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Pavement deterioration modeling and design of a composite pavement distress index for Kentucky interstate highways and parkways.

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PAVEMENT DETERIORATION MODELING AND DESIGN OF A COMPOSITE PAVEMENT DISTRESS INDEX FOR KENTUCKY INTERSTATE HIGHWAYS AND PARKWAYS

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ABSTRACT

PAVEMENT DETERIORATION MODELING AND DESIGN OF A COMPOSITE PAVEMENT DISTRESS INDEX FOR KENTUCKY INTERSTATE HIGHWAYS AND PARKWAYS

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Pavement deterioration is one of the most important driver for prioritizing pavement management and preservation (PMP) projects. The primary goal of this thesis is to provide reasonable predictive functions from multiple linear regression (MLR) models and artificial neural networks (ANN) that can be adopted by Kentucky Transportation Cabinet (KYTC). Furthermore, we use analytic hierarchy process (AHP) to design a composite pavement distress index in order to help Kentucky Transportation Cabinet (KYTC) prioritizing PMP projects based on 11 different distress indices. Numerical results show that the MLR models provide relatively high R square values of approximately 0.8. Both MLR and ANN models have small average squared errors (ASE). Finally, for all nine distress indices studied in this thesis, MRL models are recommended to KYTC due to their simplicity, interpretability along with robust performance that is comparable to the ANN model. Finally, a priority rating method is developed using analytical hierarchy process and it integrates 11 pavement distress indices into one priority score. A case study shows that the propose AHP-based rating

method overcomes the drawback of KYTC's current rating system for overemphasizing the international roughness index (IRI) among all distress indices.

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CHAPTER 1 INTRODUCTION

Pavement management systems and the need to develop an intelligent prioritization schedule have received growing attention recently for the sake of economic efficiency (see, e.g., Kim and Kim, 2006). In recent years, pavement management and preservation (PMP) are considered as important to our nation's highway infrastructure development as the construction of new infrastructures. In order for transportation authorities to properly allocate resources and prioritize among PMP projects, a prediction model for predicting pavement deterioration over time is in great need. In addition, most U.S. state-wide transportation agencies use multiple pavement distress criteria in their evaluation of treatment needs, and thus a composite pavement distress index to rate PMP projects is necessary.

The Kentucky Transportation Cabinet (KYTC) is an executive branch agency responsible for supervising the development and maintenance of a safe transportation system throughout the Commonwealth. KYTC manages more than 27,000 miles of highways, including roughly 20,500 miles of secondary roads, 3,600 miles of primary roads, and more than 1,400 interstate and parkway miles. With respect to maintaining safe roadways for Kentuckians, the Kentucky Transportation Cabinet's current PMP system requires the knowledge of predicted pavement performance for the near future in order to prioritize alternative PMP projects. To this end, we help KYTC to use the actual road condition data collected by KYTC in developing ANN and MLR models to predict the pavement deterioration for the next year. In addition to predict pavement deterioration, we also implement a composite pavement distress index using AHP that consists of 11 individual indices to rate PMP projects.

In the transportation engineering literature, many studies have been done by using ANN and MLR models to predict the deterioration of pavement in states' roadways. Both ANN and MLR models can be used for multi-factor analysis and forecasting. The data used in MLR is required to meet such conditions as independence and normality, while the data of the ANN does not require independence and normality (see, e.g., Wang and Wu, 2010). In addition to developing two types of prediction models, this thesis also performs a thorough data preprocessing to assist the development of the two models.

In order to develop a practical prediction model that can be used by KYTC staff yearly, this thesis uses actual pavement evaluation data collected by KYTC from 2003 to 2013 on an annual basis. The main goals of preprocessing data include:

- To remove the useless or erroneous data from the raw data, including the road segments without cracking index and human errors in recording cracking index.
- To exclude road segments whose pavement distress data is only present for one year, thus useless for prediction of deterioration from one year to next.
- To exclude road segments whose pavement distress data has improved from one year to another.
- To calculate the pavement age for each road segment.

When data are pre-processed, we then study the pavement deterioration for KY interstate and parkways system. In order to achieve the goals, we develop ANN and MLR using SAS Enterprise Miner (see, e.g., SAS 1989). The main goals of these prediction models include:

- Develop two models to predict the pavement distress index for next year using those for the current year.
- Evaluate and compare both models using average ASEs and R square value.
- Make a recommendation as to which model should be adopted by KYTC in their annual pavement project selection.

In particular, two models of MLR and ANN are developed to predict the deterioration of raveling (RF), other cracking (OC), out of section (OS), and appearance (APPEAR) over one year period. Particularly, two indices of "extent" and "severity" are associated with each of the indices of RF, OC and OS. For example, "RF_EXT" represents the condition rating for the extent of raveling on a particular road segment, while "OC_SEV" represents the condition rating for the severity of other cracking. Note that there is only one index on APPEAR. The input variables considered by both ANN and MLR models include: the condition for the current, pavement age and average daily traffic. The target or output variables are the corresponding condition index for the next year.

Using the input and target variables described above, this thesis first develops various MLR models for predicting roadway's condition index. In particular, they include linear function, polynomial functions of 3^{rd} order and 2^{nd} order for predicting RF_EXT, RF_SEV, OC_EXT, OC_SEV, OS_EXT, OS_SEV and APPEAR, respectively. Moreover, the various linear regression models for this index will be compared using two criteria: average squared errors over three data subsets (training, validation and testing data sets) and R square.

Second, the thesis develops various ANN models as an alternative to MLR models, they include ANN models with one through eight hidden neurons for predicting RF_EXT, RF_SEV, OC_EXT, OC_SEV, OS_EXT, OS_SEV and APPEAR, respectively. In addition, these ANN models will be compared against each other using average squared error over three data subsets (training, validation and testing data sets).

As a result, the winning MLR and winning ANN models are compared for the final recommendation for KYTC to adopt in predicting a particular condition index (e.g., RF_EXT).

Finally, a priority rating method is also important to KYTC in their annual selection of PMP project. Generally, transportation authorities often perform pavements repairs without considering the maintenance priority and without utilizing a systematic procedure. As a result, their decisions do not usually guarantee the effectiveness of budget allocation (see, e.g., Moazami et al., 2011). To this end, we develop a composite pavement distress index by using AHP and compare it with the current rating method of KYTC.

The rest of the thesis is organized as follows. Chapter 2 reviews the literature of ANN and MLR models that are related to pavement deterioration modeling, as well as the literature of the PMP projects rating method. Chapter 3 introduces the data processing procedures. Chapter 4 presents the design of the ANN model, linear regression model. Chapter 5 introduces a composite pavement distress index based on AHP. Chapter 6 discusses the results and comparison for ANN and MLR prediction models. In addition, the results for the current KYTC priority rating system and the proposed AHP-based rating method are also discussed. Finally, Chapter 7 summarizes the thesis and discusses possible future work.

CHAPTER 2 LITERATURE REVIEW

Pavement deterioration is an important driver in prioritizing pavement management preservation projects. Pavement condition prediction plays an important role in studying the deterioration of pavement. Hence, in this section we will review the literature on pavement condition prediction models.

To date, many prediction approaches have been used to forecast the pavement condition, including regression models, artificial neural network, empirical model, mechanistic models and deterministic and probabilistic models. Within these approaches, regression analysis is used by researchers as a traditional method to predict pavement deterioration rate (see, e.g., Carey and Irick, 1960). Particularly, Isa and Hwa (2005) proposed a study which established a simple, practical pavement performance model for network level of the Malaysian Federal road. They also conducted the statistical analysis by the means of multiple linear regressions to test and examine the data as well as to develop the model. In their model, relevant variables such as pavement condition, pavement strength, traffic loading and pavement age are used as input data to predict the target variable rutting depth. After evaluating various combinations of the relevant variables above, they use coefficient of determination (R^2) and standard error of estimate to decide which model provides reasonable prediction of pavement performance. The recommended regression model for the particular road network in their study has the following form:

$$Log\ Rut\ Depth\ =\ 0.415\ +\ 0.1\ (Roughness) +\ 5.473\ x\ 10(AADT)^{-6} -\ 0.004\ (SN)^2$$

Note: AADT = medium trucks annual average daily traffic; SN = structural number;

Similarly, Kim and Kim (2006) develop the asphalt pavement performance prediction models for the state highways and the interstate highways with the applications of simple and multiple regression analysis methods. Kim and Kim's model uses the pavement condition evaluation system (PACES) data rating. The PACES data rating is a very interesting and novel concept. Particularly, in their project rating, they rank all the projects based on the points after deducting the scores evaluated from each cracking index (cracking indices, such as rut depth raveling, load cracking edge distress and block cracking are similar to the ones used in this thesis). For example, initially each specific road segment (also referred to as "project" in Kim and Kim 2006) has 100 points. When the evaluation is being done, the PACES will grade each type of cracking index with points from 0 to 6 (6 is the worst case), then subtract the total points for the entire cracking index from 100 points. As a result, if one project has the lowest point, which means the specific road segment needs rehabilitation immediately. After the project rating, they develop three different models using one, two and three input variables (AADT, Pavement Age, the interaction) in applying linear and multiple regression analysis to predict the value of each road segment. In their conclusion, AADT, pavement age, and the interaction between AADT and age have significant impact on the PACES rating, the reasonable prediction equation has been drawn to forecast the PACES rating. The final recommended prediction model takes the following from:

$$Project\ Rating = 94.2 - 2.37Y + 0.131T - 0.059Y * T$$

where T = annual average daily traffic; Y = Pavement age;

In the pavement deterioration modeling, most specialists agree that no single prediction model is applicable to all pavements due to the high variability in the manner in which each agency measures its pavement. For example, they may vary in number, scale, type of pavement characteristics, and additionally the summary pavement deterioration indicators utilized (see, e.g., Roberts and Attoh-Okine, 1998). In recent years, with the development of artificial intelligence and machine learning, a method called artificial neural networks (ANN) has become more widely used. Especially for pavement deterioration prediction modeling, it has many favorable features. For example, in regression analysis, one has to pre-specify a mathematical function before fitting the data in this pre-determined function. In contrast, the ANN model will discover some implicit function by itself. To further illustrate the versatility of ANN, we will introduce two papers that use ANN model to forecast pavement condition.

Yang and Lu (2003) develop a pavement performance model applying neural network algorithm for the Florida Department of Transportation (FDOT) pavement management system. Generally, in building an neural network, there are three important components need to be considered at the first place, including the pattern of connection between neurons, which is referred to as architecture, the method of determining the weight of the connections, which is referred to as learning algorithm and the neuron activation function (see, e.g. Yang et al., 2003). In their model, a three-layered neural network with on output neuron is chosen to be the architecture, back-propagation (BP) method applied to be the learning method, at last the sigmoid function was employed as the neuron activation function. After training the neural network with historical pavement condition data, the trained ANN model can extract the information within the historical database, and then make reasonable prediction of pavement condition in the future.

Similarly, Lou and Gunaratne (2001) also developed multiyear back-propagation neural network (BPNN) models for Florida's highway network to forecast accurately the short-term time variation of cracking index (CI). In this paper, the BPNN model is not only used to predict the cracking index for the next year, but also for two-year model. The result shows that, the BPNN models not only exhibited a great ability to learn the historical crack progression trend from the CI database but also accurately forecast future CI values. In testing the results, the BPNN model was validated by comparing the forecasted CIs with measured CI data.

After reviewing the papers which use regression model and ANN models to predict the pavement condition, we found both types of models can reasonably accurately predict the pavement condition. To further compare these two kinds of models, we review some papers that apply both regression models and ANN models pavement condition prediction.

In Huang and Moore (1997), the authors use MLR and two ANN models to predict the probability of specific roughness condition for asphalt pavements. In developing these models, they tried four types of techniques as follows:

- ANN1 – back propagation neural network with one output representing either the probability of either DL1 or DL2. (DL1: Mays ride meter roughness of <60 in./mi. DL2: Mays ride meter roughness from 60 to 125 in./mi.)
- ANN2 – back propagation neural network with two outputs representing the probability of DL1 and the probability of DL2 and DL3, respectively. (DL3: Mays ride meter roughness >125 in./mi.)
- MLR – manual enter procedure in SPSS.
- MLR – stepwise procedure in SPSS.

. In their ANN model, the input layer consists of 17 independent variables including cumulative traffic expressed in 80kN equivalent single axle loads (ESAL), layer thickness, back calculated modulus values, AASHO regional factor and soil support values. Instead of predicting the distress indices, Huang and Moore (1997) forecast the probability of a certain pavement deterioration level occurring at some time in the future.

The numerical results show that the MLR model with the manual enters procedure has the success rates ranging from 70 to 90 percent, a better accuracy than that for the stepwise procedure. Between the two ANN models, the average success rate has the range from 70 to 93 percent, slightly higher than that of the two regression models.

In order to compare the MLR and ANN techniques, Huang and Moore (1997) use so called “error tolerances” to calculate success rates of prediction. Overall, they observed that the ANN models have better success rates than the MLR methods models. In addition, the authors concluded that there is no significant advantage for the ANN model with two output variables.

In addition to the papers on the application of pavement prediction models, we also review some papers that study priority rating for pavement maintenance.

In the literature, Fwa and Chan (1993) use two different priority-setting schemes to test the feasibility of using neural network models. One is a linear rating function, and the other is a nonlinear rating function. Their specific mathematical functions are listed below.

Linear function: $P = 0.1S_1 + 0.25S_2 + 0.2S_3 + 0.125S_4 + 0.15S_5 + 0.175S_6$ … … … …

Nonlinear function: $P = \frac{4}{3}S_1S_5(0.25S_2 + 0.20S_3 + 0.175S_4 + 0.125S_6)$ … … ….

$$P' = P + \Delta P \text{ … … …}$$

where P is the priority rating score, S_1 is the score for highway functional class, S_2 is the skid resistance score, S_3 is the crack width score, S_4 is the crack length score , S_5 is the pavement serviceability score, S_6 is the rut depth score , and finally ΔP = a uniformly distributed noise random variable. All the above scores, i.e., P, $S_1, \ldots, S_6$ are all normalized with a value between zero and one.

Fwa and Chan (1993) show that the ANN model can accurately predict the pavement priority rating governed by both the linear and nonlinear equations above. Further, the ANN model has a high degree of generality, thus promoted by the authors.

Finally, in current practices at KYTC, a rating function similar to the above linear rating function is used. We explain details of the KYTC rating function in Chapter 5. Nevertheless, coefficients/weights in both functions in Fwa and Chan (1993) and in current KYTC rating function are determined rather subjectively. We will propose in

Chapter 5 a more objective procedure using AHP to determine these coefficients or weights.

In summary, this chapter reviews the existing literature on forecasting pavement conditions using regression models as well as ANN. This thesis uses both approaches to predict the pavement deterioration for interstate and parkways in Kentucky. In Chapter 3, we will discuss in detail the data processing based on raw data provided by KYTC.

‘

CHAPTER 3 DATA COLLECTION, PROCESSING AND ANALYSIS

This chapter presents in detail the work of collecting, processing and analyzing road condition data that is made available to us by KYTC. In other words, final data sets are derived from raw data and are put into MLR and ANN models in SAS Enterprise Miners 12.3 (see, e.g., SAS, 1998). We break our discussion into two sections for data collection and data processing analysis, respectively.

3.1 Data Collection

The raw data collected from KYTC contains 11-year (2003-2013) worth of data on Kentucky's interstate and parkways road condition. The latter includes four types of cracking indices in terms of both extent and severity, pavement types, construction information, effective year, route ID, from point (i.e., the starting point of the road segment) and end point (i.e., the end point of the road segment) and other information. We list nine variables for four distress indices and three pavement types that are relevant to this thesis in Table 3-1.

