Improving Bridge Deterioration Modelling Using Rainfall Data from the Bureau of Meteorology

Qing Huang　　　**Kok-Leong Ong**　　　**Damminda Alahakoon**

Business Analytics, La Trobe Business Schoool, La Trobe University
Plenty Road, Bundoora, Victoria 3083
Email: 18531979@students.latrobe.edu.au, {kok-leong.ong, d.alahakoon}@latrobe.edu.au

Abstract

Failure in bridges carry serious consequences so their appropriate maintenance is paramount. Often, authorities are faced with limited funding and available contractors who are able to carry out the maintenance checks and works. Therefore, a predictive model that can forecast the future state of a bridge component will enable the authority to prioritise and deploy resources to where it is most needed. The challenge faced in this paper is the requirement from the Victorian road authorities to develop an effective predictive model. Prior attempts have been made by using different techniques to construct an alternate predictive model but with limited results. The problem lie in the data itself. With data manually recorded by different contractors, it is noisy and erroneous. Attempts to data cleaning has led to little improvement in the overall model performance. Finally we turned to data augmentation to increase the proportion of reliable data. In our quest to do so, we ended up pulling rainfall data from the BoM to augment the data provided by VicRoads. We consider rainfall data as a candidate for augmentation because literature in civil engineering has correlated bridge component deterioration to the presence of water moisture. Since high rainfall contributes to increased deterioration, leveraging the rainfall information should lead to improved predictive performance. Initial experiments on the predictive performance of the baseline and "high rainfall" models suggest the viability of this approach.

Keywords: Markov chains, bridge deterioration modelling, service life, rate of deterioration, data augmentation

1 Introduction

In many countries, bridge failures are increasing due to ageing of its components. This issue is even more acute in countries (e.g., Australia) where the population is also growing quickly thus, putting on additional stress to the infrastructure. With limited public funds to maintain a wide network of bridges, most authorities such as VicRoads in Victoria would like to deploy a Bridge Management System (BMS) to help optimise maintenance plans for thousands of bridges under its portfolio. A key component of such a system is the Bridge Deterioration model, which is a predic-

tive model that forecasts bridge conditions at a future date so as to determine maintenance priority.

Our research work was carried out in cooperation with VicRoads in the state of Victoria, Australia. VicRoads currently carries a database of more than 180,000 bridge inspection records for over 7,000 bridges state wide. VicRoads has hoped to use the inspection data to build a predictive model that will help optimise their maintenance work schedule so that the limited public funds can be effectively deployed to bridges most in need of maintenance at the lowest cost to each job. The research brief in our case is to analyse their inspection data with the goal of developing a more accurate predictive model so as to improve the effectiveness of their system.

There has been considerable research on various modelling techniques in the area of bridge deterioration including, Markov Chain models (Ranjith et al. 2011, Wellalage et al. 2014a), envelopment models (Wakchaure & Jha 2011, Ozbek et al. 2010), and ANN (artificial neural network) models (Sobanjo n.d., Huang 2010). Regardless of the techniques used, the objective is to further improve the overall predictive performance of the system. Among these techniques, Markov Chain-based models are most widely-used even though it was also well-documented in the literature recently about their limitations. Many prior works have been done to overcome these limitations and the next Section provides the elaboration on these works.

With the state of the literature suggesting that the available techniques are limited in delivering the desired predictive performance, we decided that an alternate algorithm to construct the model may not be the best "plan of attack" and so, we looked at improving the predictive performance by working on the data. Attempts to enhace the data quality led to insignificant improvements. We soon realised that this may not be a good approach too because the data is obtained through the process of recording the inspection outcomes manually. To make this worse, the inspections are done by different contractors and hence, there is a high level of noise, variation and error in the data that limits the impact of typical data cleaning techniques.

