行政院國家科學委員會專題研究計畫 成果報告

鋪面績效預測模式之構建與應用(II)
研究成果報告(精簡版)

計 畫 類 別 ： 個別型
計 畫 編 號 ： NSC 94-2211-E-032-014-
執 行 期 間 ： 94 年 08 月 01 日至 95 年 09 月 30 日
執 行 單 位 ： 淡江大學土木工程學系

計 畫 主 持 人 ： 李英豪
共 同 主 持 人 ： 葛湘瑋
計畫參與人員： 碩士班研究生-兼任助理：吳佩樺、林佳慧、林明輝、莊凱驛、李育昇

報 告 附 件 ： 出席國際會議研究心得報告及發表論文

處 理 方 式 ： 本計畫可公開查詢

中 華 民 國 95 年 12 月 31 日

行政院國家科學委員會補助專題研究計畫 ■ 成 果 報 告 □期中進度報告

（計畫名稱）

鋪面績效預測模式之構建與應用(2/3)

計畫類別：■ 個別型計畫　　□ 整合型計畫

計畫編號：NSC 94－2211－E－032－014－

執行期間：九十四年八月一日至九十五年九月三十日

計畫主持人：李英豪

共同主持人：葛湘瑋

計畫參與人員：吳佩樺、林佳慧、林明輝、莊凱驛、李育昇

成果報告類型(依經費核定清單規定繳交)：■精簡報告　□完整報告

本成果報告包括以下應繳交之附件：

□赴國外出差或研習心得報告一份

□赴大陸地區出差或研習心得報告一份

■出席國際學術會議心得報告及發表之論文各一份

□國際合作研究計畫國外研究報告書一份

處理方式：除產學合作研究計畫、提升產業技術及人才培育研究計畫、列管計畫及下列情形者外，得立即公開查詢

□涉及專利或其他智慧財產權，□一年□二年後可公開查詢

執行單位：淡江大學土木工程學系

中　華　民　國　九十五　年　九　月　三　十　日

鋪面績效預測模式之構建與應用(2/3)
Development and Applications of Pavement Performance Prediction Models

計畫編號：NSC 94－2211－E－032－014
執行期限：　94 年 8 月 1 日至 95 年 9 月 30 日
主持人：李英豪　淡江大學土木工程學系教授
共同主持人：葛湘瑋　致理技術學院國際貿易系副教授

中文摘要

鋪面績效預測模式在鋪面設計、鋪面評估與維修、與鋪面管理系統扮演著極為重要的角色。計畫主持人擬以三年三期的方式（第一、二期計畫已完成，第三期計畫已獲　貴會核定執行中），利用美國長程鋪面績效資料庫 LTPP DataPave Online (http://www.datapave.com)從事「鋪面績效預測模式的構建與應用」研究，以改善系統化的統計與工程分析方法來構建鋪面績效預測模式。第一期主要完成之研究內容包括：鋪面標準損壞調查手冊之研擬、美國長期鋪面績效資料庫之本土化應用、研擬系統化的統計與工程分析方法、以及探討鋪面動態分段在地理資訊系統之應用。本期（第二期）主要之研究工作除了延續前一期鋪面動態分段在地理資訊系統之應用外，並建立柔性鋪面疲勞裂縫與車轍之績效預測模式、以及剛性鋪面橫向裂縫、接縫碎裂、與高差等績效預測模式。

經由探索性資料分析，本研究發現鋪面績效資料常常違反了傳統迴歸法中所作常態分配、隨機誤差、與固定變異數的假設，因此不適用傳統統計迴歸方法來構建預測模式。此外，現地蒐集的 LTPP 長期鋪面績效資料變異性極大，更增添了利用多層線性模式(HLMs)或線性混合模式(LMEs)來分析 LTPP 長期鋪面績效資料庫的困難度。因此，本研究於後續分析時採用廣義線性模式(GLM)與廣義相加模式(GAM)對於反應變數的分佈情形均不給予任何假設，而是採用以概似估計法的方式測試分配適用度,其中以柏松分配之適用性較良好。並配合 Box-Cox power transformation 轉換法、視覺圖的技術，以將系統化之統計與工程分析方法應用於構建預測模式中。本研究將構建完成之預測模式檢定其適合度及針對相關的參數進行敏感度分析，最後建構之模式其適用情形與過去模式相比，有得到良好的改善。對目前建立之模式於未來亦可作更進一步之改進，使其更為完善。

關鍵詞：鋪面、績效預測、鋪面管理、地理資訊系統、長期鋪面績效資料庫、廣義線性模式、廣義相加模式。

Abstract

Improved performance predictive models are greatly needed for use in various pavement applications including design, evaluation, rehabilitation, and network management. The entire project consists of three phases (I, II, and III) to be completed within three years (the phase I and phase II have been approved and phase III is an on-going project) to conduct “development and applications of pavement performance prediction models,” using the well-known Long-Term Pavement Performance (LTPP) database (LTPP DataPave Online) (http://www.datapave.com) to improve the proposed systematic statistical and engineering approach for the development of pavement performance prediction models. The major tasks completed in Phase I include: preparation of standard pavement distress identification manuals for domestic use, domestic applications of the LTPP database, review of the proposed the systematic statistical and engineering approach, and investigation of the application of dynamic segmentation concept in GIS. In addition to continuing the implementation of dynamic segmentation databases using commercial GIS

software, the major tasks in Phase II (this year) include: development of flexible pavement fatigue cracking and rutting prediction models; and development of rigid pavement transverse cracking, joint deterioration (spalling), and faulting performance prediction models

Exploratory data analysis (EDA) of the response variables indicated that the normality assumption with random errors and constant variance using conventional regression techniques might not be appropriate for prediction modeling. Therefore, without assuming the error distribution of the response variable, generalized linear model (GLM) and general additive model (GAM) along with quasi-likelihood estimation method were Poisson distribution were adopted in the subsequent analysis. Box-Cox power transformation technique, visual graphical techniques, as well as the systematic statistical and engineering approach proposed by Lee were frequently adopted during the prediction modeling process. The goodness of the model fit was further examined through the significant testing and various sensitivity analyses of pertinent explanatory parameters. The tentatively proposed predictive models appeared to reasonably agree with the pavement performance data although their further enhancements are possible and recommended.

Keywords : Pavement, Performance Prediction, Pavement Management, Geographic Information System (GIS), LTPP, Generalized Linear Model (GLM) and General Additive Model (GAM).

一、前言

本計畫第二期（本期）之主要工作內容包括：延續前一期鋪面動態分段在地理資訊系統之應用、並建立柔性鋪面疲勞裂縫與車轍之績效預測模式、以及剛性鋪面橫向裂縫、接縫碎裂、與高差績效預測模式等三大部分。其中，本研究將透過 Visual Basic 程式之撰寫，將 ArcView 商用地理資訊系統中動態分段及圖形展示之應用方式自動化，並使其與鋪面路網資料庫管理系統、以及路網策略最佳化分析工具相結合，以建立一套具備關連式資料庫(Access 資料庫程式)、最佳化分析工具及圖形化介面之鋪面路網層級管理系統。

再者，經由探索性資料分析，本研究發現鋪面績效資料常常違反了傳統迴歸法中所作常態分配、隨機誤差、與固定變異數的假設，因此不適用傳統統計迴歸方法來構建預測模式。此外，現地蒐集的 LTPP 長期鋪面績效資料變異性極大，更增添了利用多層線性模式(HLMs)或線性混合模式(LMEs)來分析 LTPP 長期鋪面績效資料庫的困難度。

因此，本研究於後續分析時採用廣義線性模式(GLM)與廣義相加模式(GAM)對於反應變數的分佈情形均不給予任何假設，而是採用以概似估計法的方式測試分配適用度,其中以柏松分配之適用性較良好。並配合 Box-Cox power transformation 轉換法、視覺圖的技術，以將系統化之統計與工程分析方法應用於構建預測模式中。本研究並將構建完成之預測模式檢定其適合度及針對相關的參數進行敏感度分析。茲將相關之研究成果簡述如下：

二、商用地理資訊系統在鋪面管理之應用

鑑於國內對鋪面路網資料的整合與應用方式仍不甚明確，因此，本研究將以管理者需求為出發點，以「路網階層」的鋪面維修管理為首要考量，利用「均質路段」與「抽樣調查」的觀念，及明確性、可量測性、可完成性、相關性、與及時性(SMART)等原則，以原始資料蒐錄的方式來登錄資料，並配合「動態分段」的自動化程序來構建資料庫，以有效解決現有鋪面資料庫架構過大而不易執行等問題。研究中亦將透過 Visual Basic 程式之撰寫，將商用地理資訊系統之動態分段及圖形展示之功能自動化，並使其與前述鋪面路網資料庫管理系統以及路網策略最佳化分析模組相結合，以協助提升國內鋪面路網管理之效率。

2.1ＡrcView 商用地理資訊系統之簡介與選用

ArcView 為 ESRI 公司 ArcGIS 地理資訊系統系列軟體中的一套桌上型軟體。ArcView 為全世界相當普遍的桌上型地圖及地理資訊系統(GIS)軟體之一，該軟體提供圖像化、查詢、管理及分析功能，並可整合其他較大的 GIS 軟體之資料格式，且 ArcView 可作為獨立桌上型 GIS 系統，同時也可作為網路或網際網路中的用戶端應用。在 ArcGIS 8.1 版以前 ESRI 公司並未將線性參考的分析模組統合至 ArcGIS 軟體中，使用者必須自行撰寫 VB、C++等程式來進行線性參照的分析與應用。然而自 ArcGIS 8.2 版（2001 年）開始，便將線性參照模組統合至 ArcGIS 軟體中，成為 ArcGIS 的應用模組之一。使用者可以依據 ArcGIS 軟體內建的模組及使用手冊，很簡單的使用線性參照的分析、轉換、管理及展示等功能，對於鋪面管理所需應用的動態分段功能亦可簡單地達成。ArcView 9.1 軟體亦包含了各種應用模組，更能簡單的應用本研究所需之動態分段模組。若是應用於鋪面管理後不但人員訓練簡單、軟體購置費用節省且 ArcGIS 相關的軟體套件功能及相容性亦相當強，於將來在系統伺服器架設或網路應用等方面，都能有相當便利的擴充性。基於以上考量，本研究最終以 ArcGIS 9.1 作為本研究的商用 GIS 應用軟體，並利用其中的 ArcView 應用軟體來進行動態分段資料庫架構及線性參照程序的開發。

2.2 動態分段資料庫架構及線性參照

運用動態分段觀念，將屬性資料分別記錄於不同表單可以避免因資料重複紀錄而佔用資料空間的缺點，同時由於各類屬性資料係經過分類後再以表格方式存放，因此在資料庫的構建與維護上是比較傳統方法容易、迅速。使用者只需根據道路路名與樁號里程起迄點為索引，直接在該屬性資料表進行資料的更新、修改即可。經由上述的方法，依此種方式構建的資料庫，在屬性資料的查詢、編輯其分析功能的應用，可符合動態分段的要求。因此，本研究運用 ArcGIS 軟體中線性參照的功能，將路網階層所構建之道路基本資料、交通量調查與維修養護資料進行動態分段分析。於動態分段分析完成後再將路面狀況調查資料依據所分析之起迄點進行平均後匯入資料表中，以完成動態分段。

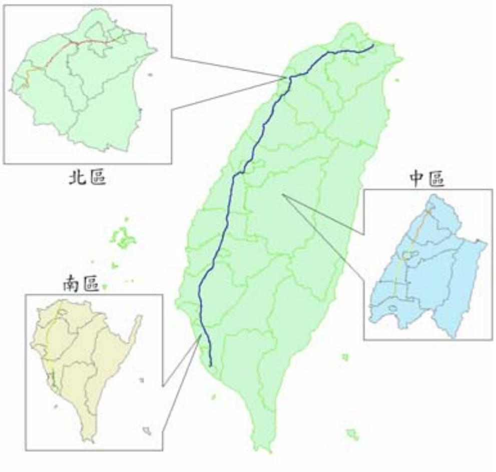
ArcView 共有超過 50 個以上的物件庫，而每個物件庫有一個以上的物件模組圖。雖然物件模組圖可以幫助程式撰寫者正確及有效的撰寫程式，但是物件模組圖中有超過 1500 個以上的類別以及超過 1600 個以上的介面。因此如何正確的選擇欲使用功能的歸類所在以及程式碼的查詢應用，確有其複雜性困難度。為了簡化使用者介面，因此本研究選擇於外部利用 VB 建立使用者介面並連接 Access 與 ArcView，以進行資料庫管理、資料分析及圖形化展示，亦可避免未來因錯誤使用其他軟體之功能，而影響系統的穩定性及正確性。

然而將動態分段自動化後，當結合表單為同名稱之分段表單，且表單欄位不變，僅更改欄位內容的話，於圖形展示便不需要重複執行，僅需開啟舊有展示檔案，開啟後其便會自動更新其表單，並依據新表單於以展示。有鑑於台灣國道工程的興建與維護為不同之工程處所負責，因此本研究相較於過去增加了北區、中區以及南區工程處的選擇，並在選擇後以該區為基準展示。且於展示後可直接在展示圖上進行路段資料之查詢，如圖一與圖二所示。

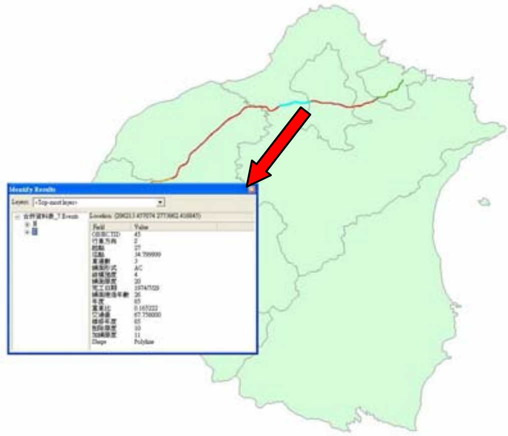
2.3 最佳化維修策略之選定與應用

本研究除了持續改善過去系統及程式中較不真實之資料，並以商用地理資訊系統的內部程式碼，利用 VB 程式撰寫於外部系統操控其動態分段與圖形化展示功能。藉此避開商用地理資訊系統繁雜的操作介面，並同時解決傳統利用資料表整合所執行之動態分段不穩定之問題。此外，本研究並將結合路網維修管理策略最佳化分析模組，將其與動態分段資料庫做連

結後，以資料庫資料作即時之分析。並將預測分析之數值回傳資料庫後，利用 GIS 圖形化展示功能，將其分析結果以 GIS 圖形展示，以達到增加使用者印象與鋪面管理效率之目的。

