an unambiguous decision boundary is defined, as shown in Figure 4 (Van Looy *et al.*, 2007). By maximising the margin (2γ) between the separated data classes, the optimal solution is found to ensure confidence around the new predictions. To do so, using vector mathematics of the closest data points to the decision boundary (namely the support vectors), the following equation is maximised

$$
\begin{aligned}
2\gamma &= \frac{1}{||\boldsymbol{w}||}\boldsymbol{w}^{\mathrm{T}}(\boldsymbol{x}_1 - \boldsymbol{x}_2) \\
&= \frac{1}{||\boldsymbol{w}||}(\boldsymbol{w}^{\mathrm{T}}\boldsymbol{x}_1 - \boldsymbol{w}^{\mathrm{T}}\boldsymbol{x}_2) \\
&= \frac{1}{||\boldsymbol{w}||}[(\boldsymbol{w}^{\mathrm{T}}\boldsymbol{x}_1 + b) - (\boldsymbol{w}^{\mathrm{T}}\boldsymbol{x}_2 + b)] = \frac{1}{||\boldsymbol{w}||}(1+1)
\end{aligned}
$$

1. $$\gamma = \frac{1}{||\boldsymbol{w}||}$$

The model gives, for each failure type and for each failure path, the probability of a pavement section failing. For a pavement section, the most probable failure path for a particular failure type is that which has the greatest failure probability.