We had to undertake a different approach to the problem. Working with the civil engineers, we learned about the factors that caused a bridge component to deteriorate. And according to (Huang et al. 2010, Zhao & Chen 2002), the most significant deterioration factors include the age of a bridge, bridge material used, traffic volume, and also the amount of rainfall a bridge was exposed to. Our assumption from this background knowledge helps formulate the hypothesis that "if factors contributing to deterioration of a bridge component" could be included in the de-

Regions	# Records	Breakdown of attributes
All Area	189,247	*Structure Information*, e.g., length, width, year constructed, featured
Eastern	25,793	crossed, etc.
Western	23,705	
Northern	28,692	*Identification information*, e.g., structure ID, road name, road number,
North East	37,565	region, etc.
South West	24,839	
Metropolitan South East	23,171	*Inspection information*, e.g., inspection date, condition ratings (PC1, PC2,
Metropolitan North West	25,482	PC3, PC4) and inspection comments

Table 1: Summary of the bridge data set from VicRoads across major regions. Note that the southern region data set is missing because the south of Melbourne is the Port Philip Bay.

velopment of a predictive model, then there will be a potential chance to increase predictive performance". More importantly, this led us to consider adding quality data to the otherwise noisy data set. This means augmenting features that would reduce the proportion of noisy data with the idea that this would help lift the predictive model over the original baseline.

Among the various factors that contribute to bridge deterioration, we found that historical rainfall data is publicly available from the Australian Bureau of Meteorology (BoM). In this paper, we report our attempt to verify the above hypothesis by augmenting the original data set with the rainfall data from the BoM. Our experiments on the baseline model (built without consideration to rainfall) and the new "high rainfall" model (built by focusing on the high rainfall data sets) suggest the viability of this approach.

To discuss the above, the rest of this paper is organised as follows. Section 2 first reviewed the current works and the outcomes of these attempts. Section 3 then presents the reader with an overview of the bridge inspection records and also introduce the rainfall data from the BoM. A discussion of how we augment the data is also mentioned before we discuss the modelling and validation in Section 4. This is where we see promising difference between the baseline bridge deterioration model and the new model built by considering the high rainfall data. Finally in Section 5, we conclude by outlining the next steps following the work in this paper.

2 Literature review

Research on bridge deterioration modelling started a decade ago and has since seen many various modelling techniques being developed. These techniques can be classified into three main categories: deterministic models, stochastic models and others.

Deterministic models identify a direct relationship between condition ratings (a number from 1 to 4 reflecting the degree of deterioration of a bridge or its components) and the factors affecting bridge deterioration. Normally this is done using a regression model. For example, (Thompson et al. 2012) described an Average Time to Failure model to determine the average life expectancy of a structure or a component. In another example, (Madanat & Ibrahim 1995) attempted to build a common linear model to describe the deterioration rate over time, in which the result was linear. These models took into consideration neither the uncertainties around bridge deterioration nor the existence of unobserved explanatory variables. Thus, stochastic models were developed and its used quickly became popular.

Stochastic models are more capable of capturing the probabilistic nature of the bridge's deterioration process. One major category of stochastic models is based on the Markov theory. For example, (Jiang & Sinha 1989) applied Markov Chains to predict the bridge service life. The transition probabilities from one state to another was solved by non-linear programming and was used to evaluate the life expectancy of a bridge. Another example of the Markovian model being used was reported in the work by (Cesare et al. 1992), where historical data of 850 bridges in the State of New York was used to predict the future condition of the bridges. The results were used to determine the repair policies then.

As stochastic models became popular, its weaknesses were also revealed. In (Thompson & Johnson 2005) for example, the authors concluded from their Markov modelling (on historical data of bridge maintenance records in California) that the quality and quantity of available data would affect the validity of the model. Most of the historical data set contained a large proportion of good condition records, from which very few state transitions can be observed. This was because many records were produced after maintenance. However the actual maintenance records were always absent so that such data cannot be identified and adjusted. In such a situation, the estimated transition probabilities did not reliably reflect the actual bridge deterioration features.

Furthermore, (Aboura et al. n.d.) pointed out that Markov Chains carry the underlying assumption that the transition probabilities are independent of time. This however contradicts the fact that the transition probabilities of a bridge condition to the next state would change as time passes by, i.e., the longer the bridge is in a current state, the higher the chance of it moving to the next successive worse state. To minimise this shortcoming, a number of improvements were made. For example, (Ng & Moses 1998) used the semi-Markov process to incorporate a time factor into traditional Markov models. To consider the age effect, (Sobanjo & Thompson 2011) proposed to incorporate the Weibull model into the Markov Chain while (Maovi & Hajdin 2014) approached this problem with an EM algorithm to improve the reliability of the estimated transition probabilities.