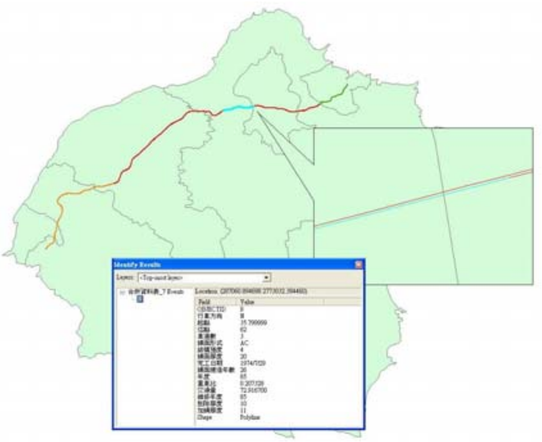


圖一 工程處分區示意圖



圖二 北區工程處之交通量查詢及展示

由於國內尚未訂出一致且具代表性之鋪面指標與績效預測模式，因此，本研究暫時以綜合性指標與美國公路績效監測系統發展出的績效預測模式來評估鋪面現況與未來之績效，並提供多種的維修策略與利益考量，配合不同的最佳化排序法(包括隨機產生、簡單排序、益本比法、增量益本比法、與線性規劃法)，藉此作為判斷維修策略的依據。研究中並構建一套鋪面路網維修管理策略最佳化分析雛型程式，除了可將鋪面路網維修管理系統之資料與數據分析結果以圖形化方式展示，並可協助管理者規劃預算分配等工作。期望能以最少的人力與物力達成協助決策者評估路網現況、預測未來狀態、選定鋪面維修管理決策、排列與分配維修經費等目標。最後使用者可以利用圖形展示之功能，結合所選擇之工程處，依照分區，將以整合或分析之資料表單與圖資結合後展示並查詢，如圖三與圖四所示。本研究建議可先以此系統為基礎，未來經由系統的資料不斷地回饋與修正、陸續擴充，使其更符合國內實際情況，進而建構成一多功能之鋪面管理系統。各項詳細內容可參考文獻[林明輝，2006]



圖三 北區工程處路段展示及路段查詢

圖四 北區工程處路段展示及資料庫查詢

三、柔性鋪面績效預測模式之構建

3.1 資料來源及擷取方法

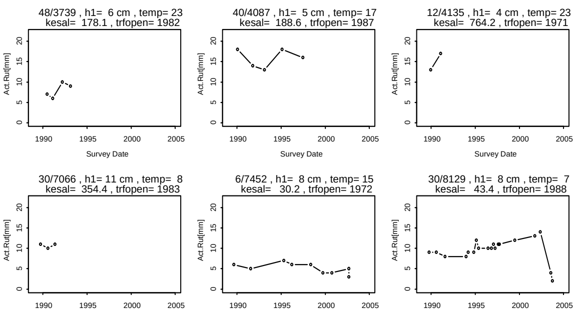
美國長程鋪面績效研究計畫主要在蒐集北美洲現場鋪面二十年績效資料，以供全世界各

國鋪面研究之用。計畫主要目標在利用各種材料與不同荷重、氣候環境、路基土壤與養護技術下，研究各種新建與維修後鋪面結構設計之長期績效，以延長公路鋪面使用年限，因此建立有史以來最大的鋪面績效資料庫，該資料庫包括 400 個表單與超過 6,000 個變數等鋪面基本資料、特殊建造、材料試驗、氣候與季節、交通、養護維修、與監測資料。LTPP 自 1997 年以來即以 DataPave 軟體光碟免費提供世界各國鋪面研究人員使用，目前最新為 LTPP DataPave Online 線上資料庫。本研究針對現有績效預測模式與 DG2002 程式所需相關參數進行資料擷取，以線上資料庫 Release 18.0 版為主要資料來源，配合 Microsoft Access 程式之關聯性功能整合所需資料庫。現有模式所需資料較少約為 10~15 項資料，但程式所需輸入的資料較為繁多約為 45~50 項資料，資料項目為現有模式 3 倍之多。由於模式所需相關參數繁多因此進行資料擷取時需謹慎判斷選擇，詳細資料擷取過程請參閱文獻。

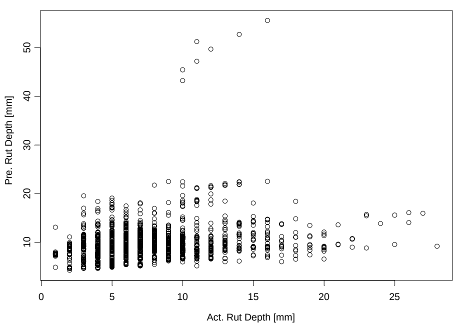
3.2 現有車轍模式結果分析

由於本研究所需資料為鋪面未經維修或養護之現地調查記錄，雖然於上述參數擷取與處理過程中已將各路段資料有維修紀錄資料初步排除，為了再次確保資料正確性，將鋪面調查日期與車轍歷年現地調查值之關係呈現如圖五，結果顯示圖中極端值於資料庫均無維修之紀錄。針對起伏狀態較明顯之路段個別細看，發現有些調查日期非常相近但是車轍深度的變化卻很大，而有些資料點在某一調查日期後產生突降的狀況，如路段 8129/30，經研究詳細判斷此類資料點可能為人員紀錄錯誤或鋪面已維修後，但於資料庫紀錄中並未標示。除了上述因素之外，亦有可能在調查過程中，現地工作人員未調查到某些資料，而紀錄人員即以零紀錄之等諸多原因。由圖五可之車轍產生深度並未隨鋪面使用年限的增加而增加，此狀況可能會對於後續模式分析或構建時造成困難，對資料經過詳的檢查後將疑似維修後資料予以刪除。

經初步分析後所得資料點大致均為原始資料，本研究將各個預測模式與現地量測車轍深度進行比較，以 SHRP P-020 模式為例預測結果如圖六所示，縱座標為資料庫實際量測之車轍深度(mm)，橫座標為模式預測之車轍深度(mm)。於預測圖中可看出有七筆資料點出現異於其他預測值，經研究結果發現在預測模式中，參數資料數值可能過大或過小，導致最後預測值出現異常。就此七筆資料點以視覺圖的方式展現參數與結果之相關性，一般瀝青面層的空氣含量大多介於 3~9%之間，但此資料點為 0.2%不合於一般資料，將參數之數值帶入預測模式後使得預測之車轍深度高達 2 英吋，因此需將此 7 筆資料刪除，並同時以視覺圖展示資料分佈情形以瞭解不同參數對鋪面破壞之影響性。



圖五　部分路段之車轍深度歷年調查狀態



圖六　全部地區模式預測結果

為了瞭解過去現有模式與 AASHTO 2002 新建模式對於績效資料庫之適用情形，選取兩模式之相同路段進行比較，利用統計軟體 S-PLUS 迴歸結果顯示 DG2002 程式及 P-020 兩者之判定係數皆很低，顯示預測能力均不佳。

3.3 車轍績效預測模式之構建

3.3.1 選取相關參數及分析

參考前述相關模式經由前面資料分析的過程，以作為此階段選取變數之參考。將各模式中影響較不明顯、資料庫中不易取得及資料不足的變數不列入考慮，進而選取對於破壞影響較明顯及易造成破壞的因素以矩陣圖方式展現出來並進行下一步分析。首先需瞭解各路段之車轍破壞深度是否有極大值或異常，以年平均車轍增加量與其他參數以矩陣圖方式發現有三筆資料年平均車轍產生深度超過 4mm。一般而言，造成柔性鋪面產生車轍破壞的最主要的原因為交通量，但此兩路段之平均交通量與路基頂部之壓應變並非極大，且鋪面厚度大約介於 5~10 公分，由變數顯示的狀態來說此三筆資料產生的破壞深度可能有誤，故將此三筆資料予以排除不列入後續分析範圍內並針對各參數進行討論。將參數以矩陣圖展開後發現當厚度較厚時鋪面產生之壓應變較大，且壓應變 ε_c 與破壞比值(L.damage)兩者之關係非常明確，當 ε_c 較大時 L.damage 亦較大，反之則較小，故於後續模式參數之選擇時可以考慮以壓應變取代破壞比值。在氣候條件之參數，研究發現交通量和年平均溫度在不同區域顯示之破壞情況不同，因此後續構建模式時可依不同的氣候條件建立不同的預測模式。

3.3.2 線性迴歸結果

在構建模式的過程中變數的選擇固然重要，但資料顯示的物理意義與一般鋪面反應是否與預期相符更重要，本研究篩選出來的一些重要變數以統計方法，配合鋪面專業知識判斷其對於模式的適用性。其係數代表自變數與依變數之間的相關性，其正號為正相關，負號為負相關。機率值 P 的大小代表因子對依變數的影響性，一般當 P 值大於 0.05 以上時，表示此變數影響性不大，可不列入考慮範圍內。並可用判定係數來衡量迴歸模型的配合度或解釋能力。其中有五個變數 P 值大於 0.05，分別為鋪面使用年限、路基回彈模數、瀝青黏滯度、破壞百分率及路基頂部產生之壓應變，表示此變數對鋪面破壞之影響性較小，在此階段不列入討論範圍。於以上分析結果中，惟累積交通量與冰凍指數符合一般鋪面破壞預期的反應，但其他條件一般預期結果並不完全符合。因此將 P 值大於 0.05 之五個變數刪除並再次進行迴歸分析，所得 R^2 為 0.2105。雖然迴歸結果與前述之 SHRP P-020 及 DG2002 預測模式為高，但是資料顯示的物理意義與一般預期反應相反，因此將後續觀察參數之分佈狀態，並應用廣義線性模式進行模式構建。

3.3.3 廣義線性模式之應用

在進行統計分析時，常需要假設資料服從某一機率分配的要求，由於絕大部分分析方式都是建立於常態分配的假設前提下，所以最常見的假設皆要求資料服從常態分配。Shaprio 與 Wilk 於 1965 所提出的單變量常態性檢定 W（以下簡稱 W 統計量）可檢定資料分配情形。廣義線性模型不在侷限於資料是否為常態型式，其假設條件較一般的迴歸模型來的寬鬆，如反應變數 Y 不再需要服從常態分配。首先以資料探索分析的方式，觀察資料分佈情形如圖 5 所示，並針對現地量測之車轍深度利用單變量常態性檢定 W 資料是否近似常態分配，檢定結果 W 統計量為 0.9541、p 值等於 0 可知資料分佈情形並非常態分配，因此需選用其他分配進行分析。配合廣義線性模型與泊松分配之分析方式進行模式構建，迴歸結果模式之判定係數為 0.1235，殘餘標準差為 3.635，資料筆數為 265 筆。雖然判定係數比前述現有模式的高，但是分析顯示某些參數對於車轍深度影響之趨勢與預期結果相反，如冰凍指數 fi、年平均溫度

temp、路基頂部之壓應變 epsilon.c、降雨量 precip。過去對於模式構建研究指出，針對輸入變數之分析亦有多種統計迴歸之方法，本研究利用廣義累加模式與 Box and Cox Transformation 轉換法進行分析，此轉換法為一乘冪轉換，經分析後若最大值落於 0 則對此變數取對數進行轉換，若最大值落於 2 即對變數取平方進行轉換，最後得到全區迴歸公式如下：

$$\ln(Rut) = -0.99 + 0.137*\sqrt{age} + 0.322*\log(kesal) + 0.38*\log(1+fi) + 0.352*\sqrt{temp} + 0.083*(epsilon.c*1000)^2 \tag{1}$$

Statistics：判定係數 R^2=0.164，殘餘標準差 SEE=1.22，資料筆數 n=265

經過轉換後車轍績效預測模式如下：

$$Rut = \exp[-0.99 + 0.137*\sqrt{age} + 0.322*\log(kesal) + 0.38*\log(1+fi) + 0.352*\sqrt{temp} + 0.083*(epsilon.c*1000)^2] \tag{2}$$

Statistics：R^2=0.155，SEE=3.568，n=265

在全部地區預測模式建構完成後，本研究依氣候條件分為四區，但由於乾燥與冰凍兩個區域的資料點較少，可能無法以客觀的立場建構模式，因此本研究只針對潮濕與不冰凍兩區進行預測模式之建構，分別如下：

$$(Rut)_{wet} = \exp[-1.489 + 0.25*\sqrt{age} + 0.6*\log(kesal) + 0.24*\log(1+fi) + 0.256*\sqrt{temp} + 0.288*(epsilon.c*1000)^2] \tag{3}$$

Statistics：R^2=0.338，SEE=3.401，n=194

$$(Rut)_{nonfreeze} = \exp[0.253 + 0.065*\sqrt{age} + 0.486*\log(kesal) + 0.187*\log(1+fi) + 0.06*\sqrt{temp} + 0.288*(epsilon.c*1000)^2] \tag{4}$$

Statistics：R^2=0.282，SEE=3.193，n=124

其中 age 為鋪面使用年限（年）、kesal 為年平均交通量（千）、fi 為冰凍指數(degree-days)、temp 為年平均溫度(℃)、epsilon.c 為路基頂部之壓應變。

3.3.4 敏感度分析

敏感度分析主要是用於主變量與因變量之分析，在固定一個或幾個主變量的不同水準下，分析其他因變量變化的情況。由於壓應變、年平均交通量、鋪面使用年限為主要影響車轍深度的產生，因此於本研究所建議的全區、潮濕、不冰凍等三個模式中，將此三個因子之相互關係展現於圖中，變數資料範圍均取最小值到最大值。在全區模式中與潮濕地區模式中變數之間的影響關係較類似。當其他參數取平均後，年平均交通量對車轍的影響性可能較小，壓應變的影響則較明顯。但站在鋪面使用年限和拉應變的角度時，壓應變的影響性就比較小反而是鋪面使用年限對鋪面的影響較大。由年平均交通量與鋪面使用年限的角度觀察，當年平均交通量小且鋪面使用年限較短時，產生之車轍深度亦較少，相反的當兩者皆增加時，對鋪面的影響性亦較大。由此可知，平均交通量與鋪面使用年限在全區與潮濕地區對於鋪面的影響比較明顯。在不冰凍地區模式中，可知交通量的大小影響比較明顯。

3.4 疲勞裂縫績效預測模式之構建

本研究亦在此階段建立柔性鋪面之疲勞裂縫績效預測模式。由於分析之方法與程序與前述系統化之分析流程相類似，詳細內容可參考文獻[Ker, Lee, & Wu, 2006; 吳佩樺，2006]。茲將其主要之研究成果簡列如下：

於構建疲勞裂縫預測模式之參數選取時，依據前述現有模式之參數並引進模式未加入相

關之因子，如凍融指數、降雨量、年平均溫度等變數，經由資料分析的過程，作為選取變數之參考。在模式構建方面，首先觀察資料之分配，再選用廣義線性模式進行分析。

3.4.1 全區預測模式之構建

首先以資料探索分析的方式，觀察資料分佈情形並針對現地量測之疲勞裂縫破壞百分比利用單變量常態性檢定 W 資料是否近似常態分配，由 W 統計量為 0.4841、p 值等於 0 的結果可得知，資料分佈情形並非常態分配。因此本研究將參考過去之研究，選取相關分配進行模式構建。Wang 與 Mahboub 等人過去曾對疲勞裂縫建立鋪面損壞年限之預測模式，其參數選用交通量、面層厚度、處理底層厚度、降雨量及凍融指數，對於模式構建則採用 gamma 分配。

本研究對於反應變數(Y)本研究並無限定其為何種分配，研究中曾嘗試應用 gamma 分配，但對於現有資料無法進行分析，亦經過泊松與 quasi 分配的分析與考量後，發現泊松分配對資料的適合度較良好，因此選擇泊松分配進行模式之構建。