Table 3-1Variables and Pavement Types

Cracking Indices:	Pavement Types:
Wheel Path Cracking (Extent, Severity)	Asphalt (AC)
Raveling (Extent, Severity)	Concrete (PCC)
Other Cracking (Extent, Severity)	Composite (AC/PCC)
Out of Section (Extent, Severity)	

Appearance	

For collecting the road condition data, the Operations and Pavement Management Branch of KYTC evaluate all interstates and parkways road condition in each spring of the year. In this evaluation process, they record pavement distress conditions and use the data they collect to recommend pavement rehabilitation treatments and prioritize projects. In order for evaluation data to be useful for predictive measures, consistent methods of distress identification and recording are critical. According to the KYTC pavement distress identification manual (2009), the extent and severity of each type of distress is scored by evaluators on various scales with integer values. For example, wheel path cracking (both extent and severity) assumes an integer value between 0 and 9, 0 representing a perfect road condition while 9 representing worst condition. Detailed range for each index can be found in the manual (i.e., KYTC pavement distress identification manual, 2009), and is summarized subsequently in this section as well.

In this thesis, we only focus on predicting reveling (RF), other cracking (OC), out of section (OS) and APPEAR of AC pavement. The prediction of wheel path cracking (WPC) is studied in Xu et al. (2014). To further illustrate the four types of distress indices, Figures 3-1 through 3-4 show the typical scene of raveling (RF), other cracking (OC), out of section (OS) and appearance (APPEAR), respectively. As mentioned previously, manual evaluation criterion of each cracking index is summarized below.

Figure 3-1 A typical example of raveling

Raveling: As shown in Figure 3-1, raveling is the wearing away of the pavement surface caused by dislodging of aggregate particles and loss of asphalt binder. Raveling ranges from loss of fines to loss of some coarse aggregate and ultimately to a very rough and pitted surface with obvious loss of aggregate (see, e.g., KYTC pavement distress identification manual, 2009).

Extent:

- 0-1: 1/2 or more of the section shows slight raveling or 1/3 or more of the section has a combination of slight and moderate raveling. No severe raveling is present.
- 2-3: 1/2 or more of the section shows moderate distress or 1/3 or more of the section has a combination including severe raveling.
- 4-5: 1/3 or more of the section shows severe raveling.

Severity:

- 0-1: Slight loss of aggregate or binder. Small amounts of pitting. Pavement appears slightly aged or rough.

- 2-3: Fine aggregate partially missing. Pitting is evident. Pavement appears moderately rough and loose particles may be present.
- 4-5: Aggregate and binder have worn away significantly. Pavement appears deeply pitted and very rough.

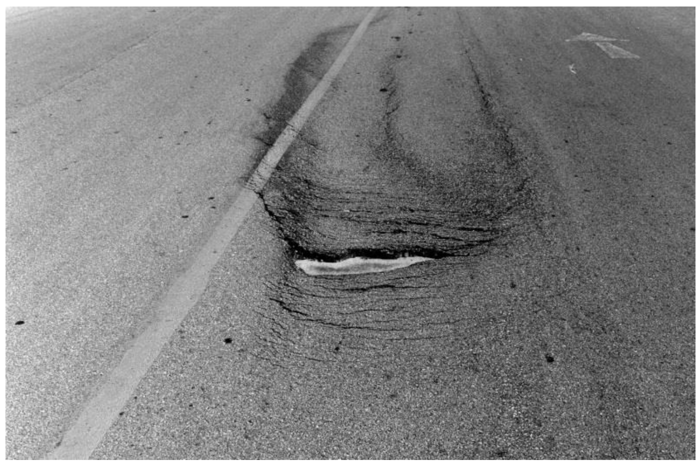


Figure 3-2 A typical example of other cracking

Other cracking: As shown in Figure 3-2, other cracking includes age related, non-load cracking. These cracks can run roughly perpendicular to the roadway center line. Joint reflective cracking from overlaid rigid pavements within the lane should be evaluated as other cracking (see, e.g., KYTC pavement distress identification manual, 2009).

Extent:

- 0-1: Transverse cracks are spaced at 150'.
- 2-3: Transverse cracks are spaced at 125' - 50'.
- 4-5: Transverse cracks are spaced closer than 50' but not less than 25'.

Severity:

- 0-1: Cracks are less than ¼" in width.
- 2-3: Cracks are ¼" to ½" wide there may be slight secondary cracking Edges may be spalled.
- 4-5: Cracks are greater than ½" and ¾ is the max allowable crack width significant secondary cracking is present. Edges are severely spalled.

Figure 3-3 A typical example of out of section

Out of section: As shown in Figure 3-3, areas that are outside of the typical section are localized depressions or elevated areas of pavement that result from settlement, pavement shoving, or displacement (see, e.g., KYTC pavement distress identification manual, 2009).

Extent:

- 0-1: Less than two localized sections per mile.
- 1.5-2: Two to four localized sections per mile.

- 2.5-3: More than four localized sections per mile.

Severity:

- 0-1: Noticeable effect on ride.
- 1.5-2: Some discomfort.
- 2.5-3: Poor ride. Safety is a concern at maintained speed limit.

Figure 3-4 A typical example of appearance

Appearance: As shown in Figure 3-4, appearance refers to the general aesthetic of the roadway to the public at large. This includes potholes, cracking, and unsightly patching (see, e.g., KYTC pavement distress identification manual, 2009).

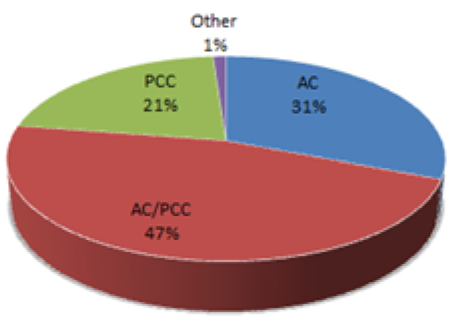
- 0: The pavement is in excellent condition. This typically represents new construction.
- 1-1.5: The pavement is in good to acceptable condition. Slight amounts of low severity distresses and/or neat patches may be present.
- 2-2.5: The pavement is in acceptable to poor condition. Moderate amounts of low or intermediate severity distresses and/or irregular patches may be present.

- 3: The pavement is in unacceptable condition. Extensive amounts of distresses along with severe distresses and/or frequent patching may be present.

3.2 Data Processing and Analysis

3.2.1 Summary Statistics for Raw Data

In this thesis, in order to make our models more practical, we use the actual data collected by KYTC. Before we start to process the raw data, the basic statistical summary on pavement type and each distress condition index is necessary. The raw data we obtained from the KYTC database is in Microsoft Excel spreadsheet format with 58 columns (attributes) and 6,045 rows (samples). From Figure 3-5, we see that AC and AC/PCC are two dominant types of pavement used in Kentucky interstate and parkways, accounting for 31% and 47% of the total road segments, respectively PCC accounts for about 21%, and the last 1% belongs to all other types of pavements.



Pavement	# of Road Segments
AC	1868
AC/PCC	2813
PCC	1296
Other	68

Figure 3-5 Overall Pavement Types of Raw Data

After entering the data into SAS Enterprise Miner, we obtain some basic statistical reports. Tables 3-2 and 3-3 show the summary statics for raw data of AC and AC/PCC, respectively. From both tables, it can be observed that there are many blank data and zero cracking indices in the raw data sets. For example, RF_EXT and RF_SEV each have 220 blank data entries for AC pavement type, and 341 blank data entries for AC/PCC pavement type. On the other hand, RF_EXT and RF_SEV have the modes of zero for both pavement types and the second mode of one for both pavement types. In both tables, the "." represents "blank".

Table 3-2 Summary statics for raw data of AC pavement

Data Role	Variable Name	Role	Number of Levels	Missing	Mode	Mode Percentage	Mode 2	Mode 2 Percentage
TRAIN	APPEAR	INPUT	8	221	0	27.05	1	17.81
TRAIN	OC_EXT	INPUT	11	220	0	31.47	1	15.21
TRAIN	OC_SEV	INPUT	11	220	0	31.47	1	19.44
TRAIN	OS_EXT	INPUT	12	221	0	60.68	0.5	13.52
TRAIN	OS_SEV	INPUT	11	221	0	60.73	.	10.64
TRAIN	RF_EXT	INPUT	12	220	0	22.81	1	16.65
TRAIN	RF_SEV	INPUT	11	220	0	22.81	1	16.22
TRAIN	WPC_EXT	INPUT	14	220	0	29.36	.	10.59
TRAIN	WPC_SEV	INPUT	14	220	0	29.26	4	10.68

Table 3-3 Summary statics for raw data of AC/PCC pavement

Data Role	Variable Name	Role	Number of Levels	Missing	Mode	Mode Percentage	Mode 2	Mode 2 Percentage
TRAIN	APPEAR	INPUT	8	342	0	27.57	1	16.98
TRAIN	OC_EXT	INPUT	11	341	0	30.27	1	15.97
TRAIN	OC_SEV	INPUT	11	341	0	30.24	1	17.82
TRAIN	OS_EXT	INPUT	12	342	0	56.6	0.5	11.18
TRAIN	OS_SEV	INPUT	12	342	0	56.7	.	11.14
TRAIN	RF_EXT	INPUT	12	341	0	22.68	1	17.76
TRAIN	RF_SEV	INPUT	12	341	0	22.68	1	17.92
TRAIN	WPC_EXT	INPUT	15	341	0	31.74	.	11.11
TRAIN	WPC_SEV	INPUT	17	341	0	31.74	.	11.11

As observed above, there is a large amount of zero cracking indices in the road condition database. From the KYTC pavement distress identification manual 2009, a zero cracking index indicates there is no cracking on the road surface and the pavement is new, thus in excellent condition.

In order to demonstrate the dynamics of the distress indices during the past 11 years of, we show the time series of both extent and severity of each cracking index.

From Figure 3-6, the average extent and average severity of RF over all available road segments exhibit similar trends during the 11 years of observation. They have a relatively small range between 1.2 and 2.2. The lowest average values (i.e., best overall road condition) are achieved in 2007 and the highest average values (i.e., worst overall road condition) are achieved in 2011.

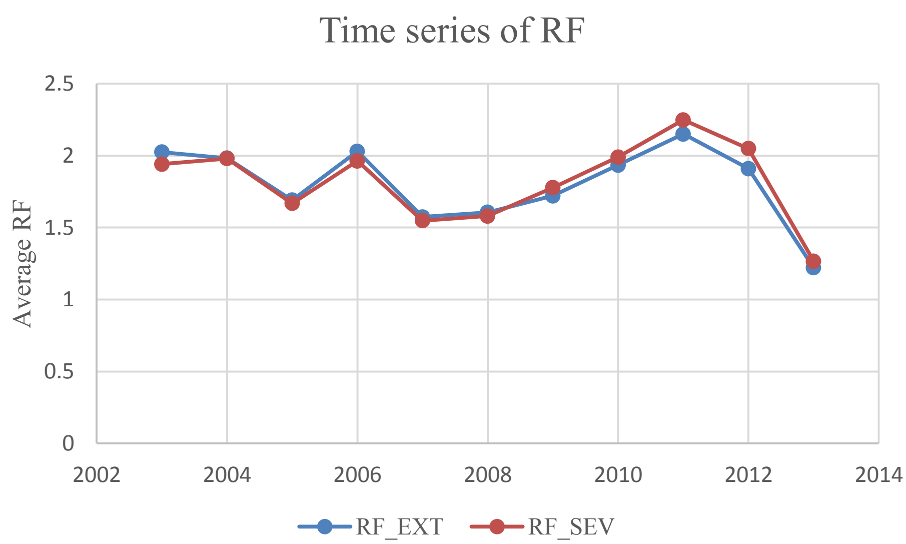


Figure 3-6 Time series of RF from 2003 to 2013

From figure 3-7, the average extent and average severity of OC over all available road segments have the similar trend during the 11 years except 2008. From 2007 to 2008, the average OC_EXT increased rather drastically from 1.58 to 2.26, and this indicates the deterioration from 2007 to 2008 is unexpectedly large for most road segments. We consulted with KYTC experts about this situation and they suspected this extreme case is caused by the inclusion of "joint cracking" into OC in 2008. They noted that 2008 is the only year when they included "joint cracking" into the "Other Cracking" (OC) category as a pilot study, and decided it was not appropriate. Then from 2009 and onwards, "joint cracking" was removed from the OC category. Besides this anomaly, time series of the OC index is similar to that of the RF index. The lowest and highest average values are achieved in 2013 and 2008, respectively.

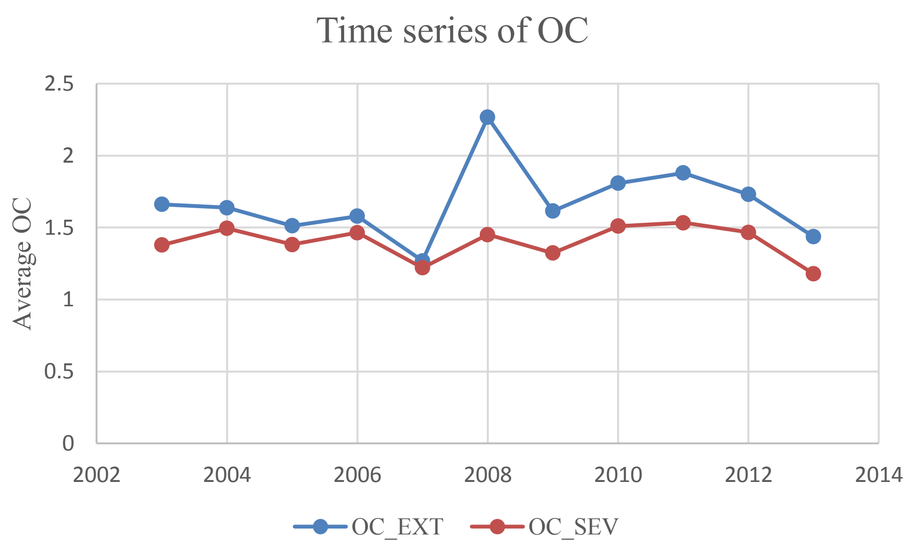


Figure 3-7 Time series of OC from 2003 to 2013

From Figure 3-8, the average extent and average severity of OS have similar trends during the 11 years. In Figure 3-8, the average extent and average severity of OS have a relatively small range between 0.22 and 0.63. The lowest and highest average values are achieved in 2003 and 2011, respectively. In Figure 3-9, the average appearance has wider range than OS which is from 0.45 to 1.33, the lowest and highest average values are also achieved in 2003 and 2011, respectively.

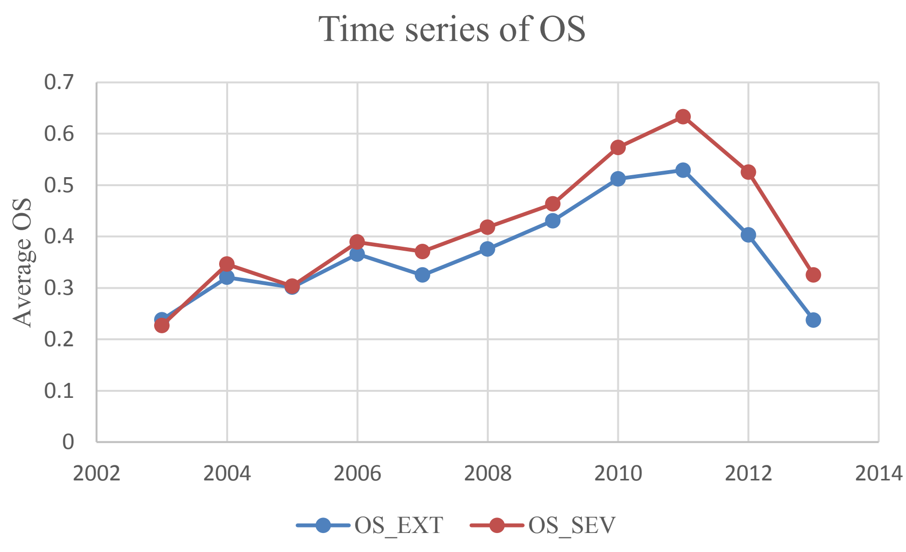


Figure 3-8 Time series of OS from 2003 to 2013

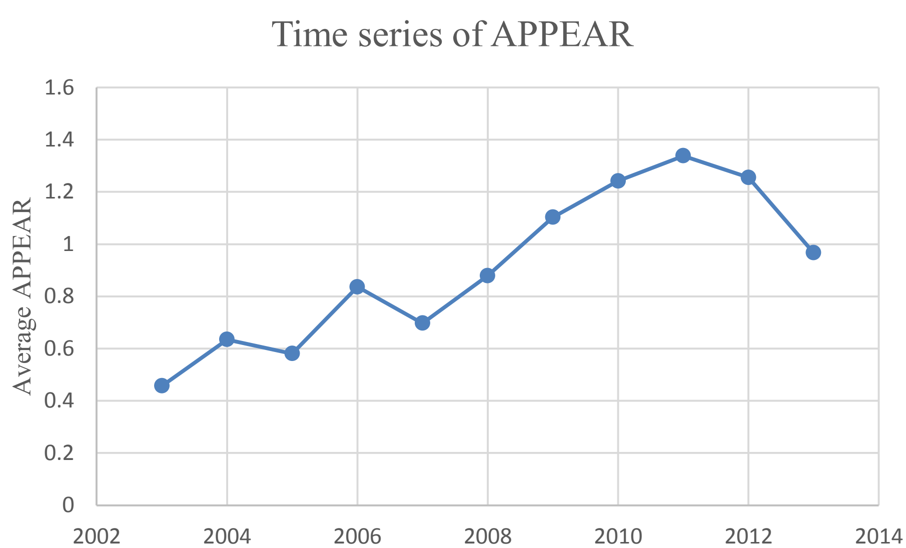


Figure 3-9 Time series of APPEAR from 2003 to 2013

To further compare the average extent and severity between RF, OC, and OS, we group all indices with respect to EXT into one Figure 3-10, and similar for all indices with respect to SEV into Figure 3-11From both figures, it can be estimated that some kind of rehabilitation or other treatment is done in years such as 2006 and 2011. Because after these years, the average EXT and SEV exhibit a decreasing trend for one or two years and then start to increase again until next cycle of rehabilitation.