In addition to Markov-based techniques, researchers have recently turned to alternate techniques in an attempt to further improve predictive performance. This include the use of Artificial Neural Network (ANN). One example is seen in (Tokdemir et al. n.d.), who used ANN (and genetic algorithms) to predict the deterioration of highway bridges. A shortcoming of the ANN (and genetic algorithms in general) is that they are computationally intensive. To reduce the computational time, a hybrid optimisation was then proposed by (Callow et al. 2013). One of the strengths of the ANN technique is its ability to deal

Station #	Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Annual	Mean
76077	1891	29.8	0.0	33.8	55.3	47.7	25.8	1.6	30.1	4.1	-	-	-	-	23.60
76077	1892	12.2	5.4	0.8	8.6	26.2	28.7	34.1	22.1	38.6	70.4	45.3	6.6	299.0	24.92
76077	1893	0.0	0.0	9.9	28.6	52.4	35.0	19.9	27.6	51.8	17.2	38.9	1.5	282.8	23.57

Table 2: A snapshot of the monthly rainfall data from the Bureau of Meteorology (BoM) website.

with some of the data issues that these types of problems have. In (Lee et al. 2008, Bu et al. 2012) for example, the Backward Prediction Model was used to generate additional data to augment the otherwise limited historical inspection records.

Despite the various techniques and approaches, Markov-chains remained popular. As (Ng & Moses 1998, Sobanjo & Thompson 2011, Maovi & Hajdin 2014) suggested, the performance of Markov models could be improved when more reliable methods are adopted to estimate the transition probabilities. Therefore, a number of advanced techniques have been used for transition probability estimation, such as Markov Chain Monte Carlo (MCMC) simulation as seen in (Karunarathna et al. 2013, Wellalage et al. 2015). Both works implemented MCMC methods to obtain transition probabilities that best described the transition features of the historical data set. While these efforts focused on the model itself, another factor, namely input data, is also of great significance and should be considered when trying to improve the model performance. As (Huang et al. 2014) pointed out, the right data is equally crucial.

This research thus makes an attempt to move towards the "right data" by augmentation of the existing data set with publicly available information. This creates a richer and also higher quality data input that we then used to establish if an improvement could be made in terms of predictive performance. If so, this method is clearly more scalable than focusing on the specific model as data would be the input to all. The success reported in this method thus scales across different approaches to building the model; not just the Markov Chains used in the experiments of this paper.

3 Overview of data sources

There are four categories of data sets from two sources used for the experiments, which are bridge inspection data and bridge location data from VicRoads, and weather station data and rainfall data from BoM.

Bridge inspection data This is a collection of historical inspection records about the condition states of Victorian bridges across regions. The information of interest is the ratings given to each bridge structure component at end of each inspection. VicRoads adopted a rating scale of 1 to 4, with '1' suggesting that the bridge structure component is in good condition and 4 to mean that the component is damaged or has failed. As shown in Table 1, there are seven regions with the data from 'All Area' containing the data from all the seven regions. Each data set contains 32 attributes detailing information about the bridge structure, identification information, condition ratings of a structure component, and comments from inspectors.

Bridge location data VicRoads also has data about the geographical information of a bridge structure in the form of 'Latitude' and 'Longitude', i.e. the coordinates of a structure. We used the bridge's location to identify the nearest weather station of a structure so as to obtain the corresponding rainfall information.

Weather station data The weather station data was obtained from BoM website. There are two attributes of interest: *station number* and *coordinates*. *Station number* was a unique ID number assigned by BoM to a weather station. We used this information to match up with the historical rainfall data on the BoM website. The coordinates of the weather stations were used together with the bridge location information to identify the bridges that are near to a weather station.

Rainfall data BoM provides rainfall data at the daily, monthly and annual levels. As the bridge inspection data was recorded with respect to each inspection year, annual rainfall amount (in millimetres) was selected for augmentation. Once the nearest weather station is determined for a structure, its corresponding inspection record was extended with an annual rainfall amount calculated from the rainfall data recorded by that weather station.

As (Huang et al. 2014) discussed, there are a few data issues regarding the bridge data that should be dealt with before applying them to the model. In this research, following data issues were considered as well as pre-processing steps were conducted.