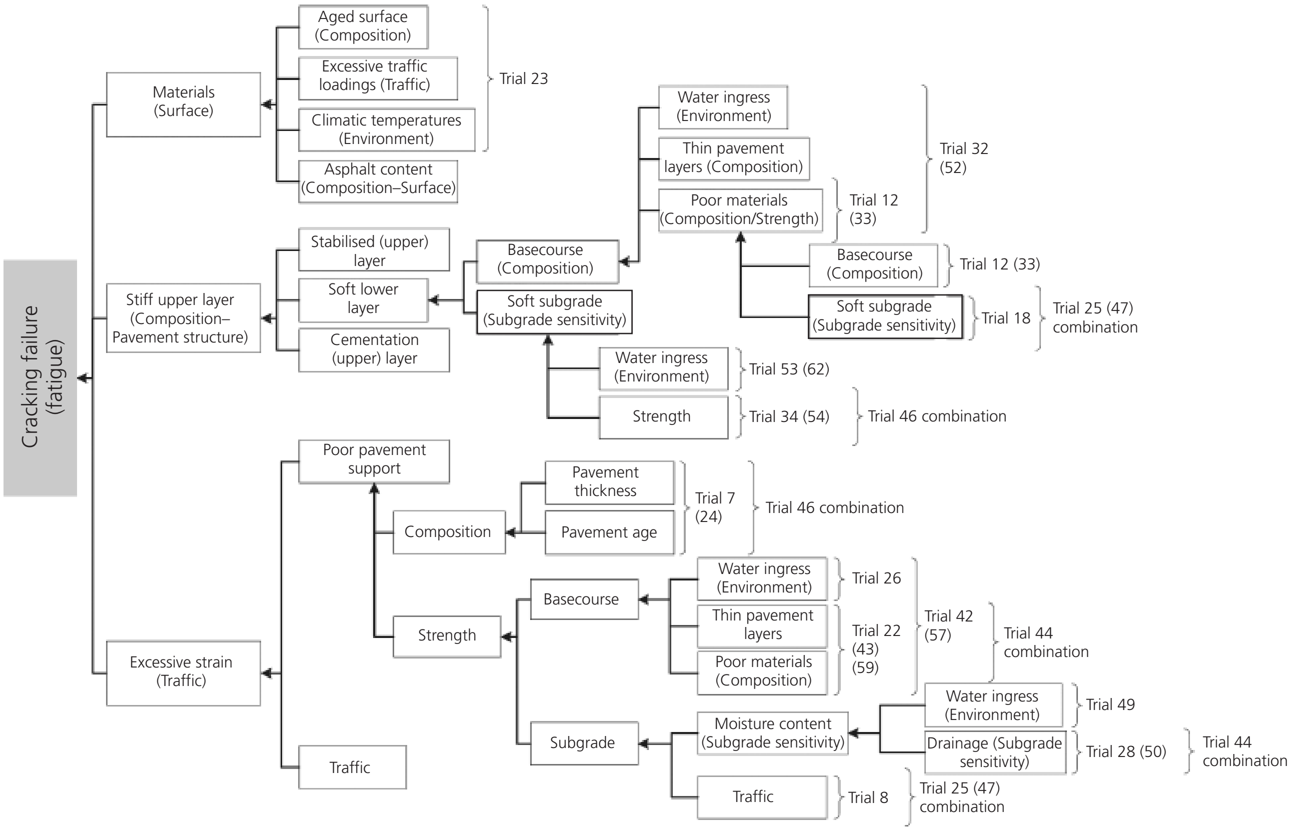

Figure 2. Fatigue cracking failure chart with the associated causes of failure identified in the methodology

The overall failure probability (P_{Failure}) for a pavement section with failure types A, B and C was calculated using Equation 2, which considers the interdependence of each failure type (Ayyub and McCuen, 2003; Mendenhall and Beaver, 1991; Schlotjes, 2013) as follows

$$\begin{aligned} P_{\text{Failure}} &= P(A \cup B \cup C) \\ &= P(A) + P(B) + P(C) - P(A \cap B) \\ &\quad - P(A \cap C) - P(B \cap C) + P(A \cap B \cap C) \end{aligned} \tag{2}$$

where $P(A \cap B) = P(A) \times P(B)$, $A =$ failure type A, $B =$ failure type B and $C =$ failure type C.

3.2 Assessing the performance of the model

Assessing model performance is an integral part of developing any machine learning tool, including the SVM model developed here. Four tests were considered – accuracy, misclassification, *f*-score and phi coefficient (Parker, 2011).

The accuracy and misclassification tests were used to determine the number of incorrectly predicted road sections and to compare the predicted output with the actual failure data. The accuracy and misclassification percentages were calculated as (Parker, 2011)

$$\text{Accuracy} = \frac{\sum T_{\text{P}} + T_{\text{N}}}{N_{\text{Total}}} \times 100 \tag{3}$$

$$\begin{aligned} \text{Misclassification} &= \frac{\sum |P_{\text{Predicted}} - P_{\text{Actual}}|}{N_{\text{Total}}} \times 100 \\ &= \frac{\sum F_{\text{P}} + F_{\text{N}}}{N_{\text{Total}}} \times 100 \end{aligned} \tag{4}$$

in which T_{P} (T_{N}) is the number of predicted true positives (negatives), N_{Total} is the total number of predictions, $P_{\text{Predicted}}$ is the predicted probability, P_{Actual} is the actual failure probability and F_{P} (F_{N}) is the number of predicted false positives (negatives).

The *f*-score is a weighted average of the fraction of the total number of correctly classified non-failed sections divided by the total number of predicted non-failed sections (precision) and of the fraction of correctly classified non-failed road sections divided by the total number of non-failed sections analysed (recall). It is calculated according to (Parker, 2011)