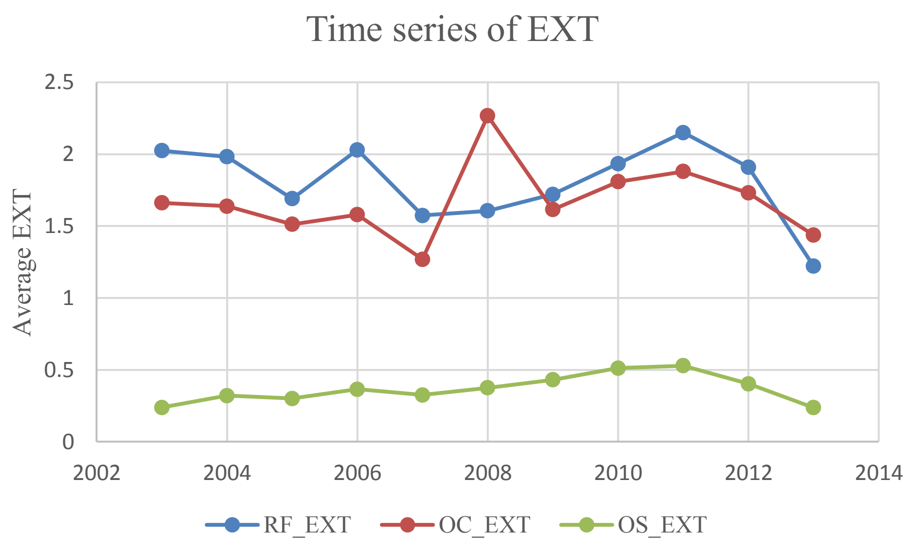


Figure 3-10 Time series of EXT from 2003 to 2013

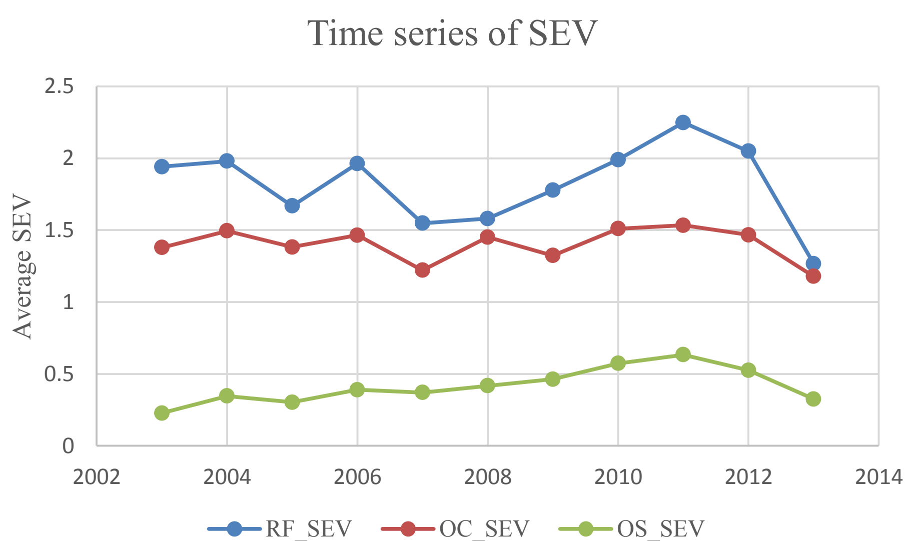


Figure 3-11 Time series of SEV from 2003 to 2013

3.2.2 Data Preprocessing

Since our raw data contains 58 columns (attributes) and 6,045 rows, we need a powerful data mange tool to help us processing this large amount of raw data. Visual Basic for Applications (VBA) allows user to define functions and write subroutines to automate much data processing, thus we choose VBA to perform all data processing.

As mentioned previously, an initial step in data processing would be to remove all data containing blank distress indices. We do this in two steps. First, if a road segment has blank values for all distress indices in a year other than 2009, then that particular sample point is deleted from the original database. Second, for a particular sample data with missing/blank indice(s) in 2009, the column of "EFF_YEAR" is incremented by 1. The latter is because the change of evaluation time from Fall to Spring starting 2010. In other words, Fall 2009's annual evaluation was moved to Spring 2010, and all evaluations were done in Spring thereafter.

When KYTC collected the pavement condition data, they evaluated road segments in fall before 2009 and they changed the evaluation to spring after 2009. Due to this reason, we detect that there are about 50% of blank cracking indices in 2009. In order to fix the problem, we considered that there is only on year different between 2008 and 2010 for cracking index, as did by Xu et al. (2014). For example, if one road segment has no cracking index in 2009 but has cracking index in year 2010, then we move the cracking index of year 2010 to 2009, and the cracking index of the year 2011 will be moved to 2010, and so on. If one road segment has cracking index in 2009, then no change will be made. After this step, we reduced the number of rows in our raw data from 5,148 to 4,586 (Xu et al., 2014).

In our data sets, each data sample (row) has several physical attributes assigned to it, such as year of evaluation, route ID, lane direction, evaluation start and end points, pavement type, etc. These types' physical attributes are very useful since it can help us to determine the same road segments with multiple years. For example, if we want to predict one specific road segment's pavement deterioration for the next year, then we have to find these road segments which have same route ID, lane direction, evaluation start and end points, with using the filter function of Microsoft Excel, we can easily access to these road segments.

Because we want to use the cracking indices of the current year to predict cracking index of the next year, we need at least two continuous years of cracking indices for each road segment. Hence, with applying same route ID, lane direction, start point and end point rules, we start to process our data. However, there is a phenomenon that many sample data points in the database have the same route ID, lane direction, but slightly different start point or end point from one year to another. Below is an example.

YEAR	ROUTE_ID	LANE_DIR	START_POINT	END_POINT
2011	I0024	L	13.8	16.073
2012	I0024	L	13.8	16.27

The two road segments evaluated in year 2011 and 2012 have the same rout ID, lane direction and end point, but the end points are slightly different. In order to handle this situation and include more sample data with multiple years, we slightly modify the START_POINT and END_POINT by rounding them to integers.

After the rounding step, we identify (modified) road segments that have multiple years of data, which will be valid sample points in our prediction model. More detailed information about this rounding procedure can be found in Xu et al. (2014). After this step, the data set reduces from 4586 to 4464.

3.2.3 Calculate pavement age

From a practical view point, pavement age is a very important factor in pavement's deterioration. However, in our raw data, "pavement age" is not readily available. Thus, we will need to derive or calculate the pavement age using information related to historical treatment projects done to a particular road segment. This is the same approach as in Xu et al. (2014). Particularly, in the original database, there is one column named "CONSTR_INFO" that contains the information of the most recent maintenance year and the type of rehabilitation. Thus, we use evaluation year minus the most recent maintenance for each sample data to get the age of the corresponding road segment.

In calculating the pavement age, ideally, if the rehabilitation was done, all distress indices and the pavement age for this specific road segment should be reset to 0. However, we found two types of data errors regarding to the calculation of the pavement age. The first type of errors involving road segments that have undergone rehabilitation but still have relatively high (poor) distress indices, and the second type involving road segments that have seen significantly improved (reduced) distress indices without any rehabilitation treatments.

In order to correct the first type of errors described above, we follow similar approach as in Xu et al. (2014) and simply reset all distress indices to zero for those have undergone major rehabilitation. In addition to that, we also deleted the road segments which do not have distress indices for the next year. This correction step has reduced our data sets from 4,644 to 3,788 (see also Xu et al., 2014)

Recall the second type of error occurs when a road segment shows a significantly reduced (improved) distress index for the next year without any rehabilitation treatment. For example, the raveling index RF_EXT was rated at 7 point last year, and this year's rating is down to 5 point without any treatment. Such inconsistency is mostly because different personnel gave more subjective rating scores in these two years. Hence, we simply remove this sample data point. After this step, our final sample data sets for raveling, other cracking, out of section and appearance have the following sizes, respectively.

- 3,043 (1,286 for AC) for RF_EXT;
- 3,023 (1,264 for AC) for RF_SEV;
- 2,925 (1,239 for AC) for OC_EXT;
- 3,000 (1,273 for AC) for OC_SEV;
- 3,152 (1,335 for AC) for OS_P_EXT;
- 3,130 (1,332 for AC) for OS_P_SEV;
- 3,150 (1,348 for AC) for APPEAR.

Once processed, the data to be used in our MLR and ANN prediction model contains the information as shown in Table 3-4. Then, our goal is to develop these prediction models to forecast the extent and severity of raveling, other cracking, out of section and appearance for next year. In other words, we will develop nine models to predict nine distress indices, i.e., WPC_E, WPC_S, R_E, R_S, OC_E, OC_S, OS_E, OS_S and APP, respectively. The input variables used include these nine distress variables, as well as pavement age, ADT and IRI (a total of 12 input variables).

Table 3-4 Part of final data set

ADT	WPC_EXT	WPC_SEV	RF_EXT	RF_SEV	OC_EXT	OC_SEV	OS_EXT	OS_SEV	APPEAR	AGE	IRI	RR_EXT (t+1)
12453	0	0	0	0	0	0	0	0	0	0	49.202	0
12453	0	0	0	0	0	0	0	0	0	1	57.014	1
12453	0	0	1	1	2	1	0	0	0.5	2	55.329	1
12453	4	3	1	1	5	2	0	0	1.5	3	57.974	2
12453	6	4	2	2	5	3	0	0	1.5	4	57.974	2
12453	8	7	3	3	5	4	0	0	1.5	8	95.631	4
12453	0	0	0	0	0	0	0	0	0	0	129.7	0
12453	0	0	0	0	0	0	0	0	0	1	58.71	0
12453	0	0	0	0	0	0	0	0	0	2	62.941	1
12453	0	0	1	1	0	0	0	0	0.5	3	61.126	2

Note: WPC_EXT = extent of wheel path cracking; WPC_SEV = severity of wheel path cracking; RF_EXT = extent of raveling; RF_SEV = severity of raveling;

OC_EXT = extent of other cracking; OC_SEV = severity of other cracking;

OS_EXT = extent of out of section; OS_SEV = severity of out of section;

APPEAR= appearance; IRI = international roughness index;

ADT = average daily traffic; AGE = pavement age;

RF_E (t+1) = extent of reveling for the next year

CHAPTER 4 THE MUTIPLE LINEAR REGRESSION AND ARTIFICIAL NEURAL NETWORKS PREDICTION MODELS

In this chapter, we discuss how to design of MLR and ANN models via SAS Enterprise Miner 12.1. First, we discuss the input variable selection and data mining strategy that will be adopted in building the models. Second, we introduce the basic concepts and principles for the working of the MLR model. Lastly, we will describe the concept and procedures of the ANN model.

4.1 Data Mining Strategies

As a general data mining strategy, the final data set will be separated into three groups: training data set, validation data set and test data set (see, e.g., McGuire and Witt, 2007). The training data set is used for preliminary model fitting, while the validation data set contains some "fresh" or unseen data to fine-tune model and is used to keep the model from over fitting. Finally, the test data set is a real test to evaluate how the developed model works on a set of "unseen" data. In our model, 50% of the input data were allocated to training, 25% was to validation and the rest 25% were allocated to testing. This is the same partition strategy used in Xu et al. (2014).

In addition to partition the final data, there is a unique problem associated with our pavement condition database. It is because the traffic indicator variable, "ADT" (i.e., average daily traffic), assumes values in a rather wide range between thousands and hundreds of thousands. In other words, these ADT values often are much larger than the remaining values for distress indices (mostly under 10). In order to stabilize variance, remove nonlinearity and have a better fit of our model, we follow the approach used in Xu et al. (2014) and use the “transform module” in SAS Enterprise 12.3 to transfer the ADT variable through LG10 method. After transformation, the new range of LG10_ADT is from 3.62 to 5.17.

4.2 MLR Model

In the two modeling approaches we used in this thesis, MLR is the most commonly used statistical techniques. Generally, MRL is a statistical technique that uses several variables to predict the outcome of a response variable. The goal MLR is to model the relationship between the input and target variables. As a result of the MLR model, one can obtain a predictive formula, understand the input variables, and the interactions between the input and response variables.

Figure 4-1 shows the development of a MLR model in SAS Enterprise 12.3 for our pavement distress index prediction. There are four steps in this development, and they are explained below.

- First, we put our final data sets into the “File Input” module, and then we decide the input variables to be used in the MLR model.
- Second, using the “StatExplore” module, we get statistical summary reports as discussed in Section 3.2.1.
- Third, the “Data Partition” module and the “Transform” module are used to separate the data and transfer variables as discussed in Section 4.1.

- Finally, in the regression module, we chose “Linear Regression” as the Regression type and we use the stepwise regression as our selection model. In SAS enterprise 12.3, the stepwise regression includes regression models in which the choice of predictive variables is carried out by an automatic procedure (SAS, 1989).

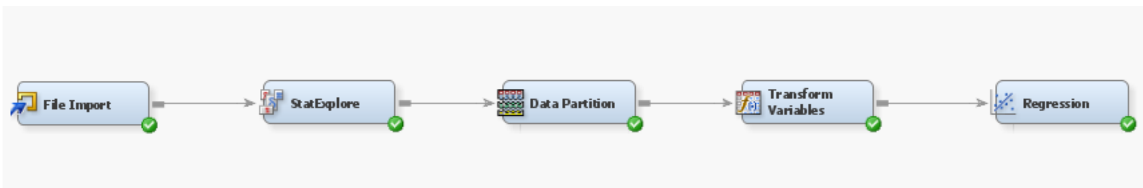


Figure 4-1 Multiple linear regression Model in SAS

4.3 ANN Model

An artificial neural network is a network based on the operation of biological neural networks (see, e.g., Attoh-Okine,1994). In general, is an emulation of biological neural system. Basically, an ANN process can be an a ANN an ANN model would relate a set of input factors and some output/target variables in a nonlinear fashion through a systematic neural network (see, e.g., Saltan and Terzi 2005).

Usually, there are three parts to consider in developing a neural network. They are architecture of the network, the training algorithm, and the neuron activation function.

4.3.1 The architecture of the ANN model

We use the “Neural Network” node in SAS Enterprise Miner 12.3 (SAS, 1998) to construct, train, and validate multilayer. In SAS, the “Neural Network” node by default constructs a network that has one hidden layer consisting of three neurons.

Figure 4-2 shows the artificial neural networks for the pavement distress prediction model. There are four steps in constructing an ANN model:

- First, we use the same procedures as in MLR model to partition and transfer our data.
- Second, the independent variables are organized into the input layer. Each independent variable point is a 'neuron' or 'processing element (PE)'.
- Third, the output layer is defined (e.g. RF_EXT_t+1, OC_SEV_t+1, etc.).
- Finally, hidden layers are established between the input and output layers.