參考過去研究[Wang et al., 2005]及前述參數分析後，選取相關變數如鋪面使用年限(age)、平均交通量(kesal)、降雨量(precip)、年平均溫度(temp)、面層底部之水平拉應變(epsilon.t)、凍融指數(ft)。並配合廣義線性模型與泊松分配之分析方式進行模式構建，迴歸結果如圖 5-22、表 5-3。結果顯示參數對疲勞裂縫影響之趨勢均符合預期反應皆為有效變數，本研究建構之全區模式如下：

$$\begin{aligned}\ln(FC) &= -7.455 + 0.121 * age + 0.00168 * kesal + 0.00269 * precip \\ &\quad + 0.0473 * temp + 12319.5 * epsilon.t + 0.0133 * ft\end{aligned} \tag{5}$$

Statistics：R^2=0.447，SEE=2.882，n=176

經轉換後，預測疲勞裂縫之預測模式如下式：

$$\begin{aligned}FC &= \exp[-7.455 + 0.121 * age + 0.00168 * kesal + 0.00269 * precip \\ &\quad + 0.0473 * temp + 12319.5 * epsilon.t + 0.0133 * ft]\end{aligned} \tag{6}$$

Statistics：R^2=0.3352，SEE=8.741，n=176

其中 age 為鋪面使用年限（年）、kesal 為平均交通量（千）、precip 為降雨量(mm)、temp 為年平均溫度(℃)、epsilon.t 為面層底部之水平拉應變、ft 為凍融指數(cycle)。

3.4.2 分區預測模式之構建

在全部地區預測模式建構完成後，將資料依潮濕、乾燥、冰凍、不冰凍等狀態分區，再次進行模式構建。迴歸結果為在潮濕及不冰凍區變數對於鋪面破壞的反應均合乎常理，在乾燥及冰凍區其預測結果變異性較大，某些變數對鋪面反應與預期結果相反。

雖然四者迴歸結果之判定係數皆差不多，但是某些參數對鋪面之影響較無顯著差異，因此本研究將乾燥地區之年平均交通量刪除，在冰凍地區將鋪面使用年限、年平均交通量刪除，並以溫度間距取代年平均溫度與凍融指數，再次分析迴歸結果比第一次佳且變數反應均與與預期結果相符，分區構建之預測模式分別如下：

(A)潮濕地區：

$$\begin{aligned}(FC)_{wet} &= \exp[-6.539 + 0.078 * age + 0.00187 * kesal + 0.000673 * precip \\ &\quad + 0.0914 * temp + 15097 * epsilon.t + 0.0272 * ft]\end{aligned} \tag{7}$$

Statistics：R^2=0.452，SEE=3.137，n=123

(B)乾燥地區之預測模式：

$$\begin{aligned}(FC)_{dry} &= \exp[-48.411 + 0.119 * age + 0.025 * precip + 1.774 * temp \\ &\quad + 2729 * epsilon.t + 0.0272 * ft]\end{aligned} \tag{8}$$

Statistics：R^2=0.421，SEE=1.117，n=53

(C)冰凍地區之預測模式：

$$(FC)_{freeze} = \exp[-5.944 + 0.00583 * precip + 41.768 * epsilon.t - 0.002 * visco + 0.4 * temp.range] \quad (9)$$

Statistics：R^2=0.498，SEE=1.624，n=86

(D)不冰凍地區之預測模式：

$$(FC)_{nofreeze} = \exp[-7.87 + 0.102 * age + 0.00219 * kesal + 0.00102 * precip + 0.0472 * temp + 15172 * epsilon.t + 0.0476 * ft] \quad (10)$$

Statistics：R^2=0.577，SEE=2.99，n=90

3.4.3 新全區預測模式之構建

過去對於模式構建研究指出，針對輸入變數之分析亦有多種統計迴歸之方法，本研究利用廣義相加模式(Generalized Additive Models)與 Box and Cox Transformation 轉換法進行分析，此轉換法為一乘冪轉換(Power Transformation)，經分析後若最大值落於 0 則對此變數取對數進行轉換，若最大值落於 2 即對變數取平方進行轉換。將前述全區模式經由此分析後可得到更良好之迴歸結果，新建構之預測模式如下：

$$FC = \exp[-18.08 + 0.943 * \sqrt{age} + 0.832 * \log(kesal) + 0.121 * \sqrt{precip} + 0.869 * \sqrt{temp} + 31.489 * (epsilon.t * 1000)^2 + 3.242 * \log(ft)] \quad (11)$$

Statistics：R^2=0.4967，SEE=7.605，n=176

其中 age 為鋪面使用年限(年)，kesal 為年平均交通量(千)，precip 為年平均降雨量(mm)，temp 為年平均溫度(℃)，epsilon.t 為面層底部之水平拉應變，ft 為凍融指數(cycle)。模式之判定係數為 0.4967，比前述之全區模式判定係數 0.3352 高。因此，得以驗證所建議之系統化分析流程之適用性。

四、剛性鋪面績效預測模式之構建

同樣地，本研究亦在此階段建立剛性鋪面之橫向裂縫、接縫碎裂、與高差等績效預測模式。由於分析之方法與程序與前述系統化之分析流程相類似，有關 LTPP 剛性鋪面資料之擷取與初步分析，以及現有預測模式之結果分析、與敏感度分析等之詳細內容可參考文獻[林佳慧，2006]。茲將其主要之研究成果簡列如下：

4.1 橫向裂縫預測

根據過去的文獻，一般都會將橫向裂縫分為 JPCP 與 JRCP 兩種預測模式，所需的參數亦不同。本研究初步選取預測模式之變數，分別為鋪面齡期 age (年)、年平均交通量 kesalpyr（千）、累積交通量 cesal (百萬)、橫向接縫間距 jtspace (m)、路基反力模數 kstatic (MPa/m)、混凝土版厚度 hpcc(cm)、底層型式 basetype、降雨量 precip (mm)、冰凍指數 fi (℃ degree-days)、年平均溫差 trange(℃)、超過 32℃的天數 days32 和凍融循環次數 ft 等。另外 JPCP 模式還有土壤分類 stype、邊緣應力 edgstress(MPa)和混凝土抗彎強度 mr(MPa)，且現地的裂縫值是以百分比表示。而 JRCP 則多了縱向鋼筋量百分比 psteel(%)，現地的裂縫值是以每公里有多少的裂縫數量表示。其中，底層型式為 1 是處理底層，0 是顆粒狀底層；土壤分類為 1 是粗顆粒土壤，0 是細顆粒土壤。除此之外，在 JPCP 模式中，還額外加入一個新的變數應力比 ratio，為邊緣應力和混凝土抗彎強度之比值。

4.1.1 JPCP 橫向裂縫預測模式

由於反應變數不服從常態分配，且現地裂縫值在類別資料上可以比率來表示，適用於泊松分配，因此利用選取的相關參數，以廣義線性模式配合泊松分配進行模式之構建，並且搭配廣義相加模式和 Box-Cox 轉換法協助模式構建。最後之新構建之 JPCP 模式如下所示，式中，cesal 為累積交通量（百萬）、precip 為降雨量(mm)、ft 為凍融循環次數、trange 為年平均

溫差(℃)和 ratio 為應力比：

$$CrackJP = \exp[-3.27 + 2.27 * \log(cesal) + 0.05 * \sqrt{precip} + 0.01 * ft - 18.15 * \frac{1}{trange} + 3.14 * \sqrt{ratio}] \quad (12)$$

統計結果：R^2=0.338，SEE=13.21，n=393

4.1.2 JRCP 橫向裂縫預測模式

同樣地，利用選取的相關參數，以廣義線性模式配合泊松分配進行模式之構建，並且搭配廣義相加模式和 Box-Cox 轉換法協助模式構建。最後之迴歸結果如下所示，式中，cesal 為累積交通量（百萬）、ft 為凍融循環次數、psteel 為縱向鋼筋量百分比(%)和 trange 為年平均溫差(℃)：

$$CrackJR = \exp[3.95 - 3.28 * \frac{1}{\sqrt{cesal}} + 0.25 * \sqrt{ft} + 0.3 * \frac{1}{\sqrt{psteel}} - 31.17 * \frac{1}{trange}] \quad (13)$$

統計結果：R^2=0.233，SEE=31.06，n=156

4.2 接縫碎裂預測

根據過去的文獻，一般都會將接縫碎裂分為 JPCP 與 JRCP 兩種預測模式，所需的參數亦不同。本研究初步選取預測模式之變數，分別為鋪面齡期 age (年)、年平均交通量 kesalpyr（千）、累積交通量 cesal (百萬)、橫向接縫間距 jtspace (m)、底層型式 basetype、預先形成的接縫 prefseal、降雨量 precip (mm)、冰凍指數 fi (℃ degree-days)、年平均溫差 trange(℃)、超過 32℃的天數 days32 和凍融循環次數 ft 等。其中，底層型式為 1 是處理底層，0 是顆粒狀底層；有預先形成的接縫為 1，反之則為 0。參考過去文獻所提供之變數以及前述本研究所用模式中之變數，接著將影響較不明顯、資料庫中不易取得及資料不足的變數不列入考慮。

同樣地，在模式構建過程中先利用傳統的迴歸技術建構新的預測模式，但是結果並不理想，因此以資料探索分析的方式，觀察資料分佈情形，並且以單變量常態性檢定 W，檢查現地的裂縫值資料是否近似常態分配。JPCP 模式的 W 統計量為 0.2878、JRCP 模式的 W 統計量為 0.5073，兩者的 P 值皆為 0，可知資料分佈情形都為非常態分配。由於反應變數不服從常態分配，因此以廣義線性模式配合泊松分配進行模式之構建，並且搭配廣義相加模式和 Box-Cox 轉換法協助模式構建。

由於 LTPP 資料庫中，絕大部分之接縫碎裂資料均為零，非常不容易尋得有意義且可接受之模式。初步新構建之 JPCP 橫向裂縫預測模式模式如下所示，式中，age 為鋪面零期（年）、fi 為冰凍指數、prefseal 為有預先形成的接縫和 days32 為超過 32℃的天數：

$$SpallJP = \exp[-1.93 + 0.49 * \sqrt{age} + 0.06 * \sqrt{fi} - 3.05 * prefseal - 0.01 * days32] \quad (14)$$

統計結果：R^2=0.079，SEE=6.401，n=346

由於分析之結果相當不理想，未來有待更近一步分析與討論改善之方式。

4.3 高差預測

根據過去之文獻及前述分析，在此將高差分為含綴縫筋及不含綴縫筋兩種。由於反應變數不服從常態分配，且現地高差值在類別資料上可以計數來表示，適用於泊松分配，因此利用選取的相關參數，以廣義線性模式配合泊松分配進行模式之構建。

4.3.1 含綴縫筋之高差模式

將所有選取的相關參數進行廣義線性迴歸分析，所得之判定係數為 0.6238，殘餘標準誤

為 0.889，資料筆數為 305 筆，雖然判定係數很高，但是分析顯示有某些參數對於高差影響之趨勢與預期結果相反，且有很多參數之 t 值反應小於 1.64，對高差影響甚小，因此需再進行修正，直到修正模式評估合適為止。

對於過去模式構建之研究[Lee, 1993]，有指出當誤差項不服從常態分配，但迴歸關係顯示為線性時，能針對反應變數 Y 進行轉換，但是有可能會使變異數穩定的轉換從直線轉為曲線，這時也要考慮對 X 轉換。本研究利用廣義相加模式(Generalized Additive Models,GAM) 與 Box and Cox Transformation 轉換法協助模式構建。GAM 是可對資料做平滑化，反映一般趨勢而不需假設關連的函數型式，且能找到產生最佳預測的某種解釋變數之複雜函數。Box- Cox 轉換法為一乘冪轉換(Power Transformation)，能自動診斷要對 Y 進行何種轉換，使誤差項之變異數穩定。若當參數最大值落於 0 則對此變數取對數進行轉換，若落於 2 即對變數取平方進行轉換，在 0 至 2 中間則取平方根。

本研究最後之迴歸結果如下所示，式中，age 為鋪面齡期（年）、kesalpyr 為年平均交通量（千）、bstress 為綴縫筋與混凝土間允許的支承應力(MPa)、precip 為降雨量(mm)、basetype 為底層型式（1 為處理底層，0 為顆粒狀底層）、stype 為土壤分類（1 為粗顆粒，0 為細顆粒）和 trange 為年平均溫差(℃)：

$$FaultD = \exp[1.98 + 0.84 * \sqrt{age} - 6.09 * \frac{1}{\sqrt{kesalpyr}} - 1.9 * \frac{1}{\sqrt{bstress}} + 0.05 * \sqrt{precip} - 0.51 * basetype - 0.33 * stype - 22.35 * \frac{1}{trange}] \tag{15}$$

統計結果：R^2=0.6039，SEE=0.9122，n=305

在模式建構過程中，發現鋪面齡期對含綴縫筋之高差破壞與判定係數的高低有很大之影響，若模式中有鋪面齡期，則判定係數會提高，亦會使綴縫筋與混凝土間允許的支承應力變得有效。雖然不用綴縫筋與混凝土間允許的支承應力，也可得到不錯的的模式，但由過去的文獻中知道，將力學參數加入模式中，對於未來鋪面設計和分析有很大之幫助。在迴歸分析中，發現年平均溫差不僅對高差破壞有很大之影響，還能幫助判定係數增加，雖然冰凍指數也是有效的參數，但會使得綴縫筋與混凝土間允許的支承應力變得較無影響，為了保留此參數，因此以年平均溫差取代冰凍指數。

4.3 不含綴縫筋之高差模式

同樣地，新構建之不含綴縫筋模式如下所示，式中，age 為 cesal 為鋪面零期、kesalpyr 為年平均交通量(千)、jtspace 為橫向接縫間距(m)、precip 為降雨量(mm)、kstatic 為路基反力模數(MPa/m)、basetype 為底層型式(1 為處理底層，0 為顆粒狀底層)和 ft 為凍融循環次數：

$$FaultND = \exp[1.77 - 3.13 * \frac{1}{\sqrt{age}} + 0.01 * \sqrt{kesalpyr} - 8.27 * \frac{1}{jtspace} + 0.0004 * precip + 5.53 * \frac{1}{\sqrt{kstatic}} - 0.47 * basetype + 0.01 * ft] \tag{16}$$

統計結果：R^2=0.2127，SEE=1.781，n=241

在構建模式時，不僅判定係數要高且截距要越接近 0，斜率要越接近 1，才是最良好的模式。本研究經過多次的建模，發現不含綴縫筋模式比含綴縫筋模式還難建構，這可能是不含綴縫筋的鋪面，在現地的高差值起伏較大。雖然新建不含綴縫筋模式的判定係數不是很好，但是所用參數的物理意義都與現地鋪面反應相符，截距 0.1946 和斜率 0.9128 都在合理範圍內。