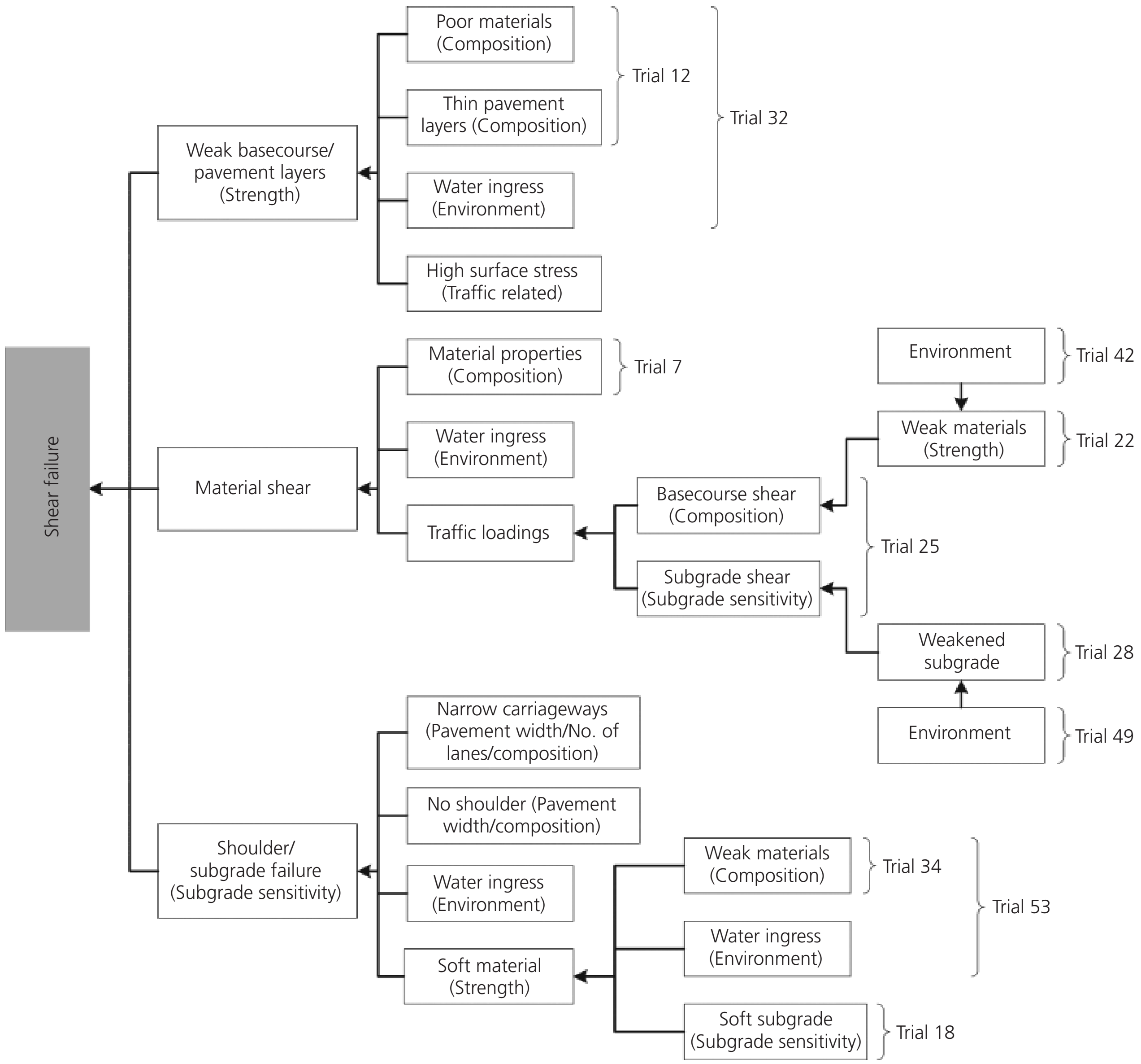

Figure 3. Shear failure chart with the associated causes of failure identified in the methodology

$$f\text{-score} = 2\left(\frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}}\right) \quad (5)$$

where

$$\text{precision} = \frac{T_\text{P}}{T_\text{P} + F_\text{P}}$$

$$\text{recall} = \frac{T_\text{P}}{T_\text{P} + F_\text{N}}$$

An *f*-score can have a value of between zero and one. The closer the value is to one, the more accurate the method is regarded (Parker, 2011; Sokolova and Lapalme, 2009).