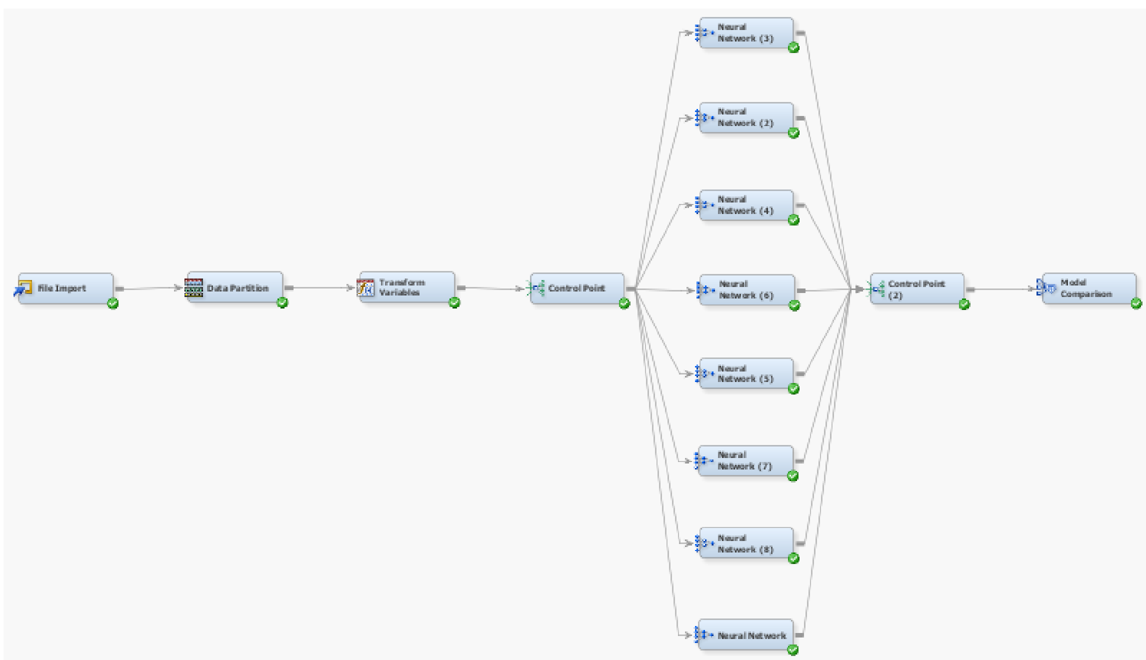


Figure 4-2 Artificial neural networks model in SAS

4.3.2 The training algorithm and neuron activation function of ANN model

After building the model, the neural network will be trained using the input data sets. In the training stage, the connection weights changes as a response to stimuli between the input layer and output layer. The result for each neuron in the hidden layer is computed by means of a transfer function, which is based on a step function or a sigmoid function (see, e.g., Bologna and Yvon, 2004). The activation function is commonly called the *dot*, or *inner*, product function. The transfer function we used in this thesis is the sigmoid function (see, e.g., Roberts and Attoh – Okine, 1988).

$$f(X,W) = y = \sum_{i=1}^{n} W_i x_i + W_0 \quad (dot\ product\ activation\ function)$$

$$g(y) = \frac{1}{1+e^{-y}} \qquad (sigmoid\ transfer\ function)$$

Similar to Xu et al. (2014), we adopted the "Error Back Propagation" method (see, e.g., Eldin and Senouci, 1995) to adjust the neurons' weights in the ANN modeling.

CHAPTER 5 A COMPOSITE PAVEMENT DISTRESS INDEX BASED ON ANALYTIC HIERARCHY PROCESS

In this chapter, we first introduce the AHP as a decision making tool; and this introduction is through the use of an example. Then we apply the AHP method to developing a composite distress index consisting of nine individual indices and a roughness index. Further, this AHP-based composite distress index is applied to a pilot set of 30 road segments, and its recommended priority for rehabilitation treatment is compared against the current rating system used by KYTC.

5.1 Introduction to AHP

The AHP is a structured technique for organizing and analyzing complex decisions, based on mathematics and psychology. In practice, AHP has been used by companies and organizations including Intel, Apple, NASA and Xerox (Forman and Gass, 2001) to make decisions on choice, prioritization, resource allocation, among others.

To illustrate the analytical hierarchy process, take an example where a person makes a decision on buying a car. The decision maker (DM) has identified price, practicality and appearance as his criteria to choose a car between three alternatives Chevrolet, Toyota, and Porsche. However the DM has not decided the weights for the three criteria in choosing a car. Figure 5-1 illustrates the hierarchy in this decision making. In this hierarchical process, the top level goal is to choose a car. The medium level includes three criteria of price, practicality and appearance, while the bottom level consists of three alternative car models under consideration.

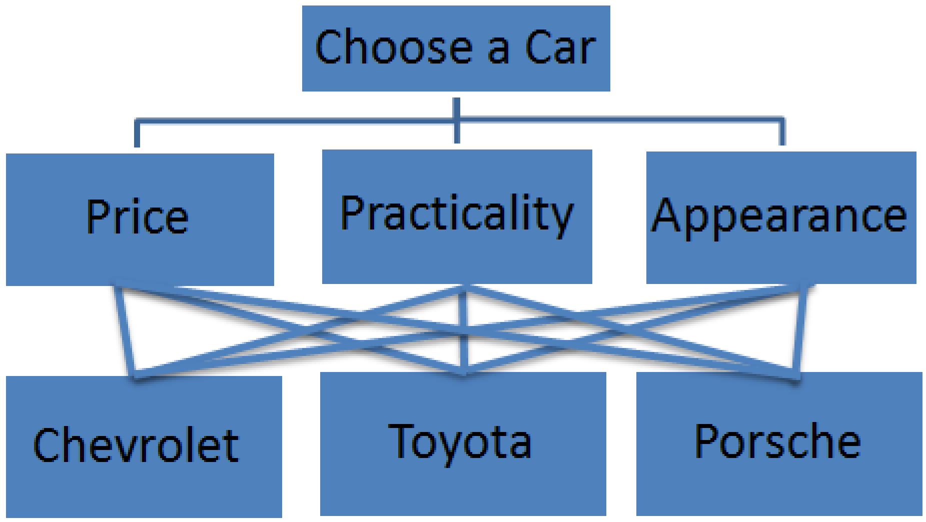


Figure 5-1 AHP for Choosing a Car

In the AHP method, the decision maker would consider 3*(3-1)/2=4 different pairs of criteria and assign relative importance to each other. Based on the scale reference in Table 5-1, the DM would develop a relative importance among three criteria. Suppose the car buyer comes up with relative importance as shown in Table 5-2. For example, the DM considers that "price" is three times as important as "practicality", and thus assigns a score of 3:1 as in the first row of Table 5-2.

Table 5-1 Reference Scale for Pairwise Comparison

Intensity of importance	Definition
1	"factor A" and "factor B" are equally important
3	"factor A" is moderately favor than "factor B"
5	"factor A" over that of "factor B" is strongly favor
7	"factor A" over that of "factor B" is very strongly favor

9	“factor A” over that of “factor B” is of the highest possible order
2,4,6,8	Ratings are between two adjacent judgments

Table 5-2 pairwise comparison for relative importance

Price	3	Practicality	1
Price	8	Appearance	1
Appearance	1	Practicality	5

After the decision maker assigns the score to all three pairs, he or she will create a matrix as in Table 5-3. For example, again the relative importance of 3:1 for “price” over “practicality” is reflected in the price-practicality cell with a value of 3, and the practicality-price cell with a value of 1/3.

Table 5-3 A Sample Scoring Matrix

	Price	Practical	Appearance
Price	1	3	8
Practicality	1/3	1	5
Appearance	1/8	1/5	1

Using this matrix, one would then calculate the priority weights for the three criteria through the computation of eigenvalues and right eigenvectors. The final weights assigned to price, practicality, and appearance, corresponding to Table 5-3, is 0.6611, 0.2717, and 0.067, respectively.

Similar to procedure to decide the final weights for the three criteria, now we do pairwise comparison for each criterion for each alternative. Suppose the scoring matrices for price, practicality and appearance for three alternative car models are as displayed in Tables 5-4 through 5-6.

Table 5-4 A Scoring Matrix Based on Price

Price	Chevrolet	Toyota	Porsche
Chevrolet	1	2	9
Toyota	1/2	1	8
Porsche	1/9	1/8	1

Table 5-5 A Scoring Matrix Based on Practicality

Practicality	Chevrolet	Toyota	Porsche
Chevrolet	1	1	9
Toyota	1	1	9
Porsche	1/9	1/9	1

Table 5-6 A Scoring Matrix Based on Appearance

Appearance	Chevrolet	Toyota	Porsche
Chevrolet	1	1/2	1/9
Toyota	2	1	1/8

Porsche	9	8	1

Using these three matrices, we calculate the weights for all three alternatives based on each criterion as follows.

- The priorities with respect to price for Chevrolet, Toyota, and Porsche are 0.5891, 0.3568, and 0.054, respectively.
- The priorities with respect to practicality for Chevrolet, Toyota, and Porsche are 0.4736, 0.4736, and 0.0526, respectively.
- The priorities with respect to appearance for Chevrolet, Toyota, and Porsche are 0.0737, 0.1218, and 0.8044, respectively.

Now that we know the priority weights of the criteria with respect to the goal, and the priority weights of the alternatives with respect to each criterion, we calculate the priorities of the alternatives with respect to the goal. We show the calculations for the alternatives with respect to each criterion in Table 5-7.

Table 5-7 Priorities w.r.t. Each Criterion

Criterion	Priority vs. Goal	Alternative	A	B	C
		Chevrolet	0.5891	0.6611	0.3895
Price	0.6611	Toyota	0.3568	0.6611	0.2359
		Porsche	0.0548	0.6611	0.0362
		Chevrolet	0.4736	0.2717	0.1287
Practicality	0.2717	Toyota	0.4736	0.2717	0.1287
		Porsche	0.0526	0.2717	0.0143
		Chevrolet	0.0737	0.067	0.0049

Appearance	0.067	Toyota	0.1218	0.067	0.0082
		Porsche	0.8044	0.067	0.0539

Note: Column "A" shows the priority weight of a particular alternative with respect to a criterion. Column "B" shows the priority weight of this criterion with respect to the goal. Column C shows the product of the two, which is the global priority of the particular alternative with respect to the goal.

Finally, we get the priority weights for three alternatives with respect to the goal, Chevrolet, with a priority of 0.5231, is the most suitable Car. Toyota, with a priority of 0.3727, is the second ranked choice, and Porsche, at 0.1044, is the third ranked choice.

Table 5-8 Final Priorities w.r.t. the Goal

Alternatives	Price	Practicality	Appearance	goal
Chevrolet	0.3895	0.1287	0.0049	0.5231
Toyota	0.2359	0.1287	0.0082	0.3727
Porsche	0.0362	0.0143	0.0539	0.1044
Total	0.6616	0.2716	0.0670	1.0002

5.2 Current Rating Method for the Pavement Management and Preservation System

In the current PMP projects rating system for interstate and parkways, the scale points for all nine distress indices along with the scale point for international roughness index (IRI) are simply added together. In other words, each road to be considered for treatment receives a total score calculated as follows:

$$\text{Toral score} = \text{WPC\_EXT} + \text{WPC\_SEV} + \text{RF\_EXT} + \text{RF\_SEV} + \text{OC\_ECT} + \text{OC\_SEV} + \text{OS\_EXT} + \text{OS\_SEV} + \text{APPEAR} + \text{JS} + \text{SIRI}, \quad (5.1)$$

where SIRI represents the scale point for IRI based on Table 5-4 shows below:

Table 5-9 Scale Point Conversion for IRI

IRI	Points	IRI	Points	IRI	Points
<=53	0	94-96	13	135-138	26
54-57	1	97-99	14	139-141	27
58-61	2	100-102	15	142-144	28
62-64	3	103-106	16	145-148	29
65-67	4	107-109	17	149-151	30
68-70	5	110-112	18	152-154	31
71-74	6	113-115	19	155-157	32
75-77	7	116-118	20	158-160	33
78-80	8	119-122	21	161-163	34
81-83	9	123-125	22	164-167	35
84-86	10	126-128	23	168-170	36
87-90	11	129-131	24	171-173	37
91-93	12	132-134	25	>=175	38

For example, if one road segment has the rating scores in all 11 categories as shown in Table 5-9, then its final rating is calculated as 6+7+4+3+5+2+2+2+8=39, where the final scale point of “8” corresponding to IRI is obtained from Table 5-9 based the IRI value of 78.

WPC _EXT	WPC _SEV	RF_E XT	RF_S EV	OC_E XT	OC_S EV	OS_ EXT	OS_ SEV	APPE AR	J S	IRI
6	7	4	3	5	2	0	0	2	2	78

Compared with other road segments, if this road segment has higher score than others, then it will have higher priority to receive treatment.

5.3 A Composite Pavement Distress Index using AHP

In the current PMP projects rating system at KYTC, the experts of KYTC have concerns that the IRI (or adjusted IRI in the case of non-interstate/parkways) receives too much weight in the overall score when recent studies suggest that the impact of roughness index on pavement life may not be significant. To this end, we propose to develop a new and rather objective method of reconciling various indices using AHP.

Similar to the car buying example presented previously, our goal for this new method is to decide the weights for WPC_EXT, WPC_SEV, RF_EXT, RF_SEV, OC_EXT, OC_SEV, OS_EXT, OS_SEV, APPEAR, JS and (adjusted)IRI in prioritizing PMP projects. Thus, in the AHP there are 11 criteria and 55 pairwise comparisons.

For each pairwise comparison, the experts will assign relative importance weights between the two indices involved. For example, suppose the KYTC expert or DM considers the relative importance of WPC_EXT over RF_EXT. If he/she thinks WPC_EXT is more important than RF_EXT, then he/she should give point "1" to RF_EXT. Then, he/she will use the fundamental scales in Table 5-1 to assign a relative importance to WPC_EXT over RF_EXT. Suppose, the decision maker thinks WPC_EXT has a strong importance over RF_EXT, he/she will assign an score of "5".

WPC_EXT	5	RF_EXT	1

Table 5-10 Ranking for 30 road segments by using current rating system

	WPC_EXT	WPC_SEV	RF_EXT	RF_SEV	OC_EXT	OC_SEV	OS_EXT	OS_SEV	APPEAR	IRI	JS
WPC_EXT	1		5								
WPC_SEV		1									

RF_EXT	1/5		1								
RF_SEV				1							
OC_EXT					1						
OC_SEV						1					
OS_EXT							1				
OS_SEV								1			
APPEAR									1		
IRI										1	
JS											1

Upon obtaining Table 5-10, we then calculate the total score for each road segment under consideration. To do so, we first modify all individual distress indices by adding "1" in order to avoid the use of a scale point of "0". Secondly, recall that the ten distress criteria have various ranges. In particular, modified WPC_EXT and WPC_SEV are in the range of [1, 10], RF_EXT, RF_SEV, OC_EXT, OC_SEV and JS are in the range of [1, 6], OS_EXT, OS_SEV, and APPEAR are in the range of [1, 4]. Hence, we normalize the range of all cracking indices to 0 to 1 using the function below.

$$Normalized(e_i) = \frac{e_1 - E_{MIN}}{E_{MAX} - E_{MIN}} \qquad (5.2)$$

Where: e_i = *distress index;* E_{min} = *the minimum value for the distress index;* E_{max} = *the maximum value for the distress index.*

For example, in one specific road segment, WPC_EXT = 7, $E_{min} = 0$, and $E_{max} = 9$. After we modify the cracking index by adding "1", the modified index and minimum and maximum values are WPC_EXT = 8, $E_{min} = 1$, and $E_{max} = 10$. Then we use equation (5.2) to normalize them as $Normalized(WPC\_EXT) = \frac{8-1}{10-1} = 0.7778$. Other distress indices and IRI will be processed similarly. Once the normalized scores are obtained for all indices, the final priority score for a road segment is calculated as the sum of 11 products between priority weight, obtained by calculating the eigenvalue and eigenvectors of the matrix in Table 5-10, and the respective normalized score.