In taking advice from (Huang et al. 2014) to ensure that the data is of high quality prior to model development, we undertook data cleaning within the constraints available. This includes the following issues.

- Some of the records have "inspection dates" that were before the registered "construction dates". Others have missing "construction dates". Such records cannot be used for Markov Chain modelling since we need to determine the age of a bridge as part of the modelling. These records were eliminated from the data set. Fortunately, these offending records only accounted for 0.03% of the entire data set.

- Most of the condition ratings are recorded as '1', suggesting that maintenance was conducted throughout the inspections. For the inspection records available for analytics, VicRoads does not have the maintenance records making it difficult to identify which inspection record was made after a maintenance. For example, an inspection on a given day was recorded with a condition rating of '2' but the following inspection record saw that condition rating being revised to a '1'. Without access to the maintenance records, it is unclear whether the change from '2' to '1' was a result of a maintenance or a difference in judgement by the inspectors. In this paper,

Data set	Features selected	Comments
Bridge inspection data	• Structure ID • Construction Date • Inspection Date • Component Number • Condition Rating	• Augmented with monthly rainfall data • Calculate parameters for Markov Chain • Input for model training
Bridge location data	• Structure ID • Coordinates (Latitude, Longitude)	• Determine nearest weather station for a structure
Weather station data	• Station number • Coordinates	• Determine nearest weather station for a structure
Rainfall data	• Station Number • Rainfall Amount	• Augment bridge inspection data with a mean annual rainfall amount

Table 3: Summary of features selected and the rationale for selecting a feature in the data set.

we assumed that the component was maintained whenever an improvement of condition was found between two consecutive records. The component age was then recalculated based on this assumption.

• Table 2 shows a snapshot of how the rainfall data looks like on the BoM. As we can see in the snapshot, the amount of rainfall is not recorded every month because there are times where the weather station did not operate as expected, or that the BoM isn't sure of the reliability of the data. In such cases, the rainfall for that month is missing. To extrapolate the annual rainfall data which we need, we impute the missing values with the statistical long term mean obtained from the BoM website. Once all values are incorporated, the annual rainfall is then calculated for our purpose.

• Lastly, we need to select the best features for building our model. According to (Guyon & Elisseeff 2003, Kira & Rendell n.d.), feature selection is an essential process in model construction especially when there are many irrelevant features in the data set. As we fuse the four data sources for model training, we should select only relevant features. This involves first creating the 'joined' data set by mapping the bridge location data and the weather station to identify the bridges' proximity to weather station. Once that's done, we can pull the relevant annual data for each bridge structure. We then obtain a subset of features as the basis for building our model. The selected features are given in Table 3.

For benchmarking purposes, we went with the popular Markov Chains approach, building both the baseline and the "high rainfall" models. The output of running the Markov Chains is a Transition Probability Matrix derived from the bridge age and condition ratings. Figure 1 shows how the data set is used to build the two models for comparison. The full data set was split into a number of sub-sets based on component number in order to examine the effects of the rainfall from component-level. Each subset, which can be named as 'all rainfall group', was then classified into 'high rainfall' group if the rainfall amount is no less than 600mm and 'low rainfall' group otherwise. The value '600mm' is a statistical long-term average annual rainfall provided by BoM website. Different rainfall groups were used to train the same Markov Chain model respectively, from which the results were used for prediction on the same testing data set in order to compare the prediction accuracy. The 90/10 split is the typical model validation ratio with 10 folds applied to each evaluation as described in Section 4.
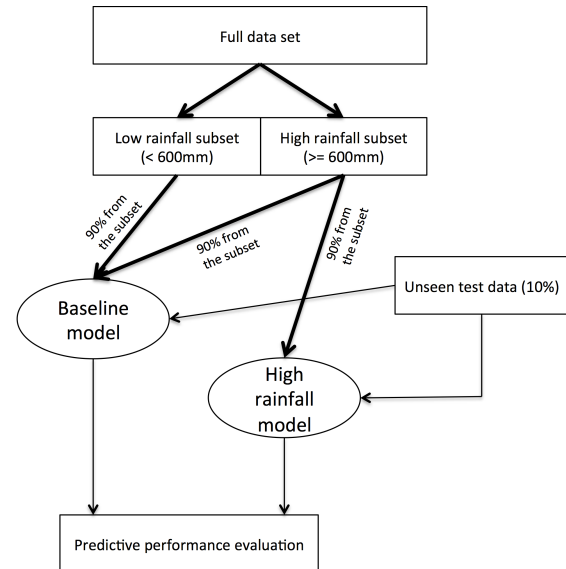

Figure 1: Building two Markov Chain models with the first using the data set from VicRoads and the second, using the data set from VicRoads that has been augmented with rainfall data. The predictive performance of these two models are then compared.