The phi coefficient was used to measure how well the SVM technique predicted pavement failures and non-failures. As a measure of performance, the phi coefficient is often favoured above the *f*-score because it takes into account all correctly predicted values, as opposed to the *f*-score where its constituent precision and recall values only take account of the correctly predicted non-failures. The phi coefficient was determined using (Parker, 2011)

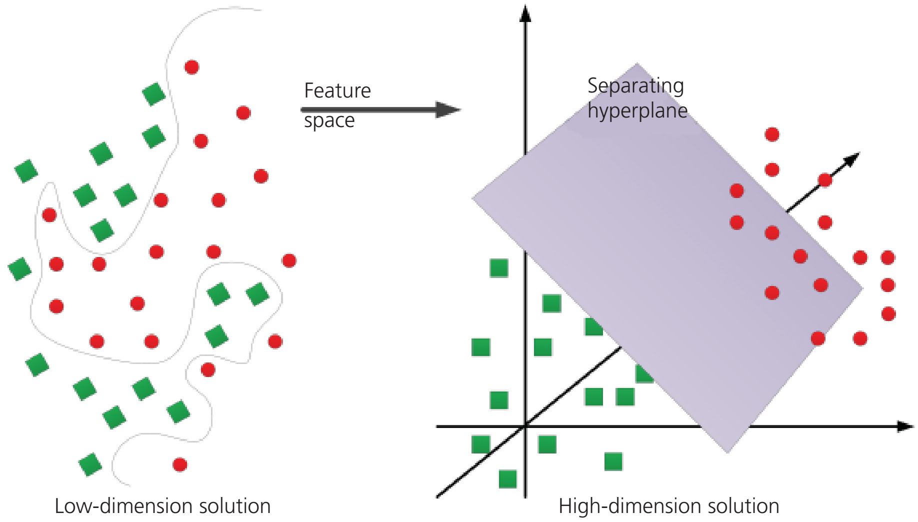

Figure 4. Overview of SVM technique (adapted from Van Looy *et al.* (2007))

$$\text{phi coefficient} = \frac{T_P T_N - F_P F_N}{(N_1 N_2 N_3 N_4)^{1/2}} \qquad 6.$$

in which N_1 is the total number of predicted non-failures, N_2 is the total number of predicted failures, N_3 is the total number of actual non-failures and N_4 is the total number of actual failures. A positive phi coefficient means that the majority of the results are correctly predicted, and vice versa. A value of zero indicates that there is no relationship between the prediction and input variables (Parker, 2011).

4. Case study

4.1 Data set

Data were obtained from the LTPP programme, which monitors 63 sites on the New Zealand SH network (Henning, 2008; Henning *et al.*, 2004). The large majority of the pavements in the network are thin, flexible, unbound granular pavements, carrying low volumes of traffic (i.e. <10 000 vehicles per day). Common structural failures on these pavement types include rutting, fatigue cracking and shear, as considered by Austroads (2012) in the design of flexible, unbound granular pavement types.

4.2 Failure charts

Although other modes of failure are recognised for other pavement types and environments, the focus of this work is on only the three predominant structural failure types on New Zealand's low-volume roads, namely rutting, load-associated fatigue cracking and shear (Schlotjes *et al.*, 2011). For each of these failure types a failure chart was developed by canvassing the opinion of a panel of experts. To achieve this, the panel identified the following six groups of factors that contribute to failure

- traffic (e.g. annual average daily traffic)
- pavement composition (e.g. number of layers, thicknesses, ages)
- pavement strength (e.g. structural number)
- environment (e.g. rainfall)
- surface condition (e.g. percentage of cracking, rutting depth)
- subgrade sensitivity (e.g. low, medium and high).

These factors were used to group the data types available in the SH LTPP data set as shown in Table 1. The factors were then sub-divided according to the opinion of the panel of experts and used to develop a failure chart for each failure type – rutting, fatigue cracking and shear. The charts so developed are presented in Figures 1–3, where the notation Trial X correlates with the combinations of factor listed in Table 2. It may be seen that some combinations of factors (failure paths) occur for more than one failure type because of the similar interactions between factors within the types of failure. For example, both rutting and fatigue cracking can be due to a combination of excessive strain and poor pavement support, as a result of composition issues (as shown by Trial 7 in Figures 1 and 2).