As we mentioned in the example of current rating system, compared with other road segments, if a road segment has a higher priority score than others, then it should be considered more highly for receiving treatments.

CHAPTER 6 RESULTS AND DISCUSSIONS

In this chapter, we report the results from the MLR model and the ANN model using the processed data sets obtained from Chapter 3. Both models are developed using SAS Enterprise Miner 12.1 (SAS, 1998). In addition, we present the results on comparing the current PMP rating method and the proposed AHP-based composite index method through a case study containing 30 pilot roads.

6.1 Model Summary

For the MLR model, the following scenarios of using various sets of input variables are done for each distress index to be predicted.

- Scenario 1. There are a total of 12 input variables, i.e., ADT, age, IRI, APPEAR, WPC_EXT, WPC_SEV, RF_EXT, RF_SEV, OC_EXT, OC_SEV, OS_EXT, and OS_SEV.
- Scenario 2. A subset of the entire 12 input variables is used based on recommendations from KYTC experts. For each distress index to be predicted, KYTC expert would recommend a set of input variables that they think would affect the deterioration of the concerned index. Compared to Scenario 1, this scenario intends to have simplified model with fewer input variables. For each distress index, we will identify in the following section the select input variables suggested by KYTC experts. All models derived under Scenario 2 are referred to as "Select" models subsequently.

- Scenario 3. Only use the target variable from the previous year as input variable to predict this variable in next year. For example, under this scenario, we would predict the severity of "Other Cracking" (or OC_SEV) for next year using OC_SEV for this year as the only input variable.
- Scenario 4. Only use the pavement age as input variable to predict any distress index for next year

Note that among the four experimental scenarios, scenario 1 is intended to be inclusive and comprehensive, but may produce a complex prediction model that is impractical to implement in real life. Scenarios 3 and 4 are intended to be simple, but may produce high prediction errors. Scenario 2 is a compromise case that is likely to produce fairly accurate prediction using reasonably simple models.

Furthermore, in the first two scenarios we apply linear, 2nd order polynomial and 3rd order polynomial MLR models. For the other two scenarios, we only use the 3rd order polynomial model due to the fact that there is only one input variable. In evaluating the results of developed models, we use the average squared error (ASE) of training, validation and testing data sets as well as the R square value.

In the ANN model, we will only use the select variables (i.e., those selected in Scenario 2) as the input variables. In our "Neural Network" module in SAS (SAS, 1998), we chose the "Multilayer Perceptron" as the architecture of the ANN. In building the neural network, we built the network by varying the number of hidden units from one to eight in the hidden layer and kept the other parameters the same. In evaluating our model, we used ASEs of the training, validation and testing data sets.

6.2 Results of RF_EXT

6.2.1 MLR Models

The results from eight different models are displayed in Table 6-1. In particular, models "Polynomial 3", "Polynomial 2" and "Linear" all belong to Scenario 1 using all 12 input variables. Models "Polynomial SLCT 3" and "Polynomial SLCT 2" and "Linear SLCT" all belong to Scenario 2, in which experts from KYTC has identified Age, RF_EXT, RF_SEV, WPC_EXT, and WPC_SEV to be the five input variables. Finally, "RF_EXT 3" and "Age_3" represent Scenarios 3 and 4, respectively.

It can be observed that except the model "Age_3", all other seven models can achieve R^2 values around 0.86 and relatively low ASE. Among the above eight models, we can see that the "Linear" model with all 12 input variables achieves a relatively low ASE of approximately 0.3258 and a high R2 value of 0.8636. Furthermore, it has only four variables in the predictive function. Hence, the "Linear" model with all 12 input variables is chosen to be the best fit MLR model for RF_EXT. The regression function of each model can be found below Table 6-1.

Table 6-1 Linear Regression Models for RF_EXT

Scenarios	Model	ASE Training	ASE Validation	ASE Testing	ASE Average	R Square
S 1	Polynomial 3	0.2838	0.3178	0.3322	0.3112	0.8749
	Polynomial 2	0.3114	0.3343	0.3608	0.3355	0.8703
	Linear	0.3104	0.3386	0.3285	0.3258	0.8636
S 2	Polynomial SLCT 3	0.2844	0.3185	0.3319	0.3116	0.8746
	Polynomial SLCT 2	0.2970	0.3227	0.3423	0.3206	0.8691
	Linear SLCT	0.3104	0.3386	0.3288	0.3259	0.8632
S 3	RF_EXT 3	0.3302	0.3511	0.3449	0.3421	0.8544
S 4	Age 3	0.8446	0.8166	0.9281	0.8631	0.6277

Polynomial 3:
$x_1: age, x_2: RF\_EXT, x_3: RF\_SEV, x_4: appearance, x_5: WPC\_EXT$
$RF\_EXT\_(t+1) = -0.0162 + 0.2091x_1 + 0.6328x_2 - 0.0151x_1^2 + 0.0267x_1x_3 + 0.00228x_4x_5^2 + 0.000265x_1^3x_3 - 0.00283x_1x_3^2$

Polynomial 2:
$x_1: age, x_2: RF\_EXT, x_3: CUR\_IRI, x_4: LG10\_ADT, x_5: RF\_SEV, x_6: WPC\_EXT$
$RF\_EXT\_(t+1) = 0.351 + 0.0719x_1 + 0.744x_2 - 0.00186x_1^2 - 0.00079x_3x_4 + 0.00166x_3x_5 + 0.00172x_4x_6 - 0.0194x_2x_6$

Linear: $x_1: age, x_2: RF\_EXT, x_3: RF\_SEV, x_4: WPC\_EXT$
$RF\_EXT\_(t+1) = 0.3436 + 0.0257x_1 + 0.7064x_2 + 0.1216\mathrm{x}_3 + 0.0358x_4$

RF_EXT 3: $x_1: RF\_EXT$
$RF\_EXT\_(t+1) = 0.3868 + 1.1035x_1 - 0.0388x_1^2$

Age 3: $x_1: age$
$RF\_EXT\_(t+1) = -0.3761 + 0.4846x_1 - 0.019x_1^2 + 0.000236x_1^3$

Polynomial SLCT 3: $x_1: age, x_2: RF\_EXT, x_3: RF\_SEV, x_4: WPC\_EXT$
$RF\_EXT\_(t+1) = -0.0188 + 0.1988x_1 + 0.7084x_2 - 0.0138x_1^2 + 0.0129x_1x_3 - 0.0208x_2x_4 + 0.00971x_4^2 + 0.000247x_1^3$

Polynomial SLCT 2: $x_1: age, x_2: RF\_EXT, x_3: RF\_SEV, x_4: WPC\_EXT$
$RF\_EXT\_(t+1) = 0.1870 + 0.07449x_1 + 0.7743x_2 + 0.077x_3 - 0.00247x_1^2 + 0.00714x_1x_3 - 0.021x_2x_4$

Linear SLCT:$x_1: age, x_2: RF\_EXT, x_3: RF\_SEV, x_4: WPC\_EXT$
$RF\_EXT\_(t+1) = 0.3436 + 0.0262x_1 + 0.7044x_2 + 0.12x_3 + 0.0371x_4$

6.2.2 ANN Models

The results from ANN models are displayed in Table 6-2. From Table 6-2, we see that when the number of hidden units is less than four, the average ASEs are relatively high. For example, when the number of hidden units is three, the average ASE is 0.3171. When the number of hidden units increases to four, the average ASE reduces to 0.3074. However, when the number of hidden units is larger than four, the ASEs remain stable.

Although five to eight hidden units also produce comparably quality results, the structure with four hidden units is finally selected in light of the greater generalization power associated with fewer hidden neurons.

Table 6-2 Evaluation of number of hidden units in ANN for RF_EXT

# of Hidden Units	Training ASE	Validation ASE	Testing ASE	Average ASE
1	0.3057	0.3335	0.3287	0.3226
2	0.2906	0.3163	0.3237	0.3102
3	0.2891	0.3193	0.3429	0.3171
4	0.2760	0.3191	0.3272	0.3074
5	0.2681	0.3239	0.3280	0.3067
6	0.2651	0.3190	0.3466	0.3102
7	0.2622	0.3123	0.3231	0.2992
8	0.2514	0.3187	0.3570	0.3090

When we compare the two best models (using MLR and ANN techniques respectively) in Table 6-3, we observe that the ANN with four hidden neurons has smaller training, validation and testing ASEs of 0.2760, 0.3191 and 0.3272, respectively. Thus the average ASE of 0.3074 for the "ANN_4" model is slightly more advantageous than the "Linear" regression model.

Table 6-3 Comparison of MLR and ANN Models for RF_EXT

Model	ASE_Training	ASE_Validation	ASE_Testing	ASE_Average
Linear	0.3104	0.3386	0.3285	0.3258
ANN_4	0.2760	0.3191	0.3272	0.3074

6.3 Results on RF_SEV

6.3.1 MLR Models

The results from eight different models are displayed in Table 6-4. In particular, models "Polynomial 3", "Polynomial 2" and "Linear" all belong to Scenario 1 using all 12 input variables. Models "Polynomial SLCT 3" and "Polynomial SLCT 2" and "Linear SLCT" all belong to Scenario 2, in which experts from KYTC has identified Age, RF_EXT, RF_SEV, WPC_EXT, and WPC_SEV to be the five input variables. Finally, "RF_SEV 3" and "Age_3" represent Scenarios 3 and 4, respectively.

Similar to the RF_EXT models, except the model "Age_3", all other seven models can achieve promising R^2 values around 0.82 and relatively low ASE. Within thesis models, the "Linear" model with 12 input variables archive the R^2 value at 0.822 and average ASE at 0.3531. Due to the simplicity of the variables in the predictive function, "Linear" model with 12 input variables is chosen to be the best fit model for predicting RF_SEV. The regression function of each model can be found below Table 6-4.

Table 6-4 Linear Regression Models for RF_SEV

Scenarios	Model	ASE Training	ASE Validation	ASE Testing	ASE Average	R Square
S 1	Polynomial 3	0.3985	0.3726	0.3143	0.3618	0.8307
	Polynomial 2	0.3797	0.3543	0.3070	0.3470	0.827
	Linear	0.3910	0.3597	0.3085	0.3531	0.822
S 2	Polynomial SLCT 3	0.3717	0.3456	0.2936	0.3370	0.8322
	Polynomial SLCT 2	0.3801	0.3543	0.3017	0.3454	0.8284
	Linear SLCT	0.3909	0.3600	0.3077	0.3529	0.8235
S 3	RF_SEV 3	0.4222	0.3919	0.3102	0.3747	0.8094
S 4	Age 3	0.9382	0.9230	0.8500	0.9037	0.5764

Polynomial 3:
$x_1: RF\_EXT, x_2: RF\_SEV, x_3: age, x_4: LG10\_ADT, x_5: WPC\_EXT, x_6: OC\_SEV, x_7: CUR\_IRI$
$x_8: OC\_EXT$
$RF\_SEV\_(t+1) = 0.2271 + 0.1857x_1 + 0.5621x_2 + 0.0263x_1x_4 - 0.0011x_1^2x_4 + 0.000351x_1^2x_5 - 0.00122x_1x_6x_5 + 0.000225x_7x_4x_8$

Polynomial 2:
$x_1: R\_F\_EXT, x_2: R\_F\_SEV, x_3: WPC\_EXT, x_4: age, x_5: LG10\_ADT$
$RF_{SEV_{t+1}} = 0.3057 + 0.2102x_1 + 0.5478x_2 + 0.045x_3 - 0.00181x_4^2 + 0.0167x_4x_5$

Linear: $x_1: age, x_2: RF\_EXT, x_3: RF\_SEV, x_4: WPC\_EXT$
$RF\_SEV\_(t+1) = 0.4331 + 0.0207x_1 + 0.2442x_2 + 0.5657\mathrm{x}_3 + 0.0459x_4$

RF_EXT 3: $x_1: RF\_SEV$
$RF\_SEV\_(t+1) = 0.4709 + 1.0975x_1 - 0.042x_1^2$

Age 3: $x_1: age$
$RF\_SEV\_(t+1) = -0.2208 + 0.4443x_1 - 0.017x_1^2 + 0.000206x_1^3$

Polynomial SLCT 3: $x_1: age, x_2: RF\_EXT, x_3: RF\_SEV, x_4: WPC\_EXT$
$RF\_EXT\_(t+1) = 0.0983 + 0.174x_1 + 0.1934x_2 + 0.5752x_3 - 0.0105x_1^2 + 0.000151x_1^3 + 0.000209x_1^2x_4$

Polynomial SLCT 2: $x_1: age, x_2: RF\_EXT, x_3: RF\_SEV, x_4: WPC\_EXT$
$RF\_SEV\_(t+1) = 0.2708 + 0.0775x_1 + 0.1995x_2 + 0.5716x_3 + 0.0389x_4 - 0.00219x_1^2$

Linear SLCT: $x_1: age, x_2: RF\_EXT, x_3: RF\_SEV, x_4: WPC\_EXT$

$RF\_SEV\_(t+1) = 0.4269 + 0.0215x_1 + 0.2395x_2 + 0.5695x_3 + 0.045x_4$

6.3.2 ANN Models

It can be observed from Table 6-5 that, when the number of hidden units increases to two, the average ASE archives at 0.3329 which is even better than the result of 0.3350 with four hidden units. Hence, the structure with 2 hidden units is selected due to the fewer hidden neurons and smaller average ASE.

Table 6-5 Evaluation of number of hidden units in ANN for RF_SEV

# of Hidden Units	Training ASE	Validation ASE	Testing ASE	Average ASE
1	0.3885	0.3518	0.3041	0.3481
2	0.3702	0.3282	0.3003	0.3329
3	0.3715	0.3493	0.3148	0.3452
4	0.3581	0.3376	0.3094	0.3350
5	0.3487	0.3413	0.3118	0.3339
6	0.3371	0.3404	0.3073	0.3282
7	0.3357	0.3478	0.3101	0.3312
8	0.3355	0.3297	0.2987	0.3213

When we compare the two best models (using MLR and ANN techniques respectively) in Table 6-6, the result shows that the "ANN_2" model with five selected variables has smaller average ASE of 0.3329, respectively. Thus the "ANN_2" model is slightly more advantageous than the "Linear" regression model.

Table 6-6 Comparison of MLR and ANN Models for RF_SEV

Model	ASE_Training	ASE_Validation	ASE_Testing	ASE_Average
Linear	0.3910	0.3597	0.3085	0.3531
ANN_2	0.3702	0.3282	0.3003	0.3329

6.4 Results on OC_EXT

6.4.1 MLR Models

The results from eight different models are displayed in Table 6-7. In particular, models "Polynomial 3", "Polynomial 2" and "Linear" all belong to Scenario 1 using all 12 input variables. Models "Polynomial SLCT 3" and "Polynomial SLCT 2" and "Linear SLCT" all belong to Scenario 2, in which experts from KYTC has identified OC_EXT, OC_SEV, and Age to be the three input variables. Finally, "OC_EXT 3" and "Age_3" represent Scenarios 3 and 4, respectively.

Like we mentioned previously, the smallest R^2 value archived at the "Age 3" model. In the "linear" model with all 12 input variables, the R^2 value reaches at 0.8199 and has average ASE of 0.4880. In order to make our model simpler, the linear model is considered to be the best fit model for OC_EXT. The regression function of each model can be found below Table 6-7.