Component Number	Component Type
24C	Abutment made of cast-in-Situ concrete
51S	Bridge railing/Barriers made of steel
52O	Bridge approaches made of other materials
54O	Waterway made of other materials
55S	Bridge approach barriers made of steel

Table 4: A description of the various components. Where "other materials" are mentioned, this means materials other than steel, precast concrete, case-in-Situ concrete or timber.

4 Modelling and Validation

Markov Chain-based model was used for data training and its performance was evaluated by the prediction accuracy of bridge future condition on testing data set. The parameters of the Markov model, namely the transition probabilities, were obtained using Metropolis-Hastings Algorithm (MHA) implemented in Matlab. MHA is one of the most popular methods of Markov Chain Monte Carlo (MCMC) simulation, which is powerful to simulate multivariate distributions [28]. A number of research, such as (Karunarathna et al. 2013, Tran 2007, Wellalage et al. 2014b), have used MHA to calibrate the Markov Chains to obtain transition probabilities.

A Markov model describes a system that transits from state i to state j at a single time interval with

Region	Western									
Component Number	24C		51S		52O		54O		55S	
	Baseline	High rainfall	Baseline	High rainfall	Baseline	High rainfall	Baseline	High rainfall	Baseline	High rainfall
Fold 1	0.899	0.078	1.151	1.126	0.839	0.836	0.757	0.867	1.250	1.334
Fold 2	0.741	0.142	1.230	1.227	0.753	0.722	0.566	0.690	1.561	1.563
Fold 3	0.695	0.725	0.959	0.862	0.909	0.904	0.655	0.740	1.307	1.204
Fold 4	0.608	0.117	1.083	1.115	1.106	1.112	0.885	0.891	1.685	1.603
Fold 5	0.211	0.170	1.408	1.338	0.770	0.757	0.771	0.765	1.432	1.428
Fold 6	0.389	0.381	0.937	0.976	0.791	0.788	0.581	0.640	1.400	1.285
Fold 7	0.195	0.143	0.969	0.897	0.972	0.990	0.517	0.542	1.217	1.154
Fold 8	0.140	0.140	1.175	1.060	0.931	0.902	1.119	1.121	1.661	1.577
Fold 9	0.302	0.314	1.153	1.134	0.595	0.565	0.604	0.627	1.309	1.258
Fold 10	0.739	0.773	1.253	1.191	0.974	1.483	0.694	0.708	1.277	1.223

Table 5: Experimental results for the Western data set over 10 folds. The numbers are the average RMSE values for the 10% test data in the given fold tested on both the baseline and the "high rainfall" model. A smaller RMSE value indicates a lower error rate between the actual "overall condition rating" (OCR) and the predicted OCR. Between the Baseline and "high rainfall", the model that has a lower RMSE value indicates better performance. As an example, in Fold 1, on Component 24C, the baseline model produces a RMSE value of 0.899 while the "high rainfall" model produces a 0.078 RMSE value. This means that the "high rainfall" model has produced a better predictive performance for this particular run.

Component	24C		51S		52O		54O		55S	
	Baseline	High rainfall	Baseline	High rainfall	Baseline	High rainfall	Baseline	High rainfall	Baseline	High rainfall
All area	0.230	0.232	1.110	1.094	0.718	0.705	0.587	0.590	1.405	1.381
Eastern	0.231	0.231	1.040	1.037	0.697	0.696	0.598	0.604	1.405	1.402
Western	0.492	0.298	1.132	1.093	0.864	0.906	0.715	0.759	1.410	1.363
MNW	0.173	0.170	0.906	0.903	0.582	0.582	0.469	0.469	1.352	1.349
SW	0.182	0.182	1.040	1.055	0.678	0.635	0.555	0.551	1.405	1.396
NE	0.203	0.227	1.209	1.202	0.800	0.797	0.713	0.715	1.405	1.405
N	0.059	0.179	1.289	1.256	0.761	0.725	0.447	0.446	1.366	1.359
MSE	0.250	0.253	0.797	0.785	0.560	0.553	0.526	0.525	1.239	1.244