4.3 Computational model

The SVM technique was used to determine the probability of failure of the road pavements in the SH LTPP network data set. The technique was used to compute, for each of the three failure types identified, the likelihood of failure of all pavement sections by each possible failure path in the failure charts. In developing the SVM model, a tenfold cross-validation approach was followed, where a random 90% sample of the data set was used for training (Rogers and Girolami, 2012). The performance of the SVM modelling technique was demonstrated using a number of measures as described below.

Factor group	Variables included in the group
Traffic	Annual average daily traffic (AADT)[a,b,c]
	Total percentage of heavy vehicles[a,b,c]
	Cumulative number of equivalent standard axles (ESA), given the base layer age[a,b,c]
	Cumulative number of ESA, given the surface layer age[b]
Pavement composition	Base layer age[a,b,c]
	Sub-base layer age[a,b,c]
	Surface age[b]
	Total pavement thickness, excluding surface thickness[a,b,c]
	Total pavement thickness, including surface thickness[b]
	Pavement width[a,b,c]
	Number of lanes[a,b,c]
Pavement strength	Strength of pavement (weak or strong)[a,b,c]
	Structural number (SNP)[a,b,c]
	Structural indices (SIs) for rutting, flexure, shear and roughness[a,b,c]
	Falling weight deflectometer (FWD) parameters[a,b,c]
Environment	Cumulative rainfall once the pavement is cracked[a,b,c]
Surface condition	Rut depths for left-hand wheelpath, right-hand wheelpath and lane[a,c]
	Rut rate for left-hand wheelpath, right-hand wheelpath and lane[a]
	Total cracking (all cracking types)[b]
	Crack rate[b]
	Number of years of continual cracking[b]
	Mechanical damage[c]
	Structural patch[c]
	Pothole diameter, depth and number[c]
	Shoving[c]
Subgrade sensitivity	Sensitivity of pavement[a,b,c]

[a] Rutting data set.
[b] Fatigue cracking data set.
[c] Shear data set.

Table 1. Factor combinations for modelling using LTPP data

4.4 Results and analysis

The results of the analysis are divided into an assessment of the performance measures to show the applicability of the SVM modelling technique for the task in hand and an analysis of the SH LTPP road network to demonstrate the usefulness of the suggested methodology.

4.4.1 Assessment of the SVM technique

Table 3 presents the average results from cross-validation tests of the performance measures, from which it may be seen that the SVM model predicted accurately the three types of pavement failure according to the accuracy, misclassification and *f*-score measures used. The relatively lower values of the phi coefficient however suggest weaker relationships between the road data set and the predicted failure for each failure type.

The prediction of rutting and fatigue cracking is slightly better than that for shear failure by the three measures of accuracy, misclassification and *f*-score. Shear failure can be strongly linked to the properties of pavement materials and, unfortunately, this information is lacking in network-level data sets. Further work is therefore required in the development of the shear failure prediction component of the model.

4.4.2 Factors associated with failure

Table 2 summarises, for each of the three failure types considered, the computed most probable causes of failure for the entire SH LTPP road network and the associated corresponding number of pavement sections. For all three failure types, strength is shown to be a major factor. As far as rutting is concerned, road pavement strength is the only significant factor for 64% of the road pavements analysed. The predominant factors associated with fatigue cracking are strength, traffic, composition, environment and subgrade sensitivity. The environment factor occurred in 46% of the pavement sections that had failed by fatigue cracking and, since environment is a measure of the cumulative amount of rainfall falling on an already cracked pavement (Table 1), would suggest that water ingress is a major factor contributing