Table 6-7 Linear Regression Models for OC_EXT

Scenarios	Model	ASE Training	ASE Validation	ASE Testing	ASE Average	R Square
S 1	Polynomial 3	0.4702	0.4446	0.5579	0.4909	0.8231
	Polynomial 2	0.4654	0.4344	0.5389	0.4796	0.8247
	Linear	0.4788	0.4405	0.5446	0.4880	0.8199
S 2	Polynomial SLCT 3	0.4703	0.4318	0.5425	0.4815	0.8261
	Polynomial SLCT 2	0.4703	0.4318	0.5425	0.4815	0.8261
	Linear SLCT	0.4841	0.4357	0.5407	0.4868	0.8210
S 3	OC_EXT 3	0.4858	0.4368	0.5539	0.4921	0.8204
S 4	Age 3	1.5257	1.6065	1.6041	1.5788	0.4359

Polynomial 3:
$x_1: OC\_EXT, x_2: LG10\_ADT, x_3: WPC\_EXT, x_4: WPC\_SEV, x_5: OC\_SEV$
$OC\_EXT\_(t+1) = 0.3395 + 1.0067x_1 + 0.0147x_2x_3 - 0.00789x_1^2x_4 + 0.00278x_4^2x_5$

Polynomial 2: $x_1: age, x_2: OC\_EXT, x_3: LG10\_ADT, x_4: WPC\_EXT$
$OC\_EXT\_(t+1) = 0.17 + 0.0536x_1 + 0.93x_2 - 0.00166x_1^2 - 0.0176x_3x_4 - 0.0169x_2x_4$

Linear: $x_1: age, x_2: OC\_EXT, x_3: WPC\_EXT$
$OC\_EXT\_(t+1) = 0.3156 + 0.0178x_1 + 0.8588x_2 + 0.0575$

RF_EXT 3: $x_1: OC\_EXT$
$OC\_EXT\_(t+1) = 0.3621 + 1.2235x_1 - 0.0571x_1^2$

Age 3: $x_1: age$
$OC\_EXT\_(t+1) = -0.0686 + 0.2607x_1 - 0.0002x_1^3$

Polynomial SLCT 3: $x_1: age, x_2: OC\_EXT$

$$OC\_EXT\_(t+1) = 0.1545 + 0.0659x_1 + 1.0596x_2 - 0.002x_1^2 - 0.0341\mathrm{x}_2^2$$

Polynomial SLCT 3: x_1: age, x_2: OC_EXT
$$OC\_EXT\_(t+1) = 0.1545 + 0.0659x_1 + 1.0596x_2 - 0.002x_1^2 - 0.0341\mathrm{x}_2^2$$

Linear SLCT:x_1: age, x_2: OC_EXT, x_3: OC_SEV
$$OC\_EXT\_(t+1) = 0.3174 + 0.0207x_1 + 0.8622x_2 + 0.1105x_3$$

6.4.2 ANN Models

From Table 6-8, we observe that when the number of hidden units increases, the average ASE does not have to reduce gradually in this case. For example, the model with 2 hidden units gets the smallest average ASE at 0.4657. To be compared, when the numbers of hidden units increase to four and eight, the average ASE also increases to 0.4706 and 0.4766. In this case, the model with two hidden units is considered to be the best due to the smallest average ASE value.

Table 6-8 Evaluation of number of hidden units in ANN for OC_EXT

# of Hidden Units	Training ASE	Validation ASE	Testing ASE	Average ASE
1	0.4783	0.4306	0.5375	0.4821
2	0.4625	0.4192	0.5153	0.4657
3	0.4585	0.4304	0.5443	0.4777
4	0.4497	0.4443	0.5177	0.4706
5	0.4419	0.4613	0.5419	0.4817
6	0.4351	0.4507	0.5418	0.4759
7	0.4322	0.4472	0.5497	0.4764
8	0.4356	0.4503	0.5440	0.4766

At the end, when we compare the two best models (using MLR and ANN techniques respectively) in Table 6-9, we observe that the “ANN_2” has smaller training, validation and testing ASE of 0.4625, 0.4192 and 0.5153, respectively. Compared with

"Linear" model, the "ANN_2" model has a smaller average ASE of approximately 0.4657.

Table 6-9 Comparison of MLR and ANN Models for OC_EXT

Model	ASE_Training	ASE_Validation	ASE_Testing	ASE_Average
Linear	0.4788	0.4405	0.5446	0.4880
ANN_2	0.4625	0.4192	0.5153	0.4657

6.5 Results on OC_SEV

6.5.1 MLR Models

The results from eight different models are displayed in Table 6-10. In particular, models "Polynomial 3", "Polynomial 2" and "Linear" all belong to Scenario 1 using all 12 input variables. Models "Polynomial SLCT 3" and "Polynomial SLCT 2" and "Linear SLCT" all belong to Scenario 2, in which experts from KYTC has identified OC_EXT, OC_SEV, and Age to be the three input variables. Finally, "OC_SEV 3" and "Age_3" represent Scenarios 3 and 4, respectively.

Table 6-10 indicates that the "Polynomial 3" model has the highest value of R^2, and the smallest average ASE is obtained from "Polynomial SLCT 3" model. Within right models, "Linear" model with 12 variables is chosen to be the best fit model for OC_SEV due to the fewer variables in the final function and relatively high R^2 value. The regression function of each model can be found below Table 6-10.

Table 6-10 Linear Regression Models for OC_SEV

Scenarios	Model	ASE Training	ASE Validation	ASE Testing	ASE Average	R Square
S 1	Polynomial 3	0.3202	0.3464	0.3095	0.3253	0.8243

	Polynomial 2	0.3223	0.3437	0.3261	0.3307	0.8229
	Linear	0.2928	0.3239	0.3162	0.3110	0.8175
S 2	Polynomial SLCT 3	0.2845	0.3133	0.3109	0.3029	0.8216
	Polynomial SLCT 2	0.2897	0.3188	0.3162	0.3082	0.8183
	Linear SLCT	0.2959	0.3302	0.3194	0.3151	0.8145
S 3	OC_SEV 3	0.3165	0.3343	0.3399	0.3302	0.8015
S 4	Age 3	0.7885	0.7697	0.8085	0.7889	0.5055

Polynomial 3:
$x_1: OC\_EXT, x_2: OC\_SEV, x_3: WPC\_SEV, x_4: CUR\_IRI, x_5: RF\_SEV, x_6: LG10\_ADT$,
$x_8: OS\_EXT, x_9: OS\_SEV$
$OC\_SEV\_(t+1) = 0.2052 + 0.1332x_1 + 0.6575x_2 + 0.1015x_3 + 0.00185x_4x_5 - 0.00576x_3x_5x_6 - 0.0138x_1x_3x_8 + 0.0218x_2^2x_9$

Polynomial 2:
$x_1: OC\_EXT, x_2: OC\_SEV, x_3: WPC\_EXT, x_4: CUR\_IRI, x_5: RF\_SEV, x_6: LG10\_ADT$,
$OC\_SEV\_(t+1) = 0.2054 + 0.1208x_1 + 0.6593x_2 + 0.0992x_3 - 0.00248x_2x_4 + 0.00244x_4x_5 + 0.0612x_2^2 - 0.0283x_3x_5$

Linear: $x_1: age, x_2: OC\_EXT, x_3: OC\_SEV, x_4: RF\_SEV$
$OC\_SEV\_(t+1) = 0.2037 + 0.0162x_1 + 0.1186x_2 + 0.7265\mathrm{x}_3 + 0.0621x_4$

OC_EXT 3: $x_1: OC\_SEV$
$OC\_SEV\_(t+1) = 0.3385 + 0.9803x_1$

Age 3: $x_1: age$
$OC\_SEV\_(t+1) = -0.1642 + 0.2653x_1 - 0.00567x_1^2$

Polynomial SLCT 3: $x_1: age, x_2: OC\_EXT, x_3: OC\_SEV$
$OC\_EXT\_(t+1) = -0.007 + 0.1277x_1 + 0.0641x_2 + 0.6775x_3 - 0.00762x_1^2 + 0.0329x_2x_3 + 0.000138x_1^3$

Polynomial SLCT 2: $x_1: age, x_2: OC\_EXT, x_3: OC\_SEV$
$OC\_SEV\_(t+1) = 0.0989 + 0.0637x_1 + 0.1119x_2 + 0.7444x_3 - 0.00177x_1^2$

Linear SLCT: $x_1: age, x_2: OC\_EXT, x_3: OC\_SEV$
$OC\_SEV\_(t+1) = 0.2128 + 0.0247x_1 + 0.1214x_2 + 0.7567x_3$

6.5.2 ANN Models

The results from ANN model are displayed in Table 6-11. It can be observed that the smallest average ASE 0.2907 is obtained in the model with 8 hidden units. However, the model which has only 2 hidden units also archives relatively low average ASE at 0.3040. Considering the huge differences between the numbers of hidden units between the two models, the structure with 2 hidden units is finally selected to be the best fit model.

Table 6-11 Evaluation of number of hidden units in ANN for OC_SEV

# of Hidden Units	Training ASE	Validation ASE	Testing ASE	Average ASE
1	0.2967	0.3314	0.3202	0.3161
2	0.2825	0.3171	0.3124	0.3040
3	0.2778	0.3263	0.3159	0.3067
4	0.2759	0.3359	0.3244	0.3120
5	0.2770	0.3210	0.3142	0.3041
6	0.2721	0.3325	0.3173	0.3073
7	0.2748	0.3285	0.3133	0.3056
8	0.2547	0.3061	0.3112	0.2907

When we compare the two best models (using MLR and ANN techniques respectively) in Table 6-12, that the ASES of “ANN_2” model are all have smaller values than the “Linear” model, while the “ANN_2” model with two hidden neurons can achieve a smaller training ASE at 0.3040. A higher average ASE is achieved by the “Linear” model at 0.3110.

Table 6-12 Comparison of MLR and ANN Models for OC_SEV

Model	ASE_Training	ASE_Validation	ASE_Testing	ASE_Average
Linear	0.2928	0.3239	0.3162	0.3110
ANN_2	0.2825	0.3171	0.3124	0.3040

6.6 Results on OS_EXT

6.6.1 MLR Models

The results from eight different models are displayed in Table 6-13. In particular, models "Polynomial 3", "Polynomial 2" and "Linear" all belong to Scenario 1 using all 12 input variables. Models "Polynomial SLCT 3" and "Polynomial SLCT 2" and "Linear SLCT" all belong to Scenario 2, in which experts from KYTC has identified OS_EXT, OS_SEV, WPC_EXT, RF_EXT, Age, IRI to be the six input variables. Finally, "OS_EXT 3" and "Age_3" represent Scenarios 3 and 4, respectively.

From Table 6-13, it can be observed that except the "Polynomial 3" model, all the other seven models have the R^2 values smaller than 0.8. Hence, the "Polynomial 3" model is chosen to be the best fit model for OS_EXT due to the highest R^2 values. Regression function of each model can be found below Table 6-13.

Table 6-13 Linear Regression Models for OS_EXT

Scenarios	Model	ASE Training	ASE Validation	ASE Testing	ASE Average	R Square
S 1	Polynomial 3	0.0476	0.1382	0.1083	0.0980	0.8392
	Polynomial 2	0.0665	0.1148	0.0884	0.0899	0.7740
	Linear	0.0698	0.1097	0.0886	0.0894	0.7601
S 2	Polynomial SLCT 3	0.0669	0.1204	0.0855	0.0909	0.7728
	Polynomial SLCT 2	0.0691	0.1160	0.0871	0.0907	0.7653
	Linear SLCT	0.0705	0.1128	0.0858	0.0897	0.7577
S 3	OC_SEV 3	0.0742	0.1167	0.0875	0.0928	0.7451
S 4	Age 3	0.2509	0.3451	0.2806	0.2922	0.1386

Polynomial 3:
$x_1: OC\_SEV, x_2: OS\_EXT, x_3: appearance, x_4: LG10\_ADT, x_5: OC\_EXT, x_6: WPC\_SEV,$
$x_7: OS\_SEV$

$OS\_EXT\_(t+1) = -0.0751 + 0.0794x_1 + 0.9372x_2 + 0.0297x_3x_4 - 0.2177x_1x_3 + 0.051x_5x_6 - 0.0252x_3^2x_5 + 0.0857x_3^2x_1 - 0.051x_3^2x_7$

Polynomial 2:
$x_1: OS\_EXT, x_2: age, x_3: OS\_SEV, x_4: CUR\_IRI, x_5: WPC\_EXT, x_6: LG10\_ADT, x_7: OC\_EXT$
$OS\_EXT\_(t+1) = -0.1401 + 1.1779x_1 - 0.00679x_2x_3 - 0.00334x_1x_4 + 0.000795x_4x_5 + 0.0109x_5^2 - 0.00193x_5x_6 + 0.0569x_3x_7$

Linear: $x_1: LG10\_ADT, x_2: OS\_EXT, x_3: WPC\_SEV$
$OS\_EXT\_(t+1) = 0.2269 + 0.0634x_1 + 0.96x_2 + 0.03096\mathrm{x}_3$

RF_EXT 3: $x_1: OS\_EXT$
$OS\_EXT\_(t+1) = 0.0856 + 1.0337x_1$

Age 3: $x_1: age$
$OS\_EXT\_(t+1) = 0.0196 + 0.034x_1$

Polynomial SLCT 3: $x_1: OS\_EXT, x_2: CUR\_IRI, x_3: WPC\_EXT$
$OS\_EXT\_(t+1) = 0.0564 + 1.2884x_1 - 0{,}00409x_1x_2 - 0.0084x_3^2 + 0.000148x_2x_3^2$

Polynomial SLCT 2: $x_1: OS\_EXT, x_2: age, x_3: WPC\_EXT, x_4: CUR\_IRI$
$OS\_EXT\_(t+1) = 0.0321 + 0.9768x_1 - 0.00097x_2x_3 + 0.000512x_3x_4$

Linear SLCT:$x_1: OS\_EXT, x_2: WPC\_EXT$
$OS\_EXT\_(t+1) = 0.0339 + 0.9789x_1 + 0.0242x_2$

6.6.2 ANN Models

From Table 6-14, we can observe that the models with two and five hidden unites give us the two relatively high average ASE, 0.0858 and 0.0853. To make our model simpler, the model with two hidden units is selected.

Table 6-14 Evaluation of number of hidden units in ANN for OS_EXT

# of Hidden Units	Training ASE	Validation ASE	Testing ASE	Average ASE
1	0.0729	0.1064	0.0877	0.0890
2	0.0636	0.1129	0.0810	0.0858
3	0.0658	0.1140	0.0890	0.0896
4	0.0592	0.1328	0.0802	0.0907
5	0.0602	0.1118	0.0840	0.0853
6	0.0597	0.1220	0.0907	0.0908
7	0.0554	0.1234	0.0851	0.0880

8	0.0549	0.1453	0.0916	0.0973

From Table 6-15, we can observe that the "ANN_2" model with 2 hidden neurons has smaller training, validation and testing ASE of 0.0636, 0.1129 and 0.0810, respectively. The average ASE of "ANN_2" is slightly smaller than that of the "Polynomial 3" model.

Table 6-15 Comparison of MLR and ANN Models for OS_EXT

Model	ASE_Training	ASE_Validation	ASE_Testing	ASE_Average
Polynomial 3	0.0476	0.1382	0.1083	0.0980
ANN_2	0.0636	0.1129	0.0810	0.0858

6.7 Results on OS_SEV

6.7.1 MLR Models

The results from eight different models are displayed in Table 6-16. In particular, models "Polynomial 3", "Polynomial 2" and "Linear" all belong to Scenario 1 using all 12 input variables. Models "Polynomial SLCT 3" and "Polynomial SLCT 2" and "Linear SLCT" all belong to Scenario 2, in which experts from KYTC has identified OS_EXT, OS_SEV, WPC_EXT, RF_EXT, Age, IRI to be the six input variables. Finally, "OS_SEV 3" and "Age_3" represent Scenarios 3 and 4, respectively.

In Table 6-16, similar to the OS_EXT MLR models, the "Polynomial 3" model gets the highest R^2 value at 0.7648, all other seven models have the R^2 values smaller than 0.72. Hence, the "Polynomial 3" model is chosen to be the best fit model for OS_SEV due to the highest R^2 values. The regression function of each model can be found below Table 6-16.