Table 6: The average RMSE value over 10 folds for each data set and a given component. This table summarises the RMSE results obtained across eight similar tables that we have used for recording our experiment results. Table 5 shows an example of what the eight tables looked like, which is used for determining the average RMSE values here.

a fixed probability p_{ij}, all of which consists a transition probability matrix (TPM). In this study, there are four discrete transition states (from 1 – 'perfect' to 4 – 'worst') in the bridge deterioration process according to VicRoads. It is assumed that the bridge condition will either remain in the present state or transit to another worse state. The one-year transition probability matrix is given in Equation 1.

$$P = \begin{bmatrix} p_{11} & p_{12} & p_{13} & p_{14} \\ 0 & p_{22} & p_{23} & p_{24} \\ 0 & 0 & p_{33} & p_{34} \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (1)$$

The initial condition state of a bridge is denoted as a condition state vector $C_0 = [\,1\ 0\ 0\ 0\,]$. The predicted condition state vector C_t after t years is calculated by Equation 2, where P is the transition probability matrix and C_t^i, $i \in [\,1, 2, 3, 4\,]$ is the probability of the bridge condition being in state i at year t.

$$C_t = C_0 \times P^t = [\,C_t^1\ C_t^2\ C_t^3\ C_t^4\,] \quad (2)$$

The result from Equation 2 is then used to calculate an "overall condition rating" (OCR) using Equation 3, which is the expected value obtained by considering the probability values in the state vector.

$$OCR = \sum_{i=1}^{4} i \times C_t^i \quad (3)$$

The modelling process was repeated based on different rainfall groups (see Figure 1). After the data preparation steps, for each component in each region, the All Rainfall Group (ARG) was split into two sets, i.e. Low Rainfall Group (LRG) and High Rainfall Group (HRG). With the assumption that high rainfall would have greater impact on bridge deterioration, ARG data and HRG data were applied to train the Markov model respectively. 90% of each data set was used for training while both groups predicted on the 10% of HRG data.

As the bridge inspection data were recorded in component-level, the same sets of components from each region should be selected for modelling in order to compare the prediction results. Moreover, the modelling results will be less valid if very little number of records for a component is available for training and testing. Therefore, five components were selected from each region with the number of testing data greater than ten. Table 4 provides the component number with its corresponding component type based on VicRoads inspection manual.

Each model was validated by using a separate testing data set as well as ten-fold validation. Also,

Component	24C	51S	52O	54O	55S
	Model comparison				
All area	-0.002	0.016	0.012	-0.002	0.023
Eastern	-0.001	0.003	0.000	-0.006	0.004
Western	0.194	0.039	-0.042	-0.044	0.047
MNW	0.003	0.004	0.000	0.000	0.003
SW	0.000	-0.015	0.043	0.005	0.009
NE	-0.024	0.006	0.003	-0.002	0.000
N	-0.120	0.032	0.036	0.000	0.006
MSE	-0.003	0.012	0.007	0.001	-0.005

Table 7: A summary of the predictive performance differences (see Table 6) between the baseline and "high rainfall" models. The numbers in this table is obtained by comparing the difference between the RMSE value of the baseline model to the "high rainfall" model. Since a higher RMSE value suggests lower predictive accuracy, a positive number in the difference suggests that the "high rainfall" model has performed better in the region's data set on a specific component. Where the "high rainfall model" performed better, the result is marked in grey. Over all the results show promising results of augmenting external data sources to improve predictive performance.

the performance of each model is validated with the root mean square error (RMSE) as shown in Equation 4, where y and $\hat{y}$ are the "overall condition rating" (OCR) predicted by the baseline and the "high rainfall" model. The closer the RMSE value is to 0, the better the model performance is.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \qquad (4)$$

An example of the RMSE values for baseline data and "high rainfall" data is given in Table 5. This data set contains inspection records from the western regions of Victoria. A high RMSE value means that the error is high and therefore lower predictive performance. In Table 5, each component is tested 10 times (folds) on a different set of test records. The predictive errors are then noted and the test conducted on both the baseline model and the "high rainfall" model for each component. Since we have eight data sets, there are eight such table of results from our experiment so Table 5 gives an idea of what the results look like. To determine if the "high rainfall" model actually performs better, we first obtained the average RMSE values across the 10 runs to arrive at the results in Table 6.