Trial	Factors	Number of pavement sections		
		Rutting	Fatigue cracking	Shear
3	Strength	3596	782	n/a[a]
7	Traffic + composition	45	547	177
8	Traffic + strength	0	0	n/a
12	Composition + strength	932	348	703
16	Strength + environment	6	n/a	n/a
18	Strength + subgrade sensitivity	0	0	865
22	Traffic + composition + strength	120	313	1150
23	Traffic + composition + environment	n/a	199	n/a
24	Traffic + composition + surface condition	n/a	45	n/a
25	Traffic + composition + subgrade sensitivity	0	131	118
26	Traffic + strength + environment	0	396	n/a
28	Traffic + strength + subgrade sensitivity	0	0	0
32	Composition + strength + environment	0	186	37
33	Composition + strength + condition	n/a	125	n/a
34	Composition + strength + subgrade sensitivity	0	239	212
39	Strength + environment + subgrade sensitivity	871	n/a	n/a
42	Traffic + composition + strength + environment	0	151	182
43	Traffic + composition + strength + surface condition	n/a	253	n/a
44	Traffic + composition + strength + subgrade sensitivity	0	n/a	962
46	Traffic + composition + environment + subgrade sensitivity	3	103	n/a
47	Traffic + composition + surface condition + subgrade sensitivity	n/a	18	n/a
49	Traffic + strength + environment + subgrade sensitivity	42	1077	614
50	Traffic + strength + surface condition + subgrade sensitivity	n/a	229	n/a
52	Composition + strength + environment + surface condition	n/a	11	n/a
53	Composition + strength + environment + subgrade sensitivity	0	239	143
54	Composition + strength + surface condition + subgrade sensitivity	n/a	4	n/a
57	Traffic + composition + strength + environment + surface condition	n/a	3	n/a
58	Traffic + composition + strength + environment + subgrade sensitivity	13	212	465
59	Traffic + composition + strength + surface condition + subgrade sensitivity	n/a	6	n/a
62	Composition + strength + environment + surface condition + subgrade sensitivity	n/a	8	n/a
63	Traffic + composition + strength + environment + surface condition + subgrade sensitivity	n/a	3	n/a
	Total	5628	5628	5628

[a] Not applicable.

Table 2. Factor combinations of the SH LTPP network per failure mechanism

	Average value over all failure paths			
	Accuracy: %	Misclassification: %	*f*-score	phi coefficient
Rutting	97·70	2·30	0·99	0·22
Fatigue cracking	98·21	1·79	0·99	0·31
Shear	94·52	5·48	0·97	0·16

Table 3. Summary of the performance measures

to the deterioration of this network. For shear failure, combinations of traffic, pavement composition and strength are the likely contributing factors towards failure of nearly half the network.

The few occurrences of surface condition in Table 2 and the fact that it does not occur alone for any of the three failure mechanisms suggest that functional pavement condition is not a good predictor of failure. This adds further credence to a fundamental concept of pavement engineering that visual road condition assessment may not be sufficient on its own to determine appropriate maintenance, even though in practice only visual condition assessment is often used to determine maintenance needs.

4.4.3 Failure probability

As the data set did not contain the necessary data to determine the probability of jointly occurring failures, a simplified version of Equation 2, which is similar to that adopted in conventional pavement design, was adopted to calculate the overall failure probability

$$P_{\text{Failure}} = \max[P(\text{Rutting}), P(\text{Fatigue cracking}), P(\text{Shear})] \quad (7)$$

It should be noted that alternative methods of calculating the probability of failure could be adopted and are discussed by Schlotjes (2013). However, this was considered to be beyond the scope of this paper.

Accordingly, three outputs were calculated

- probable causes of failure
- the probability of failure for each failure type
- the overall failure probability of road sections.

Figure 5 shows the frequency distribution of the probability of overall failure of the road pavement sections analysed and therefore the overall risk profile of the SH LTPP road network. The histogram shows that the majority (97%) of the pavement sections on the network have a probability of failure of less than 0·2, and 79% have a failure probability of less than 0·1, which suggests that the network is in good condition. However, 2% of pavement sections are predicted to fail with a high probability of failure ($P_{\text{Failure}} > 0{\cdot}5$).