Table 6-16 Linear Regression Models for OS_SEV

Scenarios	Model	ASE Training	ASE Validation	ASE Testing	ASE Average	R Square
S 1	Polynomial 3	0.0971	0.1900	0.1712	0.1528	0.7648
	Polynomial 2	0.1229	0.1674	0.1472	0.1458	0.7015
	Linear	0.1256	0.1624	0.1410	0.1430	0.6934
S 2	Polynomial SLCT 3	0.1184	0.1697	0.1426	0.1436	0.7127
	Polynomial SLCT 2	0.1252	0.1642	0.1428	0.1441	0.6946
	Linear SLCT	0.1288	0.1626	0.1396	0.1437	0.6858
S 3	OS_SEV 3	0.1369	0.1645	0.1428	0.1481	0.6656
S 4	Age 3	0.3484	0.3989	0.3591	0.3688	0.1490

Polynomial 3:
$x_1: OS\_SEV, x_2: WPC\_SEV, x_3: age, x_4: appearance, x_5: OC\_SEV, x_6: WPC\_EXT,$
$x_7: CUR\_IRI, \mathrm{x}_8: OS\_EXT, x_9: RF\_EXT, x_{10}: LG10\_ADT, x_{11}: WPC\_SEV$
$OS\_SEV\_(t+1) = -0.00473 + 0.615x_1 + 0.1332x_2 + 0.0317x_3x_4 - 0.3157x_4x_5 + 0.0307x_1x_3 + x_4^2x_6 - 0.00103x_3^2x_4 - 0.00796x_3x_4x_6 - 0.00254x_4x_7x_8 + 0.000826x_4x_6x_7 + 0.0595x_4x_5^2 + 0.0014x_2^2x_3 - 0.00000518x_7^2x_9 + 0.0104\mathrm{x}_5x_{10}^2 + 0.0227x_8x_{10}^2 - 0.0103x_6x_9x_{10} - 0.00585x_6x_{10}x_{11} - 0.0134x_5x_9x_{11} - 0.00615x_1x_{11}^2 + 0.0119x_6^2x_9 - 0.00182x_6^3$

Polynomial 2:
$x_1: OS\_SEV, x_2: WPC\_SEV, x_3: appearance, x_4: CUR\_IRI, x_5: age, x_6: RF\_SEV,$
$x_7: LG10\_ADT\mathrm{x}_8: OS\_EXT$
$OS\_SEV\_(t+1) = 0.0394 + 0.7397x_1 + 0.0351x_2 + 0.00138x_3x_4 - 0.00269x_5x_6 + 0.1042x_7x_8 - 0.3443x_1x_8 + 0.1784x_1^2$

Linear: $x_1: appearance, x_2: OS\_EXT, x_3: OS\_SEV, x_4: RF\_SEV, x_5: WPC\_SEV$
$OC\_SEV\_(t+1) = 0.0458 + 0.12x_1 + 0.1639x_2 + 0.8182\mathrm{x}_3 - 0.0367x_4 + 0.0349x_5$

OS_SEV 3: $x_1: OS\_SEV$
$OS\_SEV\_(t+1) = 0.1145 + 1.2699x_1 - 0.1104x_1^2$

Age 3: $x_1: age$
$OS\_SEV\_(t+1) = -0.1279 + 0.1237x_1 - 0.00719x_1^2 + 0.00015x_1^3$

Polynomial SLCT 3:
$x_1: OS\_SEV, x_2: WPC\_SEV, x_3: age, x_4: CUR\_IRI, x_5: OS\_EXT, x_6: RF\_SEV$
$OS\_SEV\_(t+1) = 0.0303 + 1.5502x_1 + 0.0905x_2 - 0.0105x_2x_3 - 0.00574x_4x_5 + 1.2659\mathrm{x}_5^2 - 1.3842x_1x_5 + 0.000096x_2x_3x_4 - 0.3331x_5^3 + 0.3928x_5^2x_1 - 0.0256x_2x_5x_6 + 0.0159x_1x_2x_6$

Polynomial SLCT 2: x_1: OS_SEV, x_2: WPC_SEV, x_3: age, x_4: OS_EXT
$OS\_SEV\_(t+1) = 0.0368 + 1.14037x_1 + 0.0755x_2 - 0.00254x_2x_3 + 0.1162x_4^2 - 0.225x_1x_4$

Linear SLCT: x_1: OS_EXT, x_2: OS_SEV, x_3: WPC_SEV
$OS\_SEV\_(t+1) = 0.0482 + 0.1563x_1 + 0.8544x_2 + 0.0444x_3$

6.7.2 ANN Models

The results from ANN models are displayed in Table 6-17. It can be observed that, the model with 2 hidden units gives us the smallest average ASE at 0.1431. Hence, among these models, we chose the model with 2 hidden units to be our best fit model.

Table 6-17 Evaluation of number of hidden units in ANN for OS_SEV

# of Hidden Units	Training ASE	Validation ASE	Testing ASE	Average ASE
1	0.1286	0.1655	0.1426	0.1456
2	0.1234	0.1678	0.1381	0.1431
3	0.1214	0.1699	0.1383	0.1432
4	0.1179	0.1751	0.1499	0.1477
5	0.1120	0.1726	0.1566	0.1471
6	0.1149	0.1736	0.1500	0.1462
7	0.1131	0.1745	0.1472	0.1449
8	0.1085	0.1782	0.1556	0.1474

From Table 6-18, we can observe that the “Polynomial 3” model has smaller training ASE at 0.0971, but the higher validation and testing ASE at 0.1900, and 0.1712, respectively. In comparing the average ASE, the “ANN_2” model can achieve a smaller average ASE at 0.1431.

Table 6-18 Comparison of MLR and ANN Models for OS_SEV

Model	ASE_Training	ASE_Validation	ASE_Testing	ASE_Average
Polynomial 3	0.0971	0.1900	0.1712	0.1528
ANN_2	0.1234	0.1678	0.1381	0.1431

6.8 Results on APPEAR

6.8.1 MLR Models

The results from eight different models are displayed in Table 6-19. In particular, models "Polynomial 3", "Polynomial 2" and "Linear" all belong to Scenario 1 using all 12 input variables. Models "Polynomial SLCT 3" and "Polynomial SLCT 2" and "Linear SLCT" all belong to Scenario 2, in which experts from KYTC has identified APPEAR, age, WPC_EXT to be the three input variables. Finally, "APPEAR 3" and "Age_3" represent Scenarios 3 and 4, respectively.

From Table 6-19, it can be observed that the "Polynomial 3" model achieve the highest R^2 value at 0.8281 and the smallest average ASE is obtained in the "Polynomial 2" model. Among all eight models, the "Linear" model has relative high R^2 value and small average ASE, and it has only three variables in the predictive function. Hence, the linear model is chosen to be the best fit model for APPEAR. The regression function of each model can be found below Table 6-19.

Table 6-19 Linear Regression Models for APPEAR

Scenarios	Model	ASE Training	ASE Validation	ASE Testing	ASE Average	R Square
S 1	Polynomial 3	0.1163	0.1384	0.1226	0.1258	0.8281
	Polynomial 2	0.1184	0.1248	0.1147	0.1193	0.8249
	Linear	0.1256	0.1240	0.1173	0.1223	0.8102
S 2	Polynomial SLCT 3	0.1191	0.1196	0.1145	0.1178	0.8191
	Polynomial SLCT 2	0.1216	0.1259	0.1112	0.1195	0.8155
	Linear SLCT	0.1256	0.1240	0.1172	0.1223	0.8093
S 3	OS_SEV 3	0.3489	0.3636	0.3074	0.3400	0.4704
S 4	Age 3	0.1308	0.1310	0.1192	0.1270	0.8014

Polynomial 3:
x_1: $appearance, x_2: OC\_EXT, x_3: OS\_EXT, x_4: CUR\_IRI, x_5: OS\_SEV, x_6: RF\_EXT,$
$x_7: RF\_SEV, \mathrm{x}_8: LG10\_ADT, x_9: WPC\_EXT$
$APPEAR\_(t+1) = 0.1939 + 0.8238x_1 + 0.0329x_2 + 0.219x_3 - 0.00082x_1^2x_4 +$
$0.0436x_1x_5x_6 + 0.000012x_4^2x_7 + 0.000248x_4x_8x_9 - 0.00063x_3x_4x_9 -$
$0.00019x_4x_6x_9 + 0.0323x_3x_5x_7$

Polynomial 2:
$x_1: appearance, x_2: CUR\_IRI, x_3: OS\_SEV, x_4: WPC\_EXT, x_5: OC\_EXT, x_6: LG10\_ADT,$
$x_7: RF\_SEV\mathrm{x}_8: OC\_SEV$
$APPEAR\_(t+1) = 0.1809 + 0.7508x_1 - 0.00446x_2x_3 + 0.00123x_2x_4 +$
$0.0109x_5x_6 + 0.0908x_3x_6 + 0.0186x_6x_7 - 0.0108x_4x_8 - 0.0151x_4x_7$

Linear: $x_1: appearance, x_2: age, x_3: WPC\_EXT$
$APPEAR\_(t+1) = 0.2191 + 0.8479x_1 + 0.00932x_2 + 0.035\mathrm{x}_3$

RF_EXT 3: $x_1: appearance$
$APPEAR\_(t+1) = 0.2432 + 1.1664x_1 - 0.0844x_1^2$

Age 3: $x_1: age$
$APPEAR\_(t+1) = 0.0231 + 0.1703x_1 - 0.00389x_1^2$

Polynomial SLCT 3: $x_1: appearance, x_2: age, x_3: WPC\_EXT$
$APPEAR\_(t+1) = 0.0768 + 0.8370x_1 + 0.0499x_2 + 0.1207x_3 - 0.00158x_2^2 -$
$0.0138x_2x_3 + 0.000426x_2^2x_3$

Polynomial SLCT 2: $x_1: appearance, x_2: age, x_3: WPC\_EXT$
$APPEAR\_(t+1) = 0.1432 + 0.8368x_1 + 0.0228x_2 + 0.0784x_3 - 0.00438x_2x_3$

Linear SLCT: $x_1: appearance, x_2: age, x_3: WPC\_EXT$
$APPEAR\_(t+1) = 0.2184 + 0.8511x_1 + 0.00935x_2 + 0.0342x_3$

6.8.2 ANN Models

From Table 6-20, it can be observed that when the number of hidden units is less than four, the model with 2 hidden units gives us the smallest average ASE at 0.1146. However, when the number of hidden units keeps increasing, the ASEs get comparably quality results. Hence, the structure with 2 hidden units is finally selected.

Table 6-20 Evaluation of number of hidden units in ANN for APPEAR

# of Hidden Units	Training ASE	Validation ASE	Testing ASE	Average ASE
1	0.1245	0.1244	0.1176	0.1222
2	0.1184	0.1184	0.1069	0.1146
3	0.1178	0.1214	0.1097	0.1163
4	0.1150	0.1200	0.1101	0.1150
5	0.1122	0.1209	0.1115	0.1149
6	0.1109	0.1183	0.1121	0.1138
7	0.1126	0.1179	0.1140	0.1148
8	0.1121	0.1151	0.1066	0.1113

When we compare the two best models (using MLR and ANN techniques respectively) in Table 6-21, we can observe that the "ANN_2" model has smaller training, validation and testing ASE of 0.1184, 0.1184 and 0.1069, respectively. The average ASE archive at 0.1146 of "ANN_2" model which is slightly better than the "Linear" model.

Table 6-21 Comparison of MLR and ANN Models for APPEAR

Model	ASE_Training	ASE_Validation	ASE_Testing	ASE_Average
Linear	0.1256	0.1240	0.1173	0.1223
ANN_2	0.1184	0.1184	0.1069	0.1146

6.9 Results for the AHP-based Priority Rating Method

In order to evaluate the proposed AHP-based PMP projects rating method, we conduct a pilot study using a subset of 30 road segments to compare the recommendations from the current rating system and those from the proposed rating system using AHP. We randomly selected 30 road segments from the 2010 pavement condition database that need some level of treatment.

Based on inputs from KYTC experts, the final relative importance scoring matrix is compiled as shown in Table 6-22.

Table 6-22 Relative Importance among 11 Criteria for Pavement Distress Evaluation

	WPC _EXT	WPC_ SEV	RF_E XT	RF_S EV	OC_E XT	OC_S EV	OS_E XT	OS_S EV	APPE AR	IRI	JS
WPC_E XT	1	1/3	3	3	1	1/3	5	3	5	1/2	1
WPC_S EV	3	1	5	4	5	2	7	5	7	2	3
RF_EX T	1/3	1/5	1	1	1/5	1/5	1	1/3	2	1/3	1
RF_SE V	1/3	1/4	1	1	2/3	1/3	4	2	2	1	1
OC_EX T	1	1/5	5	3/2	1	1/3	4	2	3	1	1
OC_SE V	3	1/2	5	3	3	1	5	3	4	2	2
OS_EX T	1/5	1/7	1	1/4	1/4	1/5	1	1/3	1	1/4	1/3
OS_SE V	1/3	1/5	3	1/2	1/2	1/3	3	1	3	1/2	1/3
APPEA R	1/5	1/7	1/2	1/2	1/3	1/4	1	1/3	1	1/8	1/3
IRI	2	1/2	3	1	1	1/2	4	2	8	1	3
JS	1	1/3	1	1	1	1/2	3	3	3	1/3	1

After calculating the principal right eigenvector of the above matrix using MATLAB, the priority weights for WPC_EXT, WPC_SEV, RF_EXT, RF_SEV, OC_EXT, OC_SEV, OS_EXT, OS_SEV, APPEAR, JS and (adjusted)IRI are determined to be 0.0995, 0.2423, 0.0376, 0.0646, 0.0894, 0.1710, 0.0244, 0.0521, 0.0242, 0.0745 and 0.1204, respectively. Also, we get the consistency index (CI) of 0.0725 and consistency ratio (CR) of 0.0482. The latter is less than the acceptable value of 0.1, which implies that the comparison matrix and the so obtained priority weights are valid.

Table 6-23 displays the information for all 11 individual distress indices for the 30 roads, as well as the total score obtained by KYTC's current rating system. The 30 roads are arranged in descending order with respect to the total score, i.e., the road with highest priority for treatment is listed on the top. Table 6-24 contains similar information as does Table 6-23, except the last column "total score" is calculated by the proposed new rating method.

Table 6-23 Ranking for 30 road segments by using current rating system

Road #	WPC_E	WPC_S	RF_E	RF_S	OC_E	OC_S	OS_E	OS_S	APPEAR	JS	IRI	Total Score
4	9	9	4	4	5	4	0.5	1	3	0	85.442	49.5
16	4	6	4	4	3	3	0	0	2	4	107.111	47
15	8	7	4	4	2	3	1.5	1.5	2.5	2	72.54	41.5
5	8	6	4	4	5	2	0	0	2	0	74.989	38
6	8	7	4	3	5	2	0	0	2	0	74.021	37
14	6	5	4	4	3	4	1.5	1	2.5	3	64.355	37
26	7	4	3	2	4	2	1	1	2	1	85.144	37
7	6	8	2	2	4	3	1	1	1.5	0	80.442	36.5
29	7	5	4	3	2	3	0	0	2	2	75.578	35
17	7	7	2	2	4	2	1	1.5	2	0	69.702	33.5
13	6	4	4	4	3	2	0	0	2	3	68.606	33
3	7	4	4	4	5	1	0	0	1.5	0	69.54	31.5
27	6	5	4	5	3	2	0.5	0.5	2	1	57.011	30
9	6	4	2	2	2	1	1	0.5	2.5	5	60.772	28
25	4	3	4	3	3	2	0	0	1	2	70.552	27
20	3	3	2	2	3	2	0	0	1.5	2	80.62	26.5
30	5	4	3	3	2	3	0.5	0.5	2	2	53.003	25
28	6	4	1	1	3	1	0	0	1	1	69.845	23
21	2	2	2	2	1	1	0.5	0.5	1.5	4	68.105	21.5

23	3	2	2	2	1	1	0	0	1	1	79.319	21
8	3	2	3	3	1	2	0.5	0.5	1	1	61.048	19
18	3	3	2	1	3	1	1	1.5	1.5	0	58.957	19
24	3	1	1	1	1	1	0	0	1.5	1	79.629	18.5
1	2	2	2	2	1	1	0	0	0.5	2	67.528	17.5
11	6	4	1	1	1	1	0.5	1	0.5	1	39.202	17
19	5	2	1	1	1	1	0	0	1	1	52.798	13
10	5	3	1	1	0	0	0	0	1	1	41.2	12
2	3	2	2	1	1	1	0	0	0.5	0	57.475	11.5
22	4	2	0	0	0	0	0	0	0.5	1	67.045	11.5
12	7	0.5	0	0	0	0	0	0	1	1	34.16	9.5