Finally, we compute the difference of these average RMSE scores between the baseline and the "high rainfall" model. This difference, for each component across the eight data sets, are shown in Table 7. What we can see from the experiment results is that components 51S, 52O and 55S see good performance improvements while components 24C and 54O seem not to respond well with our method. Looking at the material used for these components (Table 1, we could draw the following conclusions

- 51S and 55S are components made of steel while 24C is a component made of cast-in-Situ concrete. Consistent with the literature, a steel component is more likely to be impacted by rainfall due to water corrosion (than cast-in-Situ concrete).

- 54O is the waterway part of a bridge made of materials other than steel, precast concrete, cast-in-Situ concrete or timber. This means that this

material has to withstand the presence of water and therefore the rainfall data should not have any impact.

5 Summary and Future Work

This paper presents our preliminary results on our work with VicRoads to implement a bridge deterioration model to enable the development of a bridge management system. The challenges of the work lie with the noisiness of the data and access to information required for data cleaning is limited. Therefore an alternative approach to improve the data quality is paramount before considering the various predictive models that one can use. Our strategy was to look at augmenting the data set with sources of data that are known to be reliable. In doing so, the proportion of the noisy and erroneous data is reduced, giving the model a better chance of producing good predictive performance. The use of rainfall data from the BoM verifies the possible viability of this approach. On the five major components of interests to bridge inspectors, the overall performance improvement seen in the model that utilises the high rainfall data suggests that this is a plausible direction to take.

In the near term, we will be conducting further studies on the use of rainfall data from the BoM. This would include

- Verifying if the long term annual rainfall average (600mm) is a good determinant of the high rainfall characteristics. We are keen to investigate this long term average because our own study with the rainfall associated with our bridges average at around the 800mm mark rather than 600mm. It would be important to find out how the "high rainfall" model would perform if the cut-off point for selecting the high rainfall subset is raised to 800mm.

- Considering the use of more advanced models rather than Markov chains with this data to see what impacts the augmented data set could bring to different algorithms for building bridge deterioration models.

The outcomes of these two investigation will eventually lead to insights on the best choice of algorithm for model training and the final augmented data set to use, including the exploration of other data sources to add to the data set, e.g., traffic and weather information, which too contribute to bridge deterioration.

References

Aboura, K., Samali, B., Crews, K. & Li, J. (n.d.), Stochastic deterioration processes for bridge lifetime assessment, *in* 'Broadband Communications, Information Technology & Biomedical Applications, 2008 Third International Conference on', IEEE, pp. 437–442.

Bu, G., Lee, J., Guan, H., Blumenstein, M. & Loo, Y.-C. (2012), 'Development of an integrated method for probabilistic bridge-deterioration modeling', *Journal of Performance of Constructed Facilities* **28**(2), 330–340.

Callow, D., Lee, J., Blumenstein, M., Guan, H. & Loo, Y.-C. (2013), 'Development of hybrid optimisation method for artificial intelligence based bridge deterioration modelfeasibility study', *Automation in Construction* **31**, 83–91.

Cesare, M. A., Santamarina, C., Turkstra, C. & Vanmarcke, E. H. (1992), 'Modeling bridge deterioration with markov chains', *Journal of Transportation Engineering* **118**(6), 820–833.

Guyon, I. & Elisseeff, A. (2003), 'An introduction to variable and feature selection', *The Journal of Machine Learning Research* **3**, 1157–1182.

Huang, Q., Hasan, M. S., Ong, K.-L., Alahakoon, D. & Setunge, S. (2014), 'Beyond modelling: Shifting the focus to a holistic development of analytical models for infrastructure problems'.

Huang, R., Mao, I. & Lee, H. (2010), 'Exploring the deterioration factors of rc bridge decks: A rough set approach', *ComputerAided Civil and Infrastructure Engineering* **25**(7), 517–529.