五、結論與建議

本研究主要目的在利用美國長程鋪面績效資料庫從事「鋪面績效預測模式的構建與應用」

研究。本計畫第二期（本期）之主要工作內容包括：延續前一期鋪面動態分段在地理資訊系統之應用、並建立柔性鋪面疲勞裂縫與車轍之績效預測模式、以及剛性鋪面橫向裂縫、接縫碎裂、與高差績效預測模式等三大部分。其中，本研究將透過 Visual Basic 程式之撰寫，將 ArcView 商用地理資訊系統中動態分段及圖形展示之應用方式自動化，並使其與鋪面路網資料庫管理系統、以及路網策略最佳化分析工具相結合，以建立一套具備關連式資料庫(Access 資料庫程式)、最佳化分析工具及圖形化介面之鋪面路網層級管理系統。

再者，在構建立柔性鋪面與剛性面績效預測模式之過程中，透過探索性資料分析，本研究發現鋪面績效資料常常違反了傳統迴歸法中所作常態分配、隨機誤差、與固定變異數的假設，因此不適用傳統統計迴歸方法來構建預測模式。此外，現地蒐集的 LTPP 長期鋪面績效資料變異性極大，更增添了利用多層線性模式(HLMs)或線性混合模式(LMEs)來分析 LTPP 長期鋪面績效資料庫的困難度。

因此，本研究於後續分析時採用廣義線性模式(GLM)與廣義相加模式(GAM)對於反應變數的分佈情形均不給予任何假設，而是採用以概似估計法的方式測試分配適用度,其中以柏松分配之適用性較良好。並配合 Box-Cox power transformation 轉換法、視覺圖的技術，以將系統化之統計與工程分析方法應用於構建預測模式中。本研究並將構建完成之預測模式檢定其適合度及針對相關的參數進行敏感度分析。希望能藉此改善現有模式適用性不佳之問題，未來亦將積極持續探討將預測模式本土化應用之研究。

七、參考文獻

1. 林明輝(2006)。*商用地理資訊系統在鋪面管理上之應用*，碩士論文(初稿)，淡江大學土木工程學系，民國 95 年 12 月。
2. 吳佩樺(2006)。柔性*鋪面績效預測模式之建*立，碩士論文，淡江大學土木工程學系，民國 95 年 6 月。
3. 林佳慧(2006)。*剛性鋪面績效預測模式之建立*，碩士論文(初稿)，淡江大學土木工程學系，民國 95 年 12 月。
4. 劉耀斌、吳炘達、顏少棠、李英豪 (2002).「AASHTO 高差預估模式之分析與驗證—以 LTPP 資料庫為例」，*第三屆鋪面工程師生研究成果聯合發表會論文集*，中央大學，中壢市，中華民國九十一年七月十日，第 245~252 頁。
5. 陳克斌(2002)。*綜合性指標在鋪面工程之應用*，淡江大學土木工程學系，碩士論文，民國 91 年 5 月。
6. 洪政乾(2000)。*鋪面路網維修管理策略最佳化之研究*，碩士論文，淡江大學土木工程學系，民國八十九年十二月。
7. 盧中強(2000)。*鋪面路網資料庫與地理資訊化系統架構之研究*，碩士論文，淡江大學土木工程學系，中華民國八十九年十二月。
8. 洪政乾、李英豪、顏少棠 (2002)。鋪面路網維修管理策略最佳化之研究，*第五屆鋪面材料再生學術研討會論文集*，朝陽科技大學，台中縣，中華民國九十一年十月三、四日，第 442~449 頁。
9. 交通部台灣區國道高速公路局(1997)。*中山高速公路路面養護管理系統電腦實務運用*，期末報告，財團法人台灣營建研究院，中華民國八十六年十二月。
10. 林志棟等(2000)。*路面維護管理系統-路面管理決策支援系統之研究*，交通部公路局，中華民國八十九年十月。
11. AASHTO (1998). *Supplement to the AASHTO Guide for Design of Pavement Structures*.

12. ARA, Inc. ERES Consultants Division (2004). *Guide for Mechanistic- Empirical Design of New and Rehabilitated Pavement Structure*. NCHRP 1-37A Rep., Transportation Research Board, National Research Council, Washington, D. C.
13. FHWA (2003). *Distress Identification Manual for the Long-Term Pavement Performance Program*. Publication No. FHWA-RD-03-031, U.S. Department of Transportation, Federal Highway Administration, Washington, D.C.
14. Ioannides, A. M., Y.-H. Lee, and M. I. Darter (1990). "Control of Faulting Trough Joint Load Transfer Design," *Transportation Research Record 1286*, Transportation Research Board,National Research Council, Washington, D.C., pp. 49-56.
15. Ker, H.S. (2002). *Application of regression spline in multilevel longitudinal modeling. Ph.D. dissertation*, University of Illinois, Urbana, Illinois.
16. Ker, H.S, Wardrop, J. & Anderson, C. (2003). Application of linear mixed-effects models in longitudinal data: A case study. *Proceedings, Hawaii International Conference on Education,* January 7-10.
17. Ker, H. W., Lee, Y. H., & Wu, P. H. (2006). Development of fatigue cracking performance prediction models for flexible pavements using LTPP database. Accepted for Presentation at *the 86th Annual Meeting of the Transportation Research Board.*
18. Lee, Y. H. (1993). *Development of Pavement Prediction Models,* Ph.D. Thesis, University of Illinois, Urbana.
19. Lee, Y. H., and M. I. Darter (1995). "Development of Performance Prediction Models for Illinois Continuously Reinforced Concrete Pavements," *Transportation Research Record1505,* Transportation Research Board, Washington, D.C., 1995, pp.75-84.EI
20. Lee, Y. H., Liu, Y. B., & Ker, H. W. (2006). Application of modern regression techniques and artificial neural networks on pavement prediction modeling. Accepted for Presentation at the *86th Annual Meeting of the Transportation Research Board* and Possible Publication of the *Journal of the Transportation Research Board.*
21. Lee, Y. H., A. Mohseni, and M. I. Darter (1991). *Pavement Model Enhancements for the Highway Performance Monitoring System (HPMS),* Final Report, Illinois Department of Transportation and Federal Highway Administration.
22. Pinherio, J. C. & Bates, D. M (2000). *Mixed-effects models in S and S-Plus*. New York: Springer-Verlag.
23. Simpson, A. L., J. B. Rauhut, P. R. Jordahl, E. Owusu-Antwi, M. I. Darter, R. Ahmad, O. J. Pendleton, Y. H. Lee (1993). *Early Analyses of LTPP General Pavement Studies data,* Volume 3 - Sensitivity Analyses for Selected Pavement Distresses, Strategic Highway Research Program, National Research Council, Washington, D.C.
24. Strategic Highway Research Program (1993). *Long-Term Pavement Performance Information Management System Data Users Guide,* Report No. FHWA-RD-93-094, Federal Highway Administration.
25. SHRP (1993). *Distress Identification Manual for the Long-Term Pavement Performance Project*, SHRP-P-338, Strategic Highway Research Program, National Research Council, Washington, D.C.
26. Strategic Highway Research Program (2002). *Back-Calculation of Layer Parameters for LTPP Test Sections, Volume Ⅱ, Layered Elastic Analysis for Flexible and Rigid Pavements*, Publication No. FHWA-RD-01-113, Federal Higfway Administration.
27. Strategic Highway Research Program (2004). *Long-Term Pavement Performance Information Management System - Pavement Performance Database User Reference Guide*, Publication No. FHWA-RD-03-088, Federal Higfway Administration.
28. Venables, W. N. & Ripley, B. D. (1999). *Modern applied statistics with S-Plus* (3rd ed.). New York: Springer-Verlag.
29. Weisberg, S. (1985). *Applied linear regression* (2nd ed.). NY: John Wiley & Sons.

出席國際會議報告
第六屆國際 DUT 混凝土鋪面基礎設計與績效模型研討會

李英豪
淡江大學土木工程學系教授

一、前言

第六屆國際 DUT 混凝土鋪面基礎設計與績效模型研討會(Workshop)係由荷蘭 Delft 科技大學(Delft University of Technology)與荷蘭國家運輸與基礎建設資訊暨技術中心(CROW)所主辦，並由海德堡水泥集團(Heidelburg Cement Group)之 ENCI 荷蘭水泥公司與 CBR 比利時水泥公司、以及荷蘭水泥工業同業工會(FEBELCEM, the Federation of the Belgian Cement Industry)共同協辦。會議地點安排在比利時 Old-Turnhout 市極具歷史意義之 Priorij Corsendonk 修道院舉行，會期由二OO六年九月十四日至十七日，共四天。

荷蘭國家運輸與基礎建設資訊暨技術中心(CROW)主要的任務在從事土木與交通工程標準法規之訂定暨相關研究。本屆歐洲機場鋪面研究講習會主要議題在探討各項與機場鋪面相關的研究與發展，以便機場未來之持續服務與應用。CROW 自一九八六年起每四年舉辦一次研討會，僅邀請四十位以內的國際知名專家學者與會，讓與會人員真正有充分的時間研討、交換研究心得。由於 CROW 在最近幾年內之任務調整，因此自本屆研討會開始改由荷蘭 Delft 科技大學(Delft University of Technology)負責接辦此國際混凝土鋪面界之重要盛會。

筆者有幸曾在過去獲得該講習會主席之邀請參加在一九九八年葡萄牙 Bucaco 舉行的第四屆國際混凝土面版設計理論及驗證研討會、以及在二OO四年土耳其伊斯坦堡舉行的第五屆國際混凝土鋪面設計與績效理論模型研討會。筆者很高興能再度獲得本屆研討會主席之邀請，並獲得行政院國科會的旅費補助以參加此國際盛會。

二、會議主題

本屆研討會主要議題為鋪面材料性質之基礎模型、混凝土鋪面理論模型、鋪面績效相關之理論模型、與創新鋪面結構之設計理論。會議期間大會並邀請多位國際知名的專家學者擔任每一主要議題的主持人與提問人，以作為後續研討的主軸，研討會主席並於當日作最後之總結。在八場次的研討會中，共發表了一篇專題演講(keynote speech)與二十五篇學術論文，對促進世界各國混凝土鋪面的專家學

者與專門從業人員間之研討與交流有極大助益。

三、參加會議經過

為了順利參加本屆研討會，筆者自台北出發經曼谷短暫停留後，直飛荷蘭首都阿姆斯特丹(Amsterdam)的史基埔國際機場(Schipol International Airport)，之後再轉機至比利時首都布魯塞爾之國際機場。九月十四日下午至機場附近的 Sheraton Hotel 集合，再搭乘大會準備的遊覽車到布魯塞爾北邊約二小時車程的 Old-Turnhout 市，到達 Priorij Corsendonk 修道院後隨即辦理住宿事宜，稍作休息後，大會並隨即舉行歡迎酒會及開幕典禮，以及介紹與會貴賓、工作人員、議程與相關事項。

九月十五日上午，研討會正式開始，由會議主席 Andre A. A. Molenaar 教授親自主持，介紹所有與會人員與相關議題。之後，由大會所邀請的貴賓 Frans van Cauwelaert 教授作專題演講，演講題目為「鋪面工程五十年經驗談：過去從實務至理論/現在為何不由理論再轉回實務」(A Bit of Fifty Years Pavement Engineering – From Practice to Theory and Why Not from Theory Back to Practice)，受到與會人員的熱烈迴響。接著由會議主席 Molenaar 教授親自主持第一與第二場次的論文研討，主要議題在探討鋪面材料性質之基礎模型。其間並有短暫的中場休息時間，讓與會人員有私下交流研討之機會。

除了延續早上的議題外，當日下午的主題亦包括「混凝土鋪面理論模型 I」與「混凝土鋪面理論模型 I」，均由南非的 Pieter J. Strauss 博士擔任主持人與此子題的主要提問人。全天的研討會在下午五點半左右完成，緊接著並由會議主席 Andre A. A. Molenaar 教授總結當日與會討論的重點與結論。在結束了緊湊的議程後，稍作休息後，當日晚宴自八點鐘開始，為讓與會者有充分時間交談，可以自由回到房間時已經超過晚上十一點了。

筆者的論文「當代迴歸技術與類神經網路在鋪面預測模式之應用」(Application of Modern Regression Techniques and Artificial Neural Networks on Pavement Prediction Modeling)被安排在翌日上午的「鋪面績效相關之理論模型 I」子題下，由 Lambert J. M. Houben 教授擔任該議題二場次的主持人與主要提問人。有機會與世界各國知名的剛性鋪面專家學者分享由我國行政院國家科學委員會專題計畫補助的研究成果。當日下午，除了繼續進行上午之議題外，並發表了「創新鋪面結構之設計理論」等相關之論文，大會並邀請美國的 Halil Ceylan 教授擔任此子題的主持人與主要提問人。同樣地，全天的研討會在下午五點半左右完成，最後再由會議主席 Andre A. A. Molenaar 教授親自主持，彙整會議結論與建議未來研

究方向，以供與會人員共同研討。忙完了整日緊湊的議程，稍作休息後，大會並安排一個非常特別的中古世紀修道院式的晚宴，讓與會者共享非常特別且值得回憶的一夜，回到客房休息已經將近晚上 12 點了。十七日上午，簡單用完早餐後，該是整理行李、與會人員互道珍重再見的時候了，期待下次再相會。

本屆講習會共計發表一篇專題演講(keynote speech)與二十五篇學術論文，包括美國、丹麥、比利時、荷蘭、西班牙、日本、中華民國(台灣)、南非、德國、瑞典等十國三十一位專家學者代表與會。在大會精心安排的議程下，會議手冊及相關資料亦早已於一個月前寄達與會者參考研讀，因此真正有機會及充分的時間互相研討並交換心得，並受到與會人員的熱烈迴響，實堪國內相關學術研討會之借鏡。

四、與會心得與建議

由政府目前正積極進行之國家建設六年計畫、新十大建設五年五千億計畫、及對未來三十年台灣區國道公路網之規劃內容中可知，交通運輸工程建設是我國國家建設最首要的工作項目之一。我國中正國際機場因已超過使用年限，目前亦有全面整建之計畫正在積極進行中。事實上，不僅國內如此，世界各國隨著經濟的蓬勃發展，仰賴便捷的交通需求亦與日俱增，對交通運輸工程建設均有著同樣的迫切需求。建全的交通運輸建設與一個國家之經濟發展有著密不可分的關係，與會各國鋪面研究相關之專家學者亦指出此國家基礎建設的重要性。有幸參與此次研討會，更加深了個人對此之信念。

有機會與世界各國之專家學者交流研討，並據此得知世界各國鋪面之最新發展與相關研究乃是參加此次年會的最大收獲。筆者很慶幸能獲得行政院國科會之旅費補助，因此得以順利參加此會議，謹此致上萬分之謝意。

五、攜回資料名稱

參加本屆國際 DUT 混凝土鋪面基礎設計與績效模型研討會攜回資料包括：會議議程資料、本屆會議論文集、本屆會議與會代表名錄、及其他相關補充資料若干。

出國報告提要

第六屆國際 DUT 混凝土鋪面基礎設計與績效模型研討會(Workshop)係由荷蘭 Delft 科技大學(Delft University of Technology)與荷蘭國家運輸與基礎建設資訊暨技術中心(CROW)所主辦，地點安排在比利時 Old-Turnhout 市極具歷史意義之 Priorij Corsendonk 修道院舉行，會期由二OO六年九月十四日至十七日，共四天。本屆研討會主要議題為鋪面材料性質之基礎模型、混凝土鋪面理論模型、鋪面績效相關之理論模型、與創新鋪面結構之設計理論。在八場次的研討會中，共計發表了一篇專題演講(keynote speech)與二十五篇學術論文，包括美國、丹麥、比利時、荷蘭、西班牙、日本、中華民國(台灣)、南非、德國、瑞典等十國三十一位專家學者代表與會。

筆者有幸曾在過去獲得該講習會主席之邀請參加在一九九八年葡萄牙 Bucaco 舉行的第四屆國際混凝土面版設計理論及驗證研討會、以及在二OO四年土耳其伊斯坦堡舉行的第五屆國際混凝土鋪面設計與績效理論模型研討會。今年能再度獲得本屆研討會主席之邀請，並獲得行政院國科會的旅費補助，得以順利參加此次盛會，發表論文「當代迴歸技術與類神經網路在鋪面預測模式之應用」(Application of Modern Regression Techniques and Artificial Neural Networks on Pavement Prediction Modeling)一篇，與世界各國鋪面從業人士與專家學者分享由我國國科會專題計畫補助的研究成果，謹此致上萬分之謝意。

Application of modern regression techniques and artificial neural networks on pavement prediction modeling

Y. H. Lee & Y. B. Liu
Department of Civil Engineering, Tamkang University, Taipei, Taiwan

H. W. Ker
Department of International Trade, Chihlee Institute of Technology, Taipei, Taiwan

ABSTRACT: This study strives to illustrate the benefits of incorporating the principles of dimensional analysis, subject-related knowledge, and statistical knowledge into pavement prediction modeling process. Modern regression techniques including local regression and regression splines as well as back propagation neural networks were briefly introduced. Factorial 2-D and 3-D finite element runs and BISAR runs for different pavement systems were conducted to generate the deflection databases for the analysis. The resulting ANN model using all dominating dimensionless parameters was proved to have higher accuracy and require less network training time than the other counterpart using purely input parameters. Increasing the complexity of ANN models does not necessarily improve the modeling statistics. The results also showed that using higher number of neurons and hidden layers sometimes lead to even worse modeling statistics which was an indication of over training and should be avoided. Several local regression models requiring minimal amount of modeling time were also developed using the same databases.