Table 6-24 Ranking for 30 road segments by using composite cracking distress index

Road #	WPC_E	WPC_S	RF_E	RF_S	OC_E	OC_S	OS_E	OS_S	APPEAR	JS	IRI	Total Score
4	10	10	5	5	6	5	1.5	2	4	1	85.442	0.8432
15	9	8	5	5	3	4	2.5	2.5	3.5	3	72.54	0.7128
14	7	6	5	5	4	5	2.5	2	3.5	4	64.355	0.6721
7	7	9	3	3	5	4	2	2	2.5	1	80.442	0.6521
16	5	7	5	5	4	4	1	1	3	5	107.111	0.6509
6	9	8	5	4	6	3	1	1	3	1	74.021	0.6021
17	8	8	3	3	5	3	2	2.5	3	1	69.702	0.5996
5	9	7	5	5	6	3	1	1	3	1	74.989	0.5881
29	8	6	5	4	3	4	1	1	3	3	75.578	0.5524
26	8	5	4	3	5	3	2	2	3	2	85.144	0.5464
27	7	6	5	6	4	3	1.5	1.5	3	2	57.011	0.5191
13	7	5	5	5	4	3	1	1	3	4	68.606	0.5011
30	6	5	4	4	3	4	1.5	1.5	3	3	53.003	0.4743
3	8	5	5	5	6	2	1	1	2.5	1	69.54	0.4603
9	7	5	3	3	3	2	2	1.5	3.5	6	60.772	0.4512
25	5	4	5	4	4	3	1	1	2	3	70.552	0.4099
20	4	4	3	3	4	3	1	1	2.5	3	80.62	0.3854
28	7	5	2	2	4	2	1	1	2	2	69.845	0.3540
18	4	4	3	2	4	2	2	2.5	2.5	1	58.957	0.3325

8	4	3	4	4	2	3	1.5	1.5	2	2	61.048	0.3169
11	7	5	2	2	2	2	1.5	2	1.5	2	39.202	0.3057
21	3	3	3	3	2	2	1.5	1.5	2.5	5	68.105	0.2988
23	4	3	3	3	2	2	1	1	2	2	79.319	0.2565
1	3	3	3	3	2	2	1	1	1.5	3	67.528	0.2329
19	6	3	2	2	2	2	1	1	2	2	52.798	0.2189
24	4	2	2	2	2	2	1	1	2.5	2	79.629	0.2110
2	4	3	3	2	2	2	1	1	1.5	1	57.475	0.1878
10	6	4	2	2	1	1	1	1	2	2	41.2	0.1676
22	5	3	1	1	1	1	1	1	1.5	2	67.045	0.1404
12	8	1.5	1	1	1	1	1	1	2	2	34.16	0.0908

From Table 6-23 and Table 6-24, we can see that the top ten road segments (road #4, #5, #6, #7, #14, #15, #16, #17, #26, and #29) are exactly the same by both methods, and the only different is the ranking order. This difference is mainly caused by the emphasis given to IRI by the current method. For example, in Table 6-23 compared to road #16, road #14 is more distressed in almost all categories except for a significantly lower IRI score. As a result, it is only ranked No. 6 while #16 is ranked No. 2 overall. In contrast, the AHP-based rating method successfully addresses this overemphasis on IRI, giving road #14 a rank of No. 3 and road #16 a rank of No. 6. This indicates that AHP provides a more objective weight than the current rating system. Similarly observations can be made between roads #17 and #26, in which case road #26 have relatively high IRI thus receiving a higher ranking. Thus, we conclude that the AHP-based rating method overcomes the problem overemphasizing IRI among all distress indices.

To further illustrate the relationship between IRI and the ranking order from both rating methods, we create two plots as in Figures 6-1 and 6-2. From Figure 6-1, the blue plots show an increase trend within several subgroups of road segments, particularly among those with “priority score” of 1 through 4, and among those with “priority score” of 5 through 7. This indicates that the current rating method tends to give high priority scores to roads with high IRI values, and confirms the concern of KYTC.

In addition, our previous observations in Tables 6-22 and 6-23 regarding roads #14 and #16 are depicted in the four points in A_1, A_2, B_1 and B_2 in this figure. A_1, A_2 show that road #16 receives a high priority score of 9 under the current rating method, but a modest score of 6 under the proposed AHP-base rating method. On the other hand, B_1 and B_2 represent that road #14 receive a score of 5 and 8 under the current and new methods, respectively.

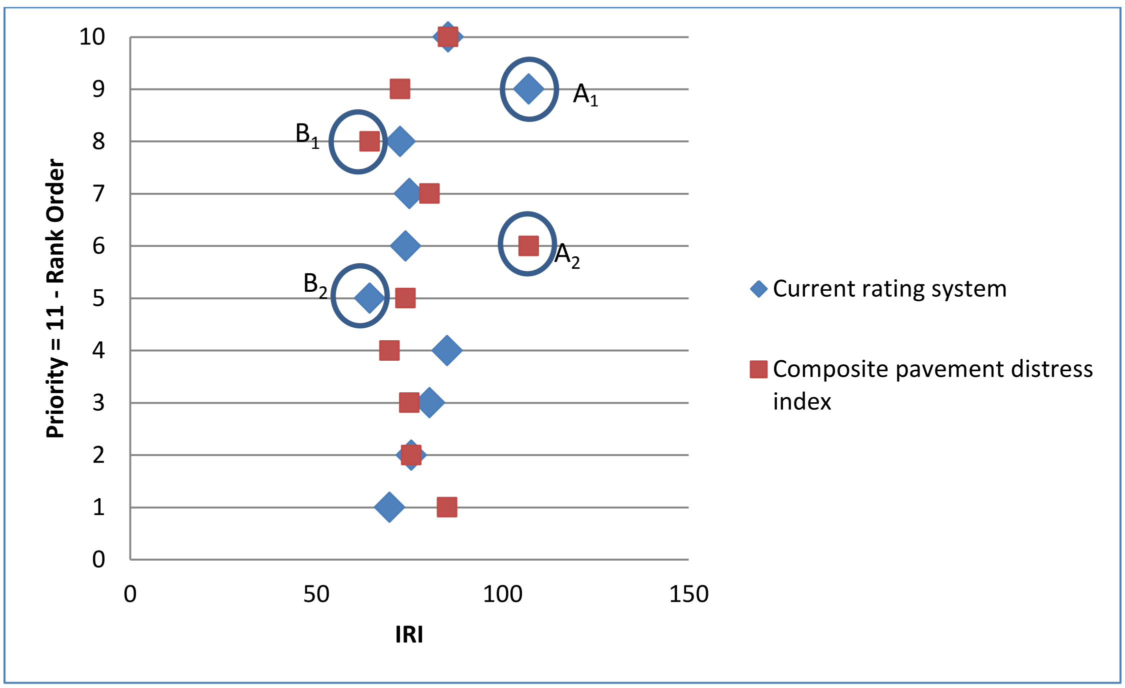


Figure 6-1 Ranking and IRI Plot for top 10 road segments

Finally, Figure 6-2 plots the priority score and IRI for the all the 30 pilot road segments. It can be observed that between a pair of two roads receiving the same high priority score (15 or higher), the points in the blue series tend to be on the right of those in the red series indicating that current rating method tend to select a road with high IRI values.

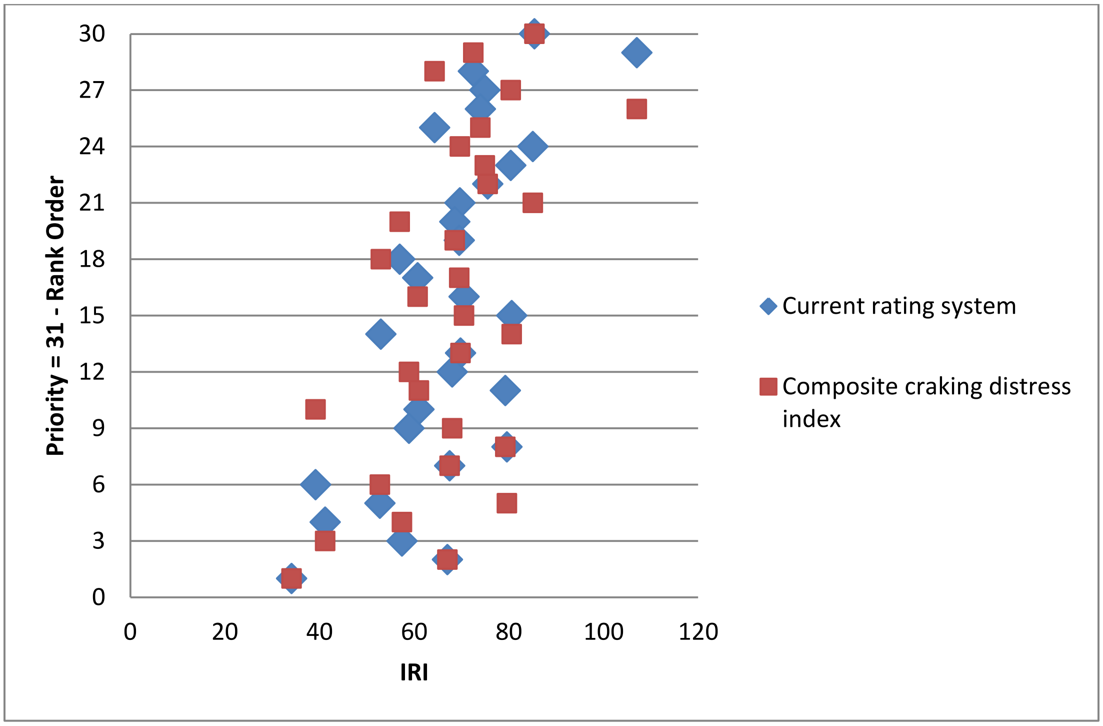


Figure 6-2 Ranking and IRI Plot for 30 road segments

CHAPTER 7 CONCLUSIONS AND FUTURE WORK

7.1 Conclusions

In this thesis, we study the pavement deterioration using MLR and ANN models to predict the pavement condition with respect to various distress indexes in next year. In addition, we also present a composite distress index and compare with the current rating method. The focus of this thesis is to provide reasonable predictive functions and a PMP project rating method that can be adopted by KYTC. Our findings from previous sections can be summarized as follows.

First, in predicting reveling, i.e., "RF" index, both MLR and ANN techniques provide the average ASE for both RF_EXT and RF_SEV of approximately 0.3. The recommended predictive functions are:

$$RF\_EXT\_(t+1) = 0.3436 + 0.0257x_1 + 0.7064x_2 + 0.1216\mathrm{x}_3 + 0.0358x_4,$$
$$where\ x_1{:}\ age, x_2{:}\ RF\_EXT, x_3{:}\ RF\_SEV, x_4{:}\ WPC\_EXT$$

$$RF\_SEV\_(t+1) = 0.4331 + 0.0207x_1 + 0.2442x_2 + 0.5657\mathrm{x}_3 + 0.0459x_4$$
$$where\ x_1{:}\ age, x_2{:}\ RF\_EXT, x_3{:}\ RF\_SEV, x_4{:}\ WPC\_EXT$$

Second, in predicting other cracking, i.e., "OC" index, both MLR and ANN techniques provide the average ASE for OC_EXT of approximately 0.3 and for OC_SEV of approximately 0.5. The recommended predictive functions are:

$$OC\_EXT\_(t+1) = 0.3156 + 0.0178x_1 + 0.8588x_2 + 0.0575,$$
$$where\ x_1{:}\ age, x_2{:}\ OC\_EXT, x_3{:}\ WPC\_EXT$$

$$OC\_SEV\_(t+1) = 0.2037 + 0.0162x_1 + 0.1186x_2 + 0.7265\mathrm{x}_3 + 0.0621x_4$$
$$where\ x_1: age, x_2: OC\_EXT, x_3: OC\_SEV, x_4: RF\_SEV$$

Third, in predicting out of section, i.e., "OS" index, both MLR and ANN techniques provide the average ASE for both OS_EXT and OS_SEV of approximately 0.12. The recommended predictive functions are:

$$OS\_EXT\_(t+1) = -0.0751 + 0.0794x_1 + 0.9372x_2 + 0.0297x_3x_4 - 0.2177x_1x_3 + 0.051x_5x_6 - 0.0252x_3^2x_5 + 0.0857x_3^2x_1 - 0.051x_3^2x_7,$$
$$where\ x_1: OC\_SEV, x_2: OS\_EXT, x_3: appearance, x_4: LG10\_ADT, x_5: OC\_EXT, x_6: WPC\_SEV, x_7: OS\_SEV$$

$$OS\_SEV\_(t+1) = -0.00473 + 0.615x_1 + 0.1332x_2 + 0.0317x_3x_4 - 0.3157x_4x_5 + 0.0307x_1x_3 + x_4^2x_6 - 0.00103x_3^2x_4 - 0.00796x_3x_4x_6 - 0.00254x_4x_7x_8 + 0.000826x_4x_6x_7 + 0.0595x_4x_5^2 + 0.0014x_2^2x_3 - 0.00000518x_7^2x_9 + 0.0104\mathrm{x}_5x_{10}^2 + 0.0227x_8x_{10}^2 - 0.0103x_6x_9x_{10} - 0.00585x_6x_{10}x_{11} - 0.0134x_5x_9x_{11} - 0.00615x_1x_{11}^2 + 0.0119x_6^2x_9 - 0.00182x_6^3,$$
$$where\ x_1: OS\_SEV, x_2: WPC\_SEV, x_3: age, x_4: appearance, x_5: OC\_SEV, x_6: WPC\_EXT, x_7: CUR\_IRI, \mathrm{x}_8: OS\_EXT, x_9: RF\_EXT, x_{10}: LG10\_ADT, x_{11}: WPC\_SEV$$

At last, in predicting appearance, i.e., "APPEAR" index, both MLR and ANN techniques provide the average ASE for both APPEAR of approximately 0.10. The recommended predictive functions are:

$$APPEAR_{t+1} = 0.2191 + 0.8479x_1 + 0.00932x_2 + 0.035\mathrm{x}_3,$$
$$where\ x_1: appearance, x_2: age, x_3: WPC\_EXT$$

In summary, the R^2 values of all the MLR models are larger than 0.8 except OS_SEV. Meanwhile, the average ASE from the MLR models is fairly small ranging from 0.1 to 0.5. On the other hand, ANN models seem to have slightly lower ASE values when compared to their MLR counterparts. The KYTC personnel are satisfied with the R^2 value from the MLR models and decide to use MRL instead of the ANN model as the main approach to predict the pavement deterioration. The decision is made mainly because the complex and non-interpretable nature of the ANN models.

In comparing the AHP-based composite distress index and current rating method, we find that the proposed composite distress index seem to address the overemphasis on IRI by the current rating method. Since a relatively high IRI value for one road segment may result in high priority ranking in project selection and postpone other road segments' much needed treatment, we recommend KYTC for further testing and pilot rollout.

7.2 Future Work

While this thesis deals with the prediction of the deterioration of Kentucky's roadways with respect to seven distress indices, there are still many extended works that can be done in the near future to satisfy KYTC's mission of providing safe roadways to the Commonwealth.

First, there is a strong interest in KYTC to extend the prediction period from one year to three years, because the latter will match well with their three-year budgeting cycle. In particularly, in this thesis, we only use the historical pavement condition data to predict the pavement deterioration for the next year. A three-year prediction would use the current year (t)'s pavement condition to predict the pavement deterioration for year (t+3). This extension presents a great challenge due to the reduced amount of data to employ, thus an increase in the prediction error. Many error reduction techniques will need to be considered in this endeavor.

Second, in all current prediction models regardless of MLR or ANN, the average daily traffic (ADT) is used, but it may not be the best variable to indicate the traffic's impact on the road condition. Aside to ADT, percentage of truck is a more direct input variable than ADT to predict pavement deterioration because trucks usually cause most damages to pavements

Third, other nonlinear regression models such as sigmoidal or power functions can be applied to the historical data to investigate if they provide better prediction than the linear regression models.

At last, in prioritizing PMP projects, pavement deterioration is not the only criterion to be considered. Other criteria such as pavement types, pavement age should also be in the AHP-based composite index in the future.

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