Huang, Y.-H. (2010), 'Artificial neural network model of bridge deterioration', *Journal of Performance of Constructed Facilities* **24**(6), 597–602.

Jiang, Y. & Sinha, K. C. (1989), 'Bridge service life prediction model using the markov chain', *Transportation research record* (1223).

Karunarathna, W., Zhang, T., Dwight, R. & El-Akruti, K. (2013), 'Bridge deterioration modeling by markov chain monte carlo (mcmc) simulation method'.

Kira, K. & Rendell, L. A. (n.d.), A practical approach to feature selection, *in* 'Proceedings of the ninth international workshop on Machine learning', pp. 249–256.

Lee, J., Sanmugarasa, K., Blumenstein, M. & Loo, Y.-C. (2008), 'Improving the reliability of a bridge management system (bms) using an ann-based backward prediction model (bpm)', *Automation in Construction* **17**(6), 758–772.

Madanat, S. & Ibrahim, W. H. W. (1995), 'Poisson regression models of infrastructure transition probabilities', *Journal of Transportation Engineering* **121**(3), 267–272.

Maovi, S. & Hajdin, R. (2014), 'Modelling of bridge elements deterioration for serbian bridge inventory', *Structure and Infrastructure Engineering* **10**(8), 976–987.

Ng, S.-K. & Moses, F. (1998), 'Bridge deterioration modeling using semi-markov theory', *A. A. Balkema Uitgevers B. V, Structural Safety and Reliability.* **1**, 113–120.

Ozbek, M. E., de la Garza, J. M. & Triantis, K. (2010), 'Efficiency measurement of bridge maintenance using data envelopment analysis', *Journal of Infrastructure Systems* **16**(1), 31–39.

Ranjith, S., Setunge, S., Gravina, R. & Venkatesan, S. (2011), 'Deterioration prediction of timber bridge elements using the markov chain', *Journal of Performance of Constructed Facilities* **27**(3), 319–325.

Sobanjo, J. (n.d.), A neural network approach to modeling bridge deterioration, *in* 'Computing in Civil Engineering (1997)', ASCE, pp. 623–626.

Sobanjo, J. O. & Thompson, P. D. (2011), 'Enhancement of the fdot's project level and network level bridge management analysis tools'.

Thompson, P. D. & Johnson, M. B. (2005), 'Markovian bridge deterioration: developing models from historical data', *Structure and Infrastructure Engineering* **1**(1), 85–91.

Thompson, P., Ford, K., Arman, M., Labi, S., Sinha, K. & Shirol, A. (2012), 'Nchrp report 713: Estimating life expectancies of highway assets: Volume 1: Guidebook', *Transportation Research Board of the National Academies, Washington, DC* .

Tokdemir, O. B., Ayvalik, C. & Mohammadi, J. (n.d.), Prediction of highway bridge performance by artificial neural networks and genetic algorithms, *in* 'Proceeding of the 17th International Symposium on Automation and Robotics in Construction (ISARC), September, Taipei, Taiwan'.

Tran, H. D. (2007), Investigation of deterioration models for stormwater pipe systems, Thesis.

Wakchaure, S. S. & Jha, K. N. (2011), 'Prioritization of bridges for maintenance planning using data envelopment analysis', *Construction Management and Economics* **29**(9), 957–968.

Wellalage, N. K. W., Zhang, T. & Dwight, R. (2014*a*), 'Calibrating markov chainbased deterioration models for predicting future conditions of railway bridge elements', *Journal of Bridge Engineering* **20**(2).

Wellalage, N. K. W., Zhang, T. & Dwight, R. (2014*b*), 'Calibrating markov chainbased deterioration models for predicting future conditions of railway bridge elements', *Journal of Bridge Engineering* **20**(2).

Wellalage, N. W., Zhang, T., Dwight, R. & El-Akruti, K. (2015), *Bridge Deterioration Modeling by Markov Chain Monte Carlo (MCMC) Simulation Method*, Springer, pp. 545–556.

Zhao, Z. & Chen, C. (2002), 'A fuzzy system for concrete bridge damage diagnosis', *Computers & structures* **80**(7), 629–641.