KEY WORDS: Pavement deflection, prediction modeling, dimensional analysis, local regression, artificial neural networks.

1. INTRODUCTION

Predictive models have been widely used in various pavement design procedures, evaluation, rehabilitation, and network management systems. Empirical and mechanistic-empirical approaches using statistical regression techniques have been utilized extensively in predicting extremely complicated pavement responses and performance indicators for more than four decades. Using purely empirical concepts to develop predictive models is not recommended. Lee (1993) proposed a systematic statistical and engineering modeling approach which strongly recommends to incorporate theoretical engineering knowledge, expert experience, heuristics, and statistical data analysis and regression techniques altogether into the framework to develop more mechanistic-based predictive models. In additional to the conventional “parametric” linear and nonlinear regression techniques, several ingenious iterative regression techniques in the area of “robust” and “nonparametric” regressions were also incorporated. The proposed approach has been successfully implemented in the development of many purely empirical predictive models (Lee et al., 1993; Lee & Darter, 1995), purely mechanistic predictive models (Lee & Darter, 1994a; 1994b) as well as the mechanistic-empirical predictive models adopted in the early analyses of LTPP general pavement studies data (Simpson et al., 1993).

Significant progress has been reported in pavement prediction modeling of simulated data using artificial neural networks (ANN). Back propagation networks (BPN) can be taught from one data space to another using representative set of data to be learned. The learning process actually refers to a multi-layered, feed-forward neural network trained by using an error back propagation algorithm or an error minimization technique (Haykin, 1999; Hecht-Nielsen, 1990). Ceylan (2004) conducted a literature search summarizing recent ANN applications in pavement structural evaluation such as backcalculating pavement layer moduli and predicting primary pavement responses (e.g., stress and deflection). As with many ANN applications in the literature (Haussmann et al., 1997; Meier et al., 1997; Ceylan et al., 1998; 1999; 2004; Ceylan & Guclu, 2005), original pertinent input parameters were used to generate the training and testing databases. This approach often requires tremendous amount of time and efforts in network training and testing. To reduce the size of the required factorial databases, researchers sometimes opt to fix certain input parameters to some prescribed values as a special case study, which may result in limiting the inference space of the resulting model.

Nevertheless, some earlier ANN literature has also illustrated that the incorporation of the principles of dimensional analysis lead to significant savings during the training set generation. Ioannides et al. (1996) trained a back propagation neural network (BPN) to determine the in situ load transfer efficiency of rigid pavement joints from Falling Weight Deflectometer (FWD) data. Khazanovich and Roesler (1997) developed an ANN-based backcalculation procedure for composite pavements. The multilayer elastic program DIPLOMAT was used to analyze a three-layer pavement system consisting of an AC surface layer over a PCC slab resting on a Winkler foundation. Ioannides et al. (1999) trained BPN models to predict the critical slab bending stress for loading-only, curling-only, and loading-and-curling cases. BPN predictions were compared against the Westergaard closed-form solutions as well as the statistical regression models developed by Lee and Darter (1994a) using a small set of factorial data with dimensionless mechanistic variables. It was re-emphasized that mature engineering judgment and in-depth understanding of the mechanics of the phenomenon remain the most reliable guides in the formation of the problems to be analyzed.

Attoh-Okine (1994) proposed the use of ANN models in predicting roughness progression of flexible pavements. Although the results were promising, some built-in functions including learning rate and momentum term which form key neural network algorithm were not investigated. Attoh-Okine (1999) used real pavement condition and traffic data and specific architecture to investigate the effect of learning rate and momentum term on BPN models for the prediction of flexible pavement performance. Sorsa et al. (1991) indicated that adding many hidden layers gets the network to learn faster and the mean square error becomes a little smaller, but the generalization ability of the network reduces.

Ripley (1993) discussed many statistical aspects of neural networks and tested it with several benchmark examples against traditional and modern regression techniques, such as generalized discriminant analysis, projection pursuit regression, local regression, tree-based classification, etc. Ripley concluded that in one sense neural networks are little more than non-linear regression and allied optimization methods. “That two-layer networks can approximate arbitrary continuous functions does not change the validity of more direct approximations such as statistical smoothers, which certainly ‘learn’ very much faster” (Ripley, 1993). Projection pursuit regression highlights the value of differentiated units and other training schemes and offers computation shortcuts through forward and backward selection. Statistical and subject-related knowledge can be used to guide modeling in most real-world problems and so enable much more convincing generalization and explanation, in ways which can never be done by ‘black-box’ learning systems (Ripley, 1993).

As part of continuous research efforts in pavement design and analysis (Lee et al., 1994a; 1998; 2004), modern regression techniques and artificial neural networks (ANN) are utilized in this study to improve the prediction accuracy of simulated pavement deflections (Wu, 2003; Liu, 2004). Factorial 2-D and 3-D finite element runs and BISAR runs for different pavement systems are conducted to generate the deflection databases for the analysis. This study strives to illustrate the benefits of incorporating the principles of dimensional analysis, subject-related knowledge, and statistical knowledge into prediction modeling process.

2. MODERN REGRESSION TECHNIQUES

2.1 Revised two-step modeling approach using projection pursuit regression

The proper selection of regression techniques is one of the most important factors to the success of prediction modeling. Since most of the regression algorithms currently available do not directly consider interaction effects during the modeling process, the interaction terms must be subjectively determined prior to performing a regression analysis. With the multi-dimensional pavement engineering problems in mind, several unresolved deficiencies are frequently identified in the use of stepwise regression and nonlinear regression. These include problems in the selection of correct functional form, violations of the embedded statistical assumptions, and failure to satisfy some engineering boundary conditions.

The projection pursuit regression (PPR), however, appears to have the most favorable features in handling these problems, which strives to model the response surface (y's) as a sum of nonparametric functions of projections of the predictor variables (x's) through the use of super smoothers. More technical details about the development process, the application, and the demonstration on modeling interactions of the PPR algorithm can be found in the literature (Friedman & Stuetzle, 1981; Friedman, 1984; Mathsoft, Inc. 1997). The S-PLUS statistical package, which has been widely used by statisticians, was selected for the analysis due to the availability of this regression technique.

As a result, a two-step regression analysis procedure was proposed by Lee and Darter (1994b) to better find the correct functional form and to better fit the response surface. With the help of the PPR, a multi-dimensional response surface is broken down into the sum of several smooth projected curves which are graphically representable in two dimensions. Plausible functional forms and applicable boundary conditions may then be easily identified and specified through visual inspection and/or engineering knowledge of physical relationships to model these individual projected curves separately. Traditional parametric regression techniques such as linear, piecewise-linear, and nonlinear regressions are then utilized for these purposes with higher confidence in the parameter estimates.

In this study, regression spline algorithm (Ker, 2002) was adopted in lieu of piecewise-linear regressions at the second step to assure smooth junctions at the change points. A spline function is a piecewise polynomial regression. An n-spline function is an n-degree polynomial with n-1 continuous derivatives at the change points. These change points are called “knots” in spline literature. Spline functions can be viewed as a data-smoothing regression function and/or a way to improve polynomial approximation of regression function. In most cases, a spline can be represented as a linear combination of some basis functions that have polynomial forms. Polynomials can be viewed as a special case of spline with no knots (Smith, 1979). In fitting a spline model, the prediction should be within the data range. Cubic splines with continuous second derivatives at the knots are most commonly used in most applications (Seber & Wild, 1989). Cubic splines are most popular in spline applications because they are of low degree and relatively smooth (assuming continuity restriction up to second derivative only), and possess the power to incorporate several different trends in the range of the data by increasing the number of knots (Smith, 1979).

2.2 Locally-weighted regression (loess) technique

The locally weighted regression (loess) technique is an approach to regression analysis by local fitting developed by Cleveland and Devlin (1988). Cleveland and Grosse (1991) provided computational methods for local regression. A particular data structure called k-d tree is used for partitioning space by recursively cutting cells in half by a hyperplane orthogonal to one of the coordinate axes. The loess approach uses a smoothing technique for fitting a nonlinear curve to the data points locally, so that any point of the curve depends only on the observations at that point and some specified neighboring points. The number of neighbors (k) is specified as the percentage of the total number of points or “span”. Local regression models provide much greater flexibility in fitting a multi-dimensional response surface as a series of many sub-divided regions with single smooth functions of all the predictors. There are no restrictions on the relationships among the predictors.

Figure 1 depicts the concept of loess k-d tree algorithm. This algorithm is available in the S-PLUS statistical package (Mathsoft, Inc., 1997). As currently implemented, locally quadratic models may have at most 4 predictor variables and locally linear models may have at most 15 predictors. The original FORTRAN and C codes for the loess algorithm can also be obtained from the ftp site: “ftp research.att.com.”

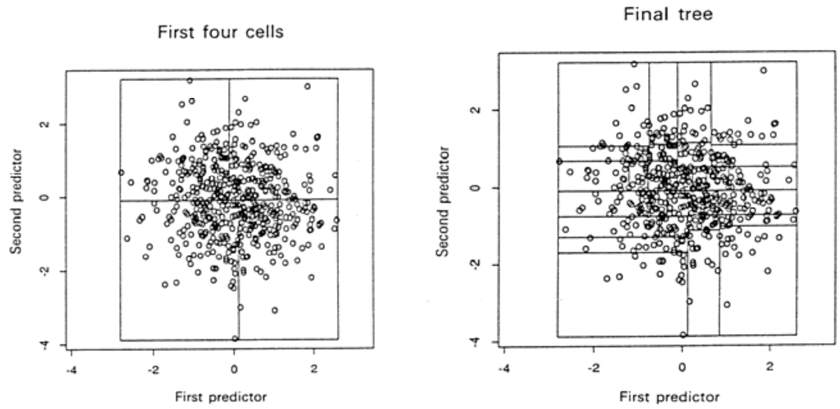


Figure 1. Illustration of loess k-d tree algorithm (Cleveland & Grosse, 1991).

3. ARTIFICIAL NEURAL NETWORKS

Artificial Neural Networks (ANN) provides a flexible way to generalize linear regression functions. They are nonlinear regression models but with so many parameters extremely flexible to approximate any smooth function. The most commonly used rule is the generalized delta rule or back propagation algorithm. Ripley (1993) provided the detail definitions and brief derivation of a back propagation network (BPN). The learning procedure has to select the weights and the biases by presenting the training examples in turn several times, while striving to minimize the total squared error:

$$E = \frac{1}{2}\sum_{p}\left\|y^{p} - c^{p}\right\|^{2} \qquad (1)$$

Where y^p is the output for input x^p, and c^p is the target output; the index p runs through the data in the training set. However, the questions of how many layers and how many neurons should be used were treated very lightly in the literature.

A neural network modeling software package called Qnet v2000 for Windows (Vesta Services, Inc. 2000) was adopted for this study. The convergence characteristics of various activation (or transfer) functions including step function, logistic or sigmoid function, hyperbolic tangent function, and radial basis function as shown in Figure 2 will be further investigated (Mehrotra et al., 1997; Smith, 1996).

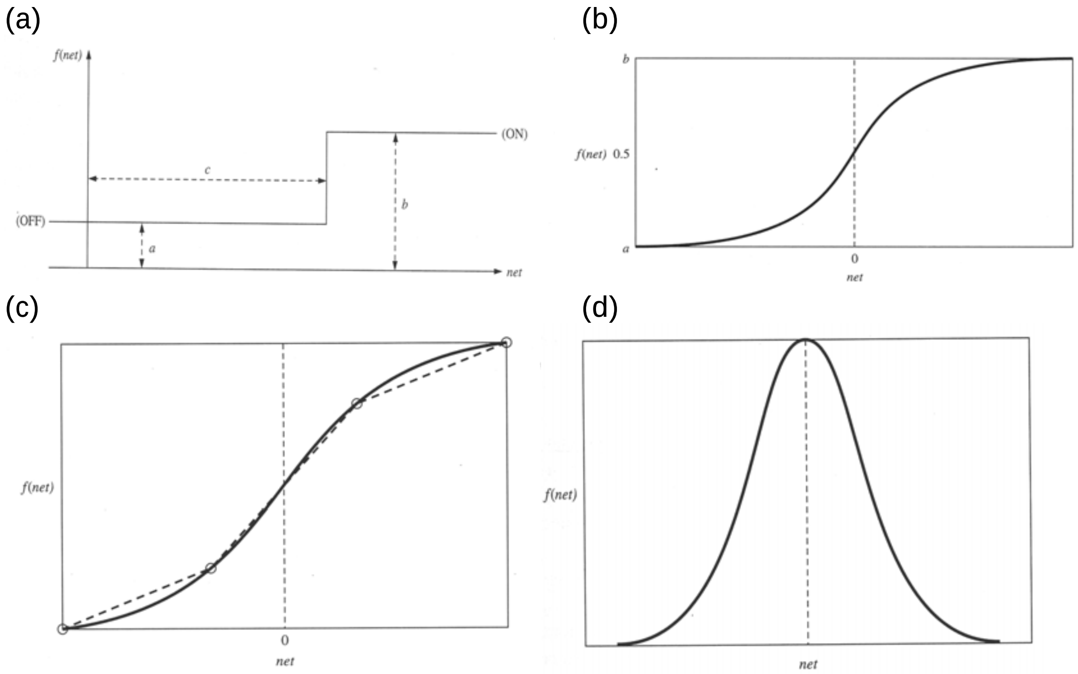


Figure 2. Illustration of various activation (or transfer) functions: (a) step function, (b) logistic or sigmoid function, (c) hyperbolic tangent function, and (d) radial basis function.