The distribution of the most probable failure modes on the SH LTPP road network shown in Figure 6 indicates that shear failure is the most probable.

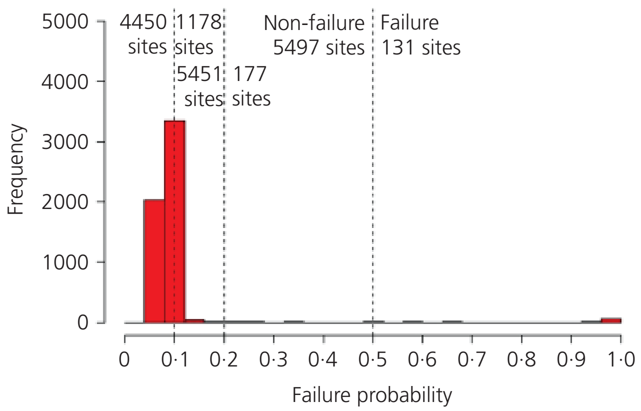

Figure 5. Overall failure probability distribution of the SH LTPP road network from the predicted outputs of the developed SVM model

4.5 Practical application

The methodology presented facilitates both project- and network-level analysis of a road network. At project level, pavement sections that have a high probability of failure can be identified, further assessed if necessary and appropriately treated. Such a predictive approach is likely to be more cost-effective than a reactive one. For failed sections of the network, the methodology allows an insight into the causes of failure, enabling an appropriate remedial treatment to be applied, and can support, or replace, expensive site investigations. For example, pavement section 3804 was identified as having failed by fatigue cracking. Using the developed model, the computed overall failure probability and those of the individual failure types are

$$P_{\text{Failure(3804)}} = \max[P_{\text{Rut}} = 0{\cdot}0442, P_{\text{Fatigue crack}} = 0{\cdot}9874, P_{\text{Shear}} = 0{\cdot}0767]$$
$$P_{\text{Failure(3804)}} = P_{\text{Fatigue crack}} = 0{\cdot}9874$$

The associated factor combination of the P_{Failure} is trial 23 (see Table 2). From the failure charts, Figure 2 in particular, it can be seen that pavement failed in fatigue cracking due to poor pavement composition (an aged pavement or insufficient pavement thickness). This resulted in poor pavement support, which when combined with excessive traffic loadings caused failure.

Pavement section 4249 failed in both rutting and shear, with computed failure probabilities of

$$P_{\text{Failure(4249)}} = \max[P_{\text{Rut}} = 0{\cdot}6935, P_{\text{Fatigue crack}} = 0{\cdot}0213, P_{\text{Shear}} = 0{\cdot}9507]$$
$$P_{\text{Failure(4249)}} = P_{\text{Shear}} = 0{\cdot}9507$$

Trial 7 is the most probable failure factor combinations for both rutting and shear. According to the failure charts (Figures 1 and 3), the most likely failure paths for both of these mechanisms are traffic and composition and, although the same factor combinations are in the critical failure paths, the most probable causes are different. Shear failure is generally related to material performance and rutting is a result of induced strains from excessive traffic loadings and strain repetitions, so the cause of these failures (both rutting and shear) can be attributed to poor composition of the pavement combined with excessive traffic loading.

At a network level, risk profiles (Figure 5) can be produced to identify the overall serviceability of the network and the predominant failure mechanism(s) (Figure 6). This enables appro-