4. APPLICATIONS OF ARTIFICIAL NEURAL NETWORKS AND MODERN REGRESSION TECHNIQUES

4.1 Rigid pavement deflection prediction models of infinite slab size

Based on the principles of dimensional analysis, Ioannides et al. (1989) indicated that the structural responses of a rigid pavement such as or the dimensionless deflection parameter ($\delta k\ell^2/P$) are dominated by the following four dimensionless variables: the normalized load radius (a/ℓ), the normalized finite slab length (L/ℓ), the normalized finite slab width (W/ℓ), and the normalized radial distance (r/ℓ) for 2-D FEM analysis. In which δ is the deflection, [L]; k is the modulus of subgrade reaction, [FL^{-3}]; P is the single wheel load, [F]; $\ell=(E*h^3/(12*(1-\mu^2)*k))^{0.25}$ is the radius of relative stiffness of the slab-subgrade system [L]; E is the modulus of the concrete slab, [FL^{-2}]; h is the thickness of the slab, [L]; μ is the Poisson's ratio. Note that primary dimension for force is represented by [F], and length is represented by [L]. To illustrate the benefits of incorporating the principles of dimensional analysis into the modeling process, the following case studies were conducted:

4.1.1 ANN models

For an infinite single slab resting on a Winkler foundation under interior loading condition, factorial ILLI-SLAB runs were conducted based on the following input parameters: single wheel load P=40 kN (9,000 lbs); tire pressure p=0.62 MPa (90 psi); modulus of the concrete slab E= 13.78~48.23 GPa (2~7 Mpsi); modulus of subgrade reaction k=13.5~175.5 MN/m^3 (50~650 pci); and slab thickness h= 15.2~76.2 cm (6~30 in.). These input parameters were such selected to cover wider ranges of practical cases. The dependent variable is the deflection δ and the explanatory variables are *E, k, h,* and *r*. The resulting deflection database consists of 12,329 data points, in which 11,329 observations were randomly selected for actual training and the remaining 1,000 data points was used to monitor the training process. Step activation function was first tried with extreme difficulty in achieving convergence. Subsequently, sigmoid activation function was chosen for the modeling process. The summary statistics of the NET1 model is shown in Table 1. Note that since certain input parameters were fixed to some prescribed values to reduce the size of the required factorial database, the applicability of this special case study is rather limited.

Table 1. Comparison of two different ANN models

ANN Type	NET1	NET2
Outputs		R
Inputs	E, k, h, r	a/ℓ, r/ℓ
Data Points	Training: 11,329 Monitoring: 1,000	Training: 394 Monitoring: 100
Hidden Layer(s)	2	1
Neurons in Each Hidden Layer	12-12	6
Learning Cycle	30,000	10,000
Learning Rate	0.5	0.1
Modeling Time	6 hrs 43 min.	42 min.
RMS	Training: 0.00290 Monitoring: 0.00420	Training: 0.00377 Monitoring: 0.00360
Coefficient of Determination, R^2	0.999	0.9999

Alternatively, the aforementioned factorial ILLI-SLAB runs may be generalized based on the following dimensionless parameters: a/ℓ=0.05~0.4 (step by 0.01) and r/ℓ ranges from 0 to 3.2 determined by automatic mesh generation. To simulate infinite slab size conditions, L/ℓ and W/ℓ were greater than or equal to 8. Thus, a 2-D rigid pavement deflection database with 494 data points was obtained (Liu, 2004). The dependent variable is the deflection ratio (R) defined as the ratio of the deflection at any radial distance to the resulting maximum deflection. In which 394 data points were used for actual ANN training and the remaining 100 observations were used to monitor the training process. The convergence characteristics of various activation functions were investigated. As shown in Figure 3(a), it was noted that sigmoid activation function has better convergence characteristics than hyperbolic tangent function. Using a single hidden layer with only 5 neurons, sigmoid function completed 10,000 training cycles in 35 minutes whereas hyperbolic tangent function needed 60 minutes, although the resulting root mean squared errors (RMS) had no much difference. Radial basis activation function was also tried with extreme difficulty in achieving convergence. In addition, increasing the number of neurons during the network training process does not necessarily improve the modeling statistics. On the contrarily, as shown in Table 2 and Figure 3(b) the resulting RMS and training time increased while increasing the number of neurons in the hidden layer. Since the model with only six neurons had the lowest RMS, it was chosen as the proposed model (NET2) as summarized in Table 1. It was also concluded that with the incorporation of dimensional analysis in the modeling process, the requirements on database generation and network training time could be greatly reduced.

Table 2. Summary statistics of different ANN models

ANN Type	Number of Neurons in the Hidden Layer					
	5	6	7	8	9	10
Training RMS	0.00416	0.00377	0.00524	0.00569	0.00554	0.00520
Monitoring RMS	0.00384	0.00360	0.00492	0.00529	0.00520	0.00490
R-Squared	0.9999	0.9999	0.9999	0.9999	0.9999	0.9999
Training Time	35 min.	42 min.	52 min.	60 min.	67 min.	82 min.

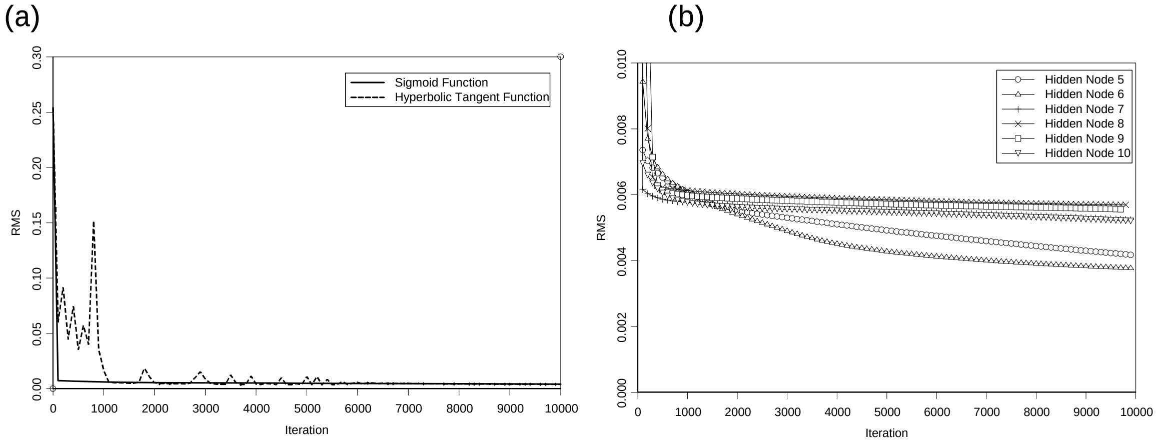


Figure 3. Comparison of convergence characteristics: (a) due to different activation functions; (b) due to different number of neurons in the hidden layer.

4.2 Rigid pavement deflection predictions of finite slab size

To further investigate the convergence characteristics of different ANN models and to illustrate the possibility of over training, the following case studies were conducted.

4.2.1 ANN models

Similarly, for a finite single slab resting on a Winkler foundation under interior loading condition, factorial ILLI-SLAB runs were conducted based on the following input parameters: a/ℓ=0.05~0.4, L/ℓ= 2~7, W/ℓ=2~7, and r/ℓ ranges from 0 to 3.2 determined by automatic mesh generation. A 2-D rigid pavement deflection database with 2,227 data points was obtained (Liu, 2004). The dependent variable is the deflection ratio (R) defined as the ratio of the deflection at any radial distance to the resulting maximum deflection. The explanatory variables are the following dimensionless variables: a/ℓ, L/ℓ, W/ℓ, and r/ℓ.

In which 2,027 data points were randomly selected for actual ANN training and the remaining 200 observations were used to monitor the training process. Similarly, it was noted that sigmoid activation function has better convergence characteristics than hyperbolic tangent function. Using a single hidden layer with only 8 neurons and learning rate = 0.01, sigmoid function completed 30,000 training cycles in 11 minutes whereas hyperbolic tangent function needed 20 minutes, although the resulting root mean squared errors (RMS) had no much difference. Radial basis activation function was also tried, but extreme difficulties were encountered in achieving convergence. By increasing the number the hidden layers from 1 to 2 and the number of neurons from 8 to 13 during the network training process, the resulting RMS and training time are summarized in Table 3. The convergence characteristics of different ANN models with 8 neurons in the first hidden layer were shown in Figure 4. The ANN model with 8 neurons in the first hidden layer and 1 neuron in the second hidden layer was chosen as the proposed model due to its relatively small RMS. The results also showed that more complicated ANN models using higher number of hidden layers and neurons sometimes lead to even worse modeling statistics which was an indication of over training and should be avoided.

Table 3. Summary statistics of ANN models with different number of layers and neurons

ANN Type		Summary Statistics	Number of Neurons in the First Hidden Layer					
			8	9	10	11	12	13
Number of Neurons in the Second Hidden Layer	0	Training RMS	0.01037	0.00965	0.00974	0.00782	0.00887	0.00925
		Monitoring RMS	0.01007	0.00966	0.01046	0.00785	0.00923	0.01011
		R-Squared	0.9988	0.9989	0.9989	0.9993	0.9991	0.9989
		Training Time	11 min.	12 min.	13 min.	15 min.	16 min.	17 min.
	1	Training RMS	0.00552	0.00550	0.00562	0.00553	0.00602	0.00539
		Monitoring RMS	0.00565	0.00594	0.00518	0.00513	0.00562	0.00568
		R-Squared	0.9997	0.9997	0.9996	0.9997	0.9997	0.9997
		Training Time	11 min.	12 min.	13 min.	16 min.	17 min.	21 min.
	2	Training RMS	0.00714	0.00620	0.00563	0.00668	0.01102	0.00589
		Monitoring RMS	0.00711	0.00604	0.00581	0.00613	0.01028	0.00713
		R-Squared	0.9994	0.9996	0.9994	0.9995	0.9988	0.9995
		Training Time	13 min.	13 min.	15 min.	18 min.	19 min.	22 min.
	3	Training RMS	0.00599	0.00751	0.00581	0.00817	0.00981	0.01008
		Monitoring RMS	0.00549	0.00831	0.00588	0.00864	0.00904	0.01061
		R-Squared	0.9997	0.9988	0.9991	0.9988	0.9979	0.9978
		Training Time	15 min.	16 min.	17 min.	19 min.	21 min.	24 min.
	4	Training RMS	0.00570	0.00748	0.00558	0.01005	0.00673	0.00671
		Monitoring RMS	0.00569	0.00803	0.00559	0.01074	0.00656	0.00726
		R-Squared	0.9993	0.9988	0.9994	0.9978	0.9978	0.9991
		Training Time	18 min.	18 min.	19 min.	22 min.	24 min.	25 min.

(a) (b)

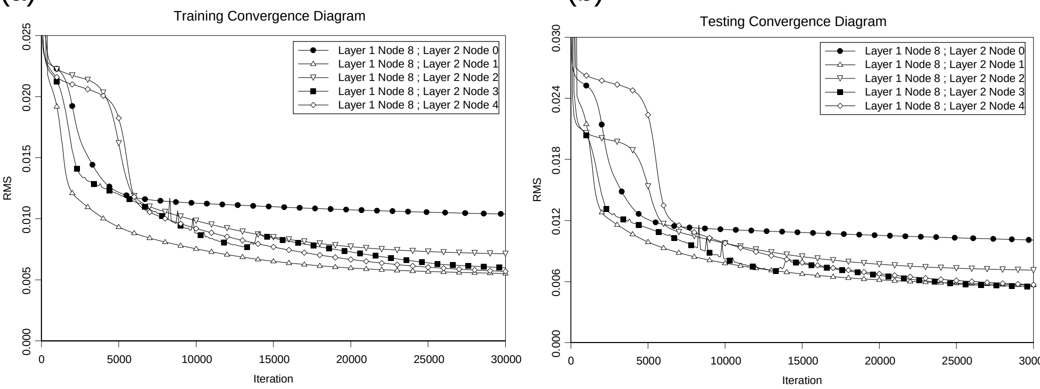


Figure 4. Comparison of convergence characteristics: (a) training data; (b) testing data.

4.2.2 Loess models

Several S-PLUS trials of local regressions were conducted using the same database. The response variable was chosen as the deflection ratio (R) and the explanatory variables were a/ℓ, L/ℓ, W/ℓ, and r/ℓ. The resulting loess model was easily obtained requiring minimal amount of modeling time, in which the smoothing parameter “span” was chosen as 0.1, whereas the “cell” argument was chosen as 0.01. The following regression statistics were obtained: the number of observations = 2,227; equivalent number of parameters = 31.9; residual standard error = 0.006376; and multiple R-squared = 1. The resulting errors were still relatively small even when the proposed loess model was quite simple.

4.3 Three-dimensional rigid pavement deflection predictions

With the introduction of three-dimensional (3-D, ABAQUS) FEM (Hibbitt et al., 2000) and all the promising features reported in the literature, its applications on pavement engineering become inevitable (Wu, 2003). Based on the principles of dimensional analysis, Ioannides and Salsilli-Murua (1989) indicated that the dimensionless deflection parameter ($\delta k\ell^2/P$) is only a function of a/ℓ, L/ℓ, and W/ℓ for 2-D FEM analysis. Extreme difficulties were encountered while using only these three dimensionless variables (a/ℓ, L/ℓ, W/ℓ) to determine $\delta k\ell^2/P$ for 3-D FEM analysis. Subsequently, an additional dominating dimensionless variable (h/a) defined as the ratio of slab thickness (h) and load radius (a) was identified to account for the theoretical differences between 2-D and 3-D FEM analyses (Lee et al., 2004). A series of 3-D FEM factorial runs was conducted for a single squared slab resting on a Winkler foundation under interior loading condition with the following dimensionless parameters: a/ℓ=0.05, 0.1~0.5 (step by 0.1); L/ℓ=2~8 (step by 1); $W/\ell=L/\ell$; and h/a=0.5~6 (step by 0.5). These ranges were carefully selected to cover a very wide range of highway and airfield rigid pavement conditions. An automated analysis program was developed using the Visual Basic software package (Microsoft, 1998) to automatically construct FEM models, generate the input files, conduct the runs, as well as summarize the results to avoid untraced human errors. A 3-D rigid pavement deflection database with 504 data points was obtained (Liu, 2004).

4.3.1 ANN models

In which, 404 observations were randomly chosen for actual training and the remaining 100 data points were used for monitoring the training process. Deflection ratio (R) defined as the ratio of 3-D FEM results to Westergaard solutions was treated as the response variable. Sigmoid activation function was chosen in this case study. The learning rate was set as 0.02 for the cases analyzed. In the first ANN model (NET1), no transformation was made on the response variable. As shown in Table 4 and in Figure 5, the modeling statistics and the convergence characteristics of the NET1 model were satisfactory.