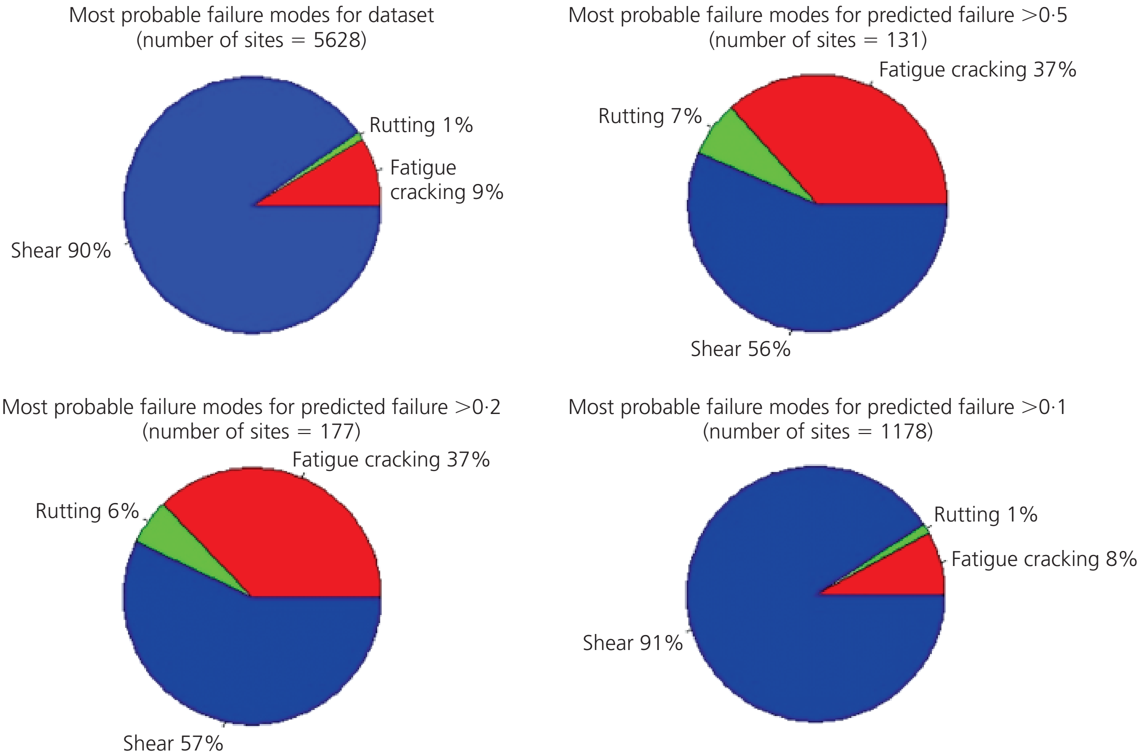

Figure 6. Most probable failure modes of the SH LTPP road network from the predicted outputs of the SVM model

priate and timely maintenance to be carried out along with any adjustments to maintenance regimes. Furthermore, potential changes in the external environment can be quantified in terms of potential effects on network condition. For example, if traffic loading on the network is set to increase, the projected increase in loading can be included in the input parameters in the SVM and the effects modelled. Similarly, the effects of potential changes in precipitation due to climate change could be estimated.

5. Conclusion

A method that is capable of assessing the probability of structural failure of road pavements has been developed. The method is based on using expert judgement to develop failure charts for the predominant types of failure on a road pavement, which can be used to identify the contributing factors to pavement failure. A computational technique, known as SVM, was developed to analyse the probability of failure of pavement data sets and to determine the most probable failure paths for each failure type. The resulting probabilities for each failure type were used, in a simple approach, to determine an overall probability of pavement failure. Further work is being undertaken to calculate the overall failure probability within the SVM modelling process.

A case study using data from the New Zealand SH LTPP programme was used to demonstrate the performance of the proposed methodology. Four performance measures were used to assess the precision of the SVM technique in determining the probability of failure of pavements via rutting, fatigue cracking and shear failure. Although the SVM performed satisfactorily in predicting failures, further development in the prediction of shear failure and consideration of combined failure modes are both desirable and necessary. Analysis of the New Zealand data set showed that the network may be regarded as being in good condition, although a small number of pavement sections within the network have a high likelihood of failure. It is evident that measured functional pavement condition alone is not a good identifier of failure and the inclusion of a parameter related to strength, such as pavement deflection, is essential.

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