Table 4. Comparison of two different ANN models

ANN Type	NET1	NET2
Outputs	R	1/R
Inputs	a/ℓ, L/ℓ, h/a	a/ℓ, L/ℓ, h/a
Hidden Layer(s)	2	2
Neurons in Each Hidden Layer	10-4	10-4
Learning Cycle	30,000	30,000
RMS	Training: 0.00989 Monitoring: 0.01019	Training: 0.00539 Monitoring: 0.00478
Coefficient of Determination, R^2	0.9988	0.9999

Nevertheless, it is worth mentioning that since Westergaard's closed-from deflection is very small for thicker pavements or larger load sizes (larger h/a and a/ℓ), the resulting 3-D FEM deflections can be several times of the theoretical solutions due to possible compression across the slab thickness. Since the resulting 3-D FEM deflections are always higher than the Westergaard solutions, the reciprocal of the deflection ratio (1/R) always ranges from 0 to 1. Wu (2003) has illustrated that using 1/R as the response variable lead to better physical meanings (or interpretations) of the proposed PPR model. With the incorporation of subject-related knowledge into the modeling process, it was shown that smaller root mean squared errors (RMS) and higher coefficient of determination (R^2) have been achieved in the NET2 model, although the convergence rate was slightly slower.

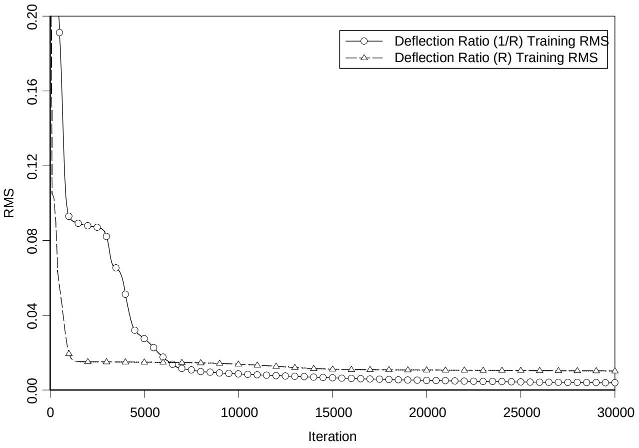


Figure 5. Comparison of the convergence results of two trained ANN modles.

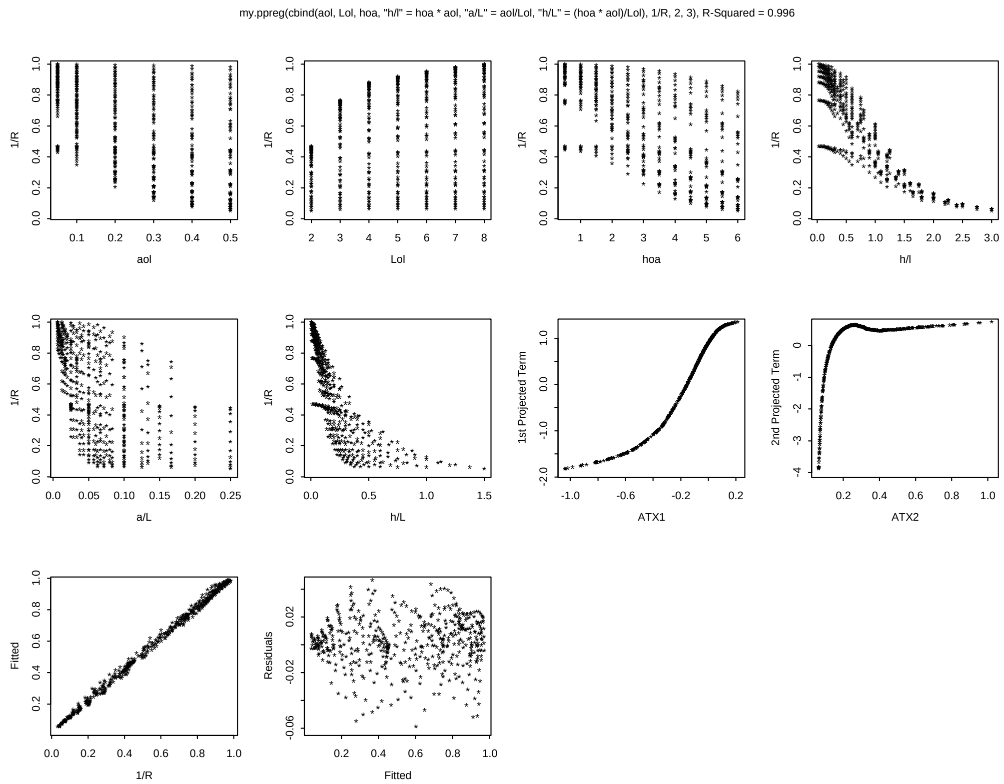


Figure 6. Proposed PPR model for the 3-D deflection database

4.3.2 Revised two-step modeling approach using PPR and regression splines

To facilitate future possible applications of the 3-D rigid pavement deflection database, the following predictive model as shown in Figure 6 was developed using projection pursuit regression technique (Lee & Darter, 1994b; Friedman & Stuetzle, 1981). The response variable was chosen as the reciprocal of the deflection ratio (1/R) and the explanatory variables were *a/ℓ*, *L/ℓ*, *h/a*, and their variations. Regression spline algorithm was adopted in lieu of piecewise-linear regressions at the second step to assure smooth junctions at the change points. Consequently, the coefficient of determination (R^2) was slightly reduced from 0.996 to 0.9942 as the expense of this smoothing. The tentative predictive model and its regression statistics are as follows: (In which, N is the number of observations and SEE is the standard error of the estimation.)

$$
\begin{aligned}
&1/R = 0.54008 + 0.29653\ \Phi_1 + 0.09667\,\Phi_2 \\
&\Phi_1 = 1.28770 + 10.04098(\mathrm{A1}) + 11.76579(\mathrm{A1})^2 + 4.88399(\mathrm{A1})^3 \\
&\qquad -16.23312(A1 > -0.3) * (A1 + 0.3)^3 - 20.95209(A1 > -0.1) * (A1 + 0.1)^3 \\
&\Phi_2 = -11.68986 + 180.53050(\mathrm{A2}) - 895.12897(\mathrm{A2})^2 + 1482.36407(\mathrm{A2})^3 \\
&\qquad -1468.55407(A2 > 0.2) * (A2 - 0.2)^3 - 16.40377(A2 > 0.4) * (A2 - 0.4)^3 \qquad (2) \\
&A1 = \quad 0.42473\mathrm{x1} + 0.01922\mathrm{x2} - 0.00925\mathrm{x3} - 0.49378\mathrm{x4} - 0.60805\mathrm{x5} + 0.45343\mathrm{x6} \\
&\mathrm{A2} = -\,0.28347\mathrm{x1} + 0.03160\mathrm{x2} + 0.00071\mathrm{x3} + 0.37804\mathrm{x4} + 0.53626\mathrm{x5} - 0.69868\mathrm{x6} \\
&X = [\mathrm{x1}, \mathrm{x2}, \mathrm{x3}, \mathrm{x4}, \mathrm{x5}, \mathrm{x6}] = \left[\frac{\mathrm{a}}{\ell}\ ,\ \frac{L}{\ell}\ ,\ \frac{h}{a}\ ,\ \frac{h}{a}*\frac{\mathrm{a}}{\ell}\ ,\ \frac{\mathrm{a}}{\ell}/\frac{L}{\ell}\ ,\ \frac{h}{a}*\frac{\mathrm{a}}{\ell}/\frac{L}{\ell}\right] \\
&\text{Statistics}: \mathrm{N} = 504, \mathrm{R}^2 = 0.9942, \mathrm{SEE} = 0.02241
\end{aligned}
$$

4.3.3 Loess models

Several S-PLUS trials of local regressions were conducted using the same database. Again, the response variable was chosen as the reciprocal of the deflection ratio (1/R) and the explanatory variables were a/ℓ, L/ℓ, and h/a. The resulting loess model was easily obtained at a greatly reduced amount of modeling time, in which the smoothing parameter “span” was chosen as 0.1, whereas the “cell” argument was chosen as 0.1. The following regression statistics were obtained: the number of observations = 504; equivalent number of parameters = 56.6; residual standard error = 0.004784; and multiple R-squared = 1.

4.4 Flexible pavement deflection predictions

Based on the multi-layer elastic theory and the principles of dimensional analysis, the following dominating dimensionless variables were identified for a three-layer pavement system: E_1/E_2, E_2/E_3, h_1/h_2, and a/h_2. In which, a is the radius of the applied load, [L]; h_1 and h_2 are the thickness of the surface and base layers, [L]; E_1, E_2, and E_3 are the Young's moduli of the surface layer, base layer, and subgrade, respectively, [FL^{-2}]. A series of factorial BISAR runs was conducted with the following ranges to cover most practical pavement data: $0.5 \leqq E_1/E_2 \leqq 170$, $0.5 \leqq E_2/E_3 \leqq 170$, $0.2 \leqq h_1/h_2 \leqq 2.4$, and $0.5 \leqq a/h_2 \leqq 5.0$. A BASIC program written by Dr. Alaeddin Mohseni was used to automatically generate the input files and summarize the results to avoid untraced human errors. A pavement response database including the aforementioned dimensionless variables, deflections at the center of load (D_0), horizontal strain (ε_t) and vertical strain (ε_v) at the bottom of the surface layer was obtained. A training database with 3,600 data points and an independent testing database with 1,728 data points were used in this study (Liu, 2004).

4.4.1 ANN models

The training database was randomly separated into 3,400 data points for actual training and the remaining 200 observations for monitoring the training process. Hyperbolic tangent activation function was chosen in this case study. The learning rate was set as 0.01. At the first trial (NET1) as shown in Table 5, no transformation was made on both explanatory and response variables. Extreme difficulty was encountered in obtaining reasonable convergence.

Based on the basic assumptions of conventional regression techniques that the random errors are mutually uncorrelated and normally distributed with zero mean and constant variance, and additive and independent of the expectation function, it is desirable to check the normality of the response variable. The Box-Cox (1964) transformation procedure was adopted to find the approximate power transformation of the response variable (D_0). As shown in Figure 7(a), the maximum likelihood estimator λ was approximate 0 indicating that a logarithm transformation was appropriate for D_0 (Weisberg, 1985). Figure 7(b) is the normal Q-Q plot which graphically compares the distribution of log(D_0) to the normal distribution represented by a straight line. This indicates that the logarithm of D_0 is approximate to normally-distributed. In the second trial (NET2), convergence was obtained though the number of learning cycles and modeling time were still very high. The root mean squared (RMS) errors were computed accordingly.

Table 5. Comparison of three different ANN models

ANN Type	NET1	NET2	NET3
Outputs	D_0	Log(D_0)	Log(D_0)
Inputs	E_1/E_2, E_2/E_3, h_1/h_2, a/h_2	E_1/E_2, E_2/E_3, h_1/h_2, a/h_2	log(E_1/E_2), log(E_2/E_3), h_1/h_2, a/h_2
Hidden Layer(s)	3	3	2
Neurons in Each Hidden Layer	20-10-5	15-10-5	12-6
Learning Cycle	Cannot converge	200,000	27,000
Modeling Time	> 24 hrs	10 hrs	26 min
RMS	---	Training: 0.0048 Monitoring: 0.0045	Training: 0.0040 Monitoring: 0.0039

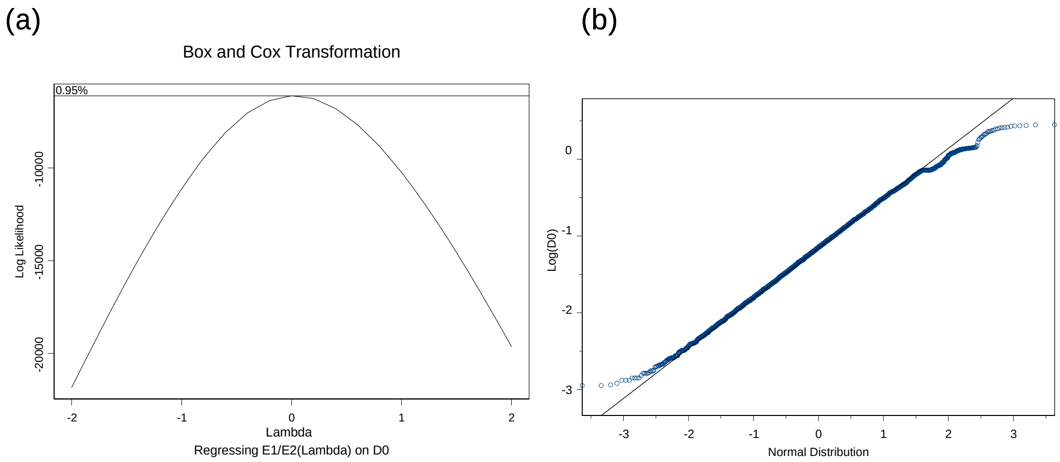


Figure 7. (a) Box-Cox transformation result; and (b) normal Q-Q plot of log(D_0).

According to general statistical principles or using the alternating conditional expectations (ACE) algorithm (Breiman & Friedman, 1985) together with the Box-Cox power transformation technique proposed by Lee (1993), logarithm transformations of D_0, E_1/E_2, and E_2/E_3 were recommended for NET3 model. As shown in Table 5, with more statistical knowledge incorporated into the ANN modeling process, the resulting ANN model was proved to have higher accuracy and less network training time than the other counterpart using purely input parameters. Figures 8(a) and 8(d) depict the network convergence results for NET2 and NET3 during the training process. The goodness of the prediction of log(D_0) and the goodness of the prediction of D_0 for NET2 and NET3 were also provided in Figures 8(b)~8(c) and 8(e)~8(f) during the testing phase, respectively. With more statistical knowledge incorporated into the modeling process, the resulting ANN model was proved to have higher accuracy and less network training time than the other counterpart using purely input parameters.

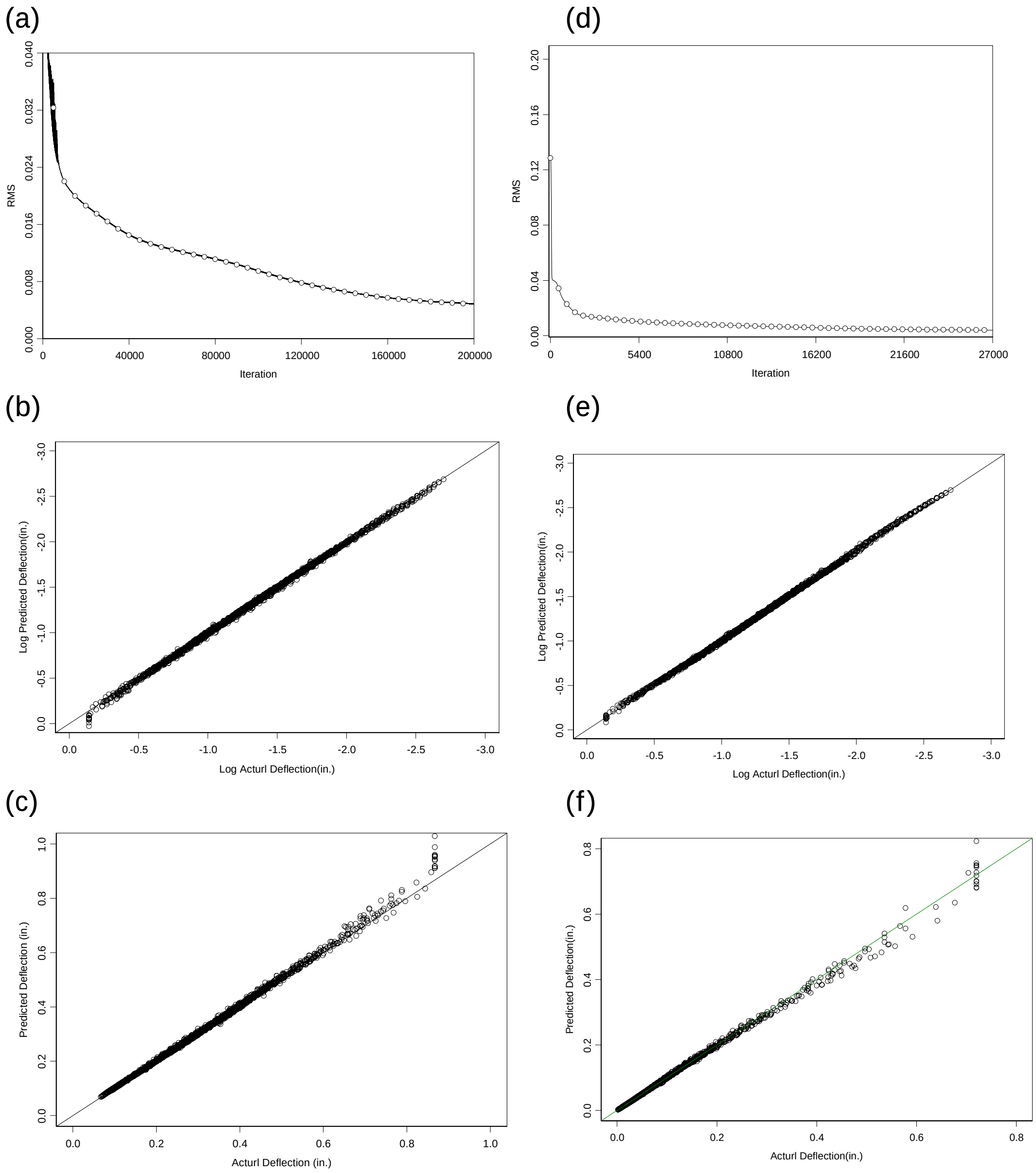


Figure 8. (a) ~ (c) NET2 network convergence results, goodness of the prediction of log(D_0), and prediction of D_0; and (d) ~ (f) for NET3 network, respectively.

4.4.2 Loess models

Several S-PLUS trials of local regressions were conducted using the same training and testing databases. Again, the logarithm transformations of D_0, E_1/E_2, and E_2/E_3 were adopted here. The response variable is log(D_0) and the explanatory variables are log(E_1/E_2), log(E_2/E_3), h_1/h_2, and a/h_2. The resulting loess model was obtained at a greatly reduced amount of modeling time, in which the smoothing parameter “span” was chosen as 0.1, whereas the “cell” argument was chosen as 0.1. The following regression statistics were obtained: number of observations = 3,600; equivalent number of parameters = 31.9; residual standard error = 0.02792; and multiple R-squared = 1. The goodness of the prediction of log (D_0) and D_0 were presented in Figures 9(a) and 9(b), respectively.

The resulting loess model was compared to the aforementioned NET2 and NET3 models for the goodness of D_0 predictions during the testing phase. Reasonable good predictions can be achieved using both ANN and modern regression techniques.

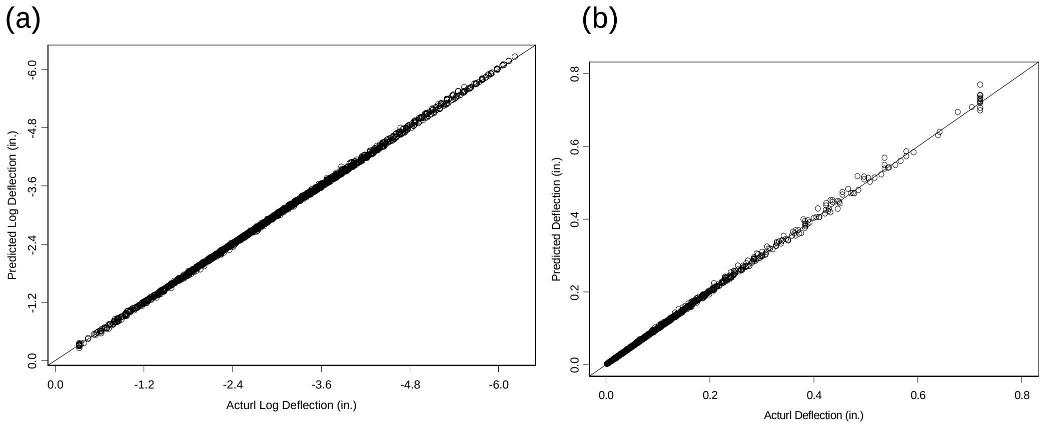


Figure 9. Local regression model: (a) goodness of the prediction of log (D_0) and (b) goodness of the prediction of D_0.

5. CONCLUDING REMARKS

Several case studies were conducted to illustrate the benefits of incorporating the principles of dimensional analysis, subject-related knowledge, and statistical knowledge into pavement prediction modeling process. The resulting ANN model using all dominating dimensionless parameters was proved to have higher accuracy and require less network training time than the other counterpart using purely input parameters. Increasing the complexity of ANN models does not necessarily improve the modeling statistics. The results also showed that using higher number of neurons and hidden layers sometimes lead to even worse modeling statistics which was an indication of over training and should be avoided. Several local regression models requiring minimal amount of modeling time were also developed using the same databases. The resulting loess model was compared to the aforementioned ANN models for the goodness of predictions. Reasonable good predictions can be achieved using both ANN and modern regression techniques. Statistical and subject-related knowledge can be used to guide modeling in most real-world problems and so enable much more convincing generalization and explanation, in ways which can never be done by 'black-box' learning systems (Ripley, 1993).

6. REFERENCES

Attoh-Okine, Nii O. (1994). "Predicting Roughness Progression in Flexible Pavements Using Artificial Neural Networks." *Proceedings*, *Third International Conference on Managing Pavements*, Vol. 1, San Antonio, TX, 55-62.

Attoh-Okine, Nii O. (1999). "Analysis of Learning Rate and Momentum Term in Backpropagation Neural Network Algorithm Trained to Predict Pavement Performance." *Advances in Engineering Software*, v 30, n 4, 291-302.

Box, G. E. P. and Cox, D. R. (1964). "An Analysis of Transformations (With Discussion)." *Journal of the Royal Statistical Society*, B, Vol. 26, 211-246.

Breiman, L., and Friedman, J. H. (1985). "Estimating Optimal Transformations for Multiple Regression and Correlation (With Discussion)." *Journal of the American Statistical Association*, Vol. 80, 580-619.

Ceylan, H. (2004). "Use of Artificial Neural Networks for the Analysis & Design of Concrete Pavement Systems." *CD-ROM, the 5th CROW Workshop on Concrete Pavements*, Istanbul, Turkey, March 31-April 3, 2004.

Ceylan, H., and Guclu, A. (2005). "Effects of Combined Temperature and Gear Loading on the Response of Concrete Airfield Pavements Serving the Airbus A380-800 Aircraft." *CD-ROM,* *the 1st European Airport Pavement Workshop*, Amsterdam, the Netherlands, May 11-12, 2005.

Ceylan, H., Tutumluer, E., and Barenberg, E. J. (1998). "Artificial Neural Networks as Design Tools in Concrete Airfield Pavement Design." *Proceedings, ASCE 25th International Air Transportation Conference*, Austin, Texas, pp. 447-465.

Ceylan, H., Tutumluer, E., and Barenberg, E. J. (1999). "Analysis of Concrete Airfield Slabs Serving the Boeing 777 Aircraft Using Artificial Neural Networks." *Journal of the Transportation Research Board, Transportation Research Record 1684*, 110-117.

Ceylan, H., Tutumluer, E., and Barenberg, E. J. (2004). "Artificial Neural Networks for the Analysis of Slabs Under Simultaneous Aircraft and Temperature Loading." Presented at the 15th ASCE Engineering Mechanics Conference at Columbia University, New York, June 4, 2002. In *Recent Advances in Materials Characterization and Modeling of Pavement Systems*, Edited by Tutumluer, E., Najjar, Y. M., and Masad, E., ASCE, 223-238.

Cleveland, W. S., and Devlin, S. J. (1988). "Locally-Weighted Regression: An Approach to Regression Analysis by Local Fitting." *Journal of the American Statistical Association, 83*, 596-610.

Cleveland, W.S., and Grosse, E. (1991). "Computational Methods for Local Regression." *Statistics and Computing, 1*, 47-62.

Friedman, J. H., and Stuetzle, W. (1981). "Projection Pursuit Regression." *Journal of the American Statistical Association*, 76, 817-823.

Friedman, J. H. (1984). *SMART User's Guide*, Technical Report No. 1, LCS, Department of Statistics, Stanford University, Stanford, CA.

Haussmann, L. D., Tutumluer, E., and Barenberg, E. J. (1997). "Neural Network Algorithms for the Correction of Concrete Slab Stresses from Linear Elastic Layered Porgrams." *Transportaion Research Record 1568*, 44-51

Haykin, S. *Neural Networks: A Comprehensive Foundation*. Prentice-Hall, Inc., New Jersey, 1994.

Hecht-Nielsen, R. *Neurocomputing*. Addison-Wesley, New York, 1990.

Hibbitt, Karlsson, and Sorensen (2000). *ABAQUS/Standard User's Manual*. Vol. I & Ⅱ.

Ioannides, A. M., Alexander, D. R., Hammons, M. I., and Davis, C. M. (1996). "Application of Artificial Neural Networks to Concrete Pavement Joint Evaluation." *Transportation Research Record 1540*, Transportation Research Borad, Washington, D.C., 56-64.

Ioannides, A. M., Barenberg, E. J., and Lary, J. A. (1989). "Interpretation of Falling Weight Deflectometer Results Using Principles of Dimensional Analysis." *Proceedings, Fourth International Conference on Concrete Pavement Design and Rehabilitation*, Purdue University.

Ioannides, A. M., Davis, C. M., and Weber, C. M. (1999). "Westergaard Curling Solution Reconsidered." *Transportation Research Record 1684*, Transportation Research Borad, Washington, D.C., 61-70.

Ioannides, A. M. and Salsilli-Murua, R. A. (1989). "Temperature Curling in Rigid Pavements: An Application of Dimensional Analysis." *Transportation Research Record* 1227, 1-11.

Ker, H. W. (2002). *Application of Regression Spline in Multilevel Longitudinal Modeling*. Ph.D. Dissertation, University of Illinois, Urbana.

Khazanovich, L., and Roesler, J. (1997). "DIPLOBACK: Neural-Network-Based Backcalculation Program for Composite Pavements." *Transportation Research Record 1570*, 1997, 143-150.

Lee, Y. H. (1993). *Development of Pavement Prediction Models*. Ph.D. Dissertation, University of Illinois, Urbana.

Lee,Y. H., and Darter, M. I. (1994a). "Loading and Curling Stress Models for Concrete Pavement Design." *Transportation Research Record 1449*, Transportation Research Board, National Research Council, Washington, D.C., 101-113.

Lee, Y. H., and Darter, M. I. (1994b). "New Predictive Modeling Techniques for Pavements."

Transportation Research Record 1449, Transportation Research Board, National Research Council, Washington, D.C., 234-245.

Lee, Y. H., and Darter, M. I. (1995). “Development of Performance Prediction Models for Illinois Continuously Reinforced Concrete Pavements.” *Transportation Research Record 1505*, Transportation Research Board, Washington, D.C., 1995, 75-84.

Lee, Y. H., Lee, C. T., and Bair, J. H. (1998). “Modified Deflection Ratio Procedures for Backcalculation of Concrete Pavements.” In *Airport facilities: Innovations for the Next Century; Proc., 25th International Air Transportation Conference*, ASCE, M. T. McNerney, eds., Austin, Texas, June 14-17, 480-495.

Lee, Y. H., Mohseni, A. and Darter, M. I. (1993). “Simplified Pavement Performance Models.” *Transportation Research Record 1397*, Transportation Research Board, National Research Council, Washington, D.C., 7-14.

Lee, Y. H., Wu, H. T., and Yen, S. T. (2004). “Parameter Studies on Three-Dimensional Finite Element Analysis of Rigid Pavements.” *CD-ROM, the 5th CROW Workshop on Concrete Pavements*, Istanbul, Turkey, March 31-April 3, 2004.

Liu, Y. B. (2004). *Application of Modern Regression Techniques and Neural Network on Rigid Pavement Backcalculation*. M. S. Thesis, Department of Civil Engineering, Tamkang University, Taipei, Taiwan (In Chinese).

Mathsoft, Inc. (1997). *S-PLUS for Windows (Ver. 4.0) User's Manual, Reference Manual, and Guide to Statistics*.

Mehrotra, K., Mohan, C. K., and Ranka, S. (1997). *Elements of Artificial Neural Networks*. Massachusetts Institute of Technology.

Ripley, B. D. (1993). “Statistical Aspects of Neural Networks.” In *Networks and Chaos - Statistical and Probabilistic Aspects*, Barndorff-Nielsen, O. E., Jensen, J. L., and Kendall, W. S., eds., Chapman & Hall, London, 41-123.

Seber, G. A. F., and Wild, C. J. (1989). *Nonlinear Regression*. New York: Wiley.

Simpson, A. L., Rauhut, J. B., Jordahl, P. R., Owusu-Antwi, E., Darter, M. I., Ahmad, R., Pendleton, O. J., and Lee, Y. H. (1993). *Early Analyses of LTPP General Pavement Studies data*, *Volume 3 - Sensitivity Analyses for Selected Pavement Distresses*. Strategic Highway Research Program, National Research Council, Washington, D.C.

Smith, P. L. (1979). Spline as a Useful and Convenient Statistical Tool. *The American Statistician*, 33, 57-62.

Smith, M. (1996). *Neural Networks for Statistical Modeling*. International Thompson Computer Press.

Sorsa, T., Koivo, H. N., Koivisto, H. (1991). “Neural Nerworks in Process Fault Diagnosis.” *IEEE Transactions on Systems*, *Man and Cybernetics*, 21(4): 815-825.

Vesta Services, Inc. (2000). *Qnet v2000 for Windows*, http://www.qnetv2k.com/.

Weisberg, S. (1985). *Applied Linear Regression*. Second Edition, Weiley Series in Probability and Mathematical Statistics, John Wiley & Sons, Inc.

Wu, H.-T. (2003). *Parameter Analysis and Verification for Jointed Concrete Pavements*. M.S. Thesis, Tamkang University, Tamsui, Taiwan, January 2003. (In Chinese)