行政院國家科學委員會專題研究計畫 成果報告

美國最新公路鋪面暫行手冊之評估與應用(II)
研究成果報告(精簡版)

計 畫 類 別 ：個別型
計 畫 編 號 ：NSC 97-2221-E-032-034-
執 行 期 間 ：97 年 08 月 01 日至 98 年 07 月 31 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

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 99 年 01 月 05 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

美國最新公路鋪面暫行手冊之評估與應用(II)

計畫類別：■ 個別型計畫　　□ 整合型計畫
計畫編號：NSC 97－2221－E－032－034
執行期間：九十七年八月一日至九十八年七月三十一日

計畫主持人：李英豪
共同主持人：葛湘瑋
計畫參與人員：李彥志、黃思齊、莊侃諾、黃自強、李家瑋、
林世泰

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　九十八　年　十　月　三　十　一　日

美國最新公路鋪面暫行手冊之評估與應用(II)
Reevaluation and Application of the AASHTO Mechanistic-Empirical Pavement Design Guide (II)

計畫編號：NSC 97-2221-E-032-034
執行期限： 97年08月01日至98年07月31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

鑑於在過去研究成果中發現，鋪面績效資料分析常常違反了傳統迴歸法對於隨機誤差所做的假設。鋪面績效資料屬於多層次資料的一種，傳統迴歸方法不適合用來處理分析多層次資料。因為資料的結構具有層級性，多層次模式的資料探索分析、統計模式的建立及模式評估比標準複迴歸複雜。因此，極需利用上述方法以改善系統化的統計與工程分析方法來改善現有鋪面績效預測模式。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，本計畫擬以三年三期的方式，從事「美國最新鋪面暫行手冊之評估與應用」研究，除了將持續利用 LTPP 資料庫外，並將利用美國 AASHO 道路試驗的原始資料，配合線性混合模式與當代迴歸技術之分析與應用，深入探討 AASHTO 柔性鋪面與剛性鋪面設計公式與標準軸重當量(ESAL)觀念之適用性，以及暫行手冊之本土應用問題。本年度(第二期)主要的研究內容包括：(1)利用視覺圖法與線性混合模式來分析柔性鋪面道路試驗資料。(2)利用視覺圖法與線性混合模式來分析剛性鋪面道路試驗資料。(3)利用當代迴歸技術來分析柔性鋪面道路試驗資料。(4)利用當代迴歸技術來分析剛性鋪面道路試驗資料。(5)檢視標準軸重當量之觀念並探討其適用性。此外，本研究最後並將驗證研究成果的正確性與適用性，以期將此成果應用在未來鋪面分析與管理工作上，使我國有限經費做最有效之利用。

關鍵詞：鋪面、績效、預測、力學與經驗設計法、標準軸重當量、長程鋪面績效研究、多層次資料、多層次線性模式、線性混合模式。

Abstract

Based on the research findings of past research projects, the performance data often violated the normality assumptions with random errors and constant variance using conventional regression techniques. Pavement performance data is a very common example of multilevel data. Using conventional regression techniques to analyze this type of data is inappropriate. Hierarchical linear models (HLMs) or linear mixed-effects (LMEs) models are often utilized to analyze multilevel data. Because of the hierarchy of data structure, the exploratory analysis, statistical modeling, and examination of model-fit of multilevel data are more complicated than those of standard multiple regressions. Thus, it is very crucial to investigate its possible applications to the existing systematic statistical and engineering approach for the improvements of existing pavement performance prediction models. Furthermore, the variability of in-service Long-Term Pavement Performance (LTPP) data was found to be extremely high, which will unfortunately increase the difficulty of the analysis using HLMs/LMEs . Thus, this project consists of three phases to be completed within three years to reevaluate the AASHTO Mechanistic-Empirical Pavement Design Guide (MEPDG) and its potential domestic applications. The research approach includes continuously utilizing the LTPP database and analyzing the original AASHO Road Test data using LMEs and modern

regression techniques, so as to investigate the applicability of the AASHTO flexible and rigid pavement design models and the 18-kip equivalent single axle load (ESAL) concept. The major tasks of this year (Phase II) include: (1) Analysis of the flexible pavement road test data using LMEs and visual graphical methods; (2) Analysis of the rigid pavement road test data using LMEs and visual graphical methods; (3) Analysis of the flexible pavement road test data using modern regression techniques; (4) Analysis of the rigid pavement road test data using modern regression techniques; and (5) Reexamination of the applicability of the 18-kip ESAL concept. The completion of this study will, hopefully, provide a sound basis for future pavement analysis and management activities so as to assure the best use of our limited resources.

Keywords : Pavement, Performance, Prediction, MEPDG, ESAL, LTPP, Multilevel Data, Hierarchical Linear Models, Linear Mixed-Effects Models.

一、前言

在鋪面設計方法中，AASHTO(美國州公路暨運輸官員司協會)、AI(美國瀝青協會)、與PCA(美國波特蘭水泥協會)的鋪面厚度設計方法最常被世界各國(包括我國)所採用[李英豪、張德文，2002]。其中，AASHTO與AI鋪面厚度設計方法傳統上係採用18,000磅標準軸重當量(18-kip ESAL)的觀念，而PCA鋪面厚度設計方法則採用軸重分佈(或軸重頻譜)的方式來分析預期之交通荷重。自1960年代美國AASHO道路試驗之後，鋪面研究人員雖然對標準軸重當量(ESAL)觀念的採用有相當多的意見與質疑，卻又無法否定其必要性與易用性。然而，自2002年起在美國最新的國家公路合作研究計畫報告NCHRP 1-37A中建議採用新的力學與經驗鋪面設計指導綱領或暫行手冊(Mechanistic-Empirical Pavement Design Guide, MEPDG)(http://www.2002designguide.com)，其中最主要的改變為捨棄標準軸重當量的觀念，改採軸重頻譜的方式來分析交通荷重[ARA, 2004]。對此影響未來鋪面設計觀念如此重大且深遠的改變，美國產官學研各界相繼提出各項質疑，對此暫行手冊不斷地評估再評估，卻又遲遲無法定案，至2006年底仍難以公佈施行。

國內公路主管單位亦採用AASHTO鋪面厚度設計方法作為柔性與剛性鋪面設計的主要依據[交通部台灣區國道高速公路局，1997]，面對如此重大的更新建議，未來對國內鋪面相關工作的進行勢必產生深遠的影響。再者，新建立的績效預測模式是否可適用在溼熱多雨的台灣地區，或必須經由何種程度上的修正，都是未來國內相關單位必須面臨的挑戰。鑑於國內缺少較為完整的鋪面績效資料庫[周家蓓等，1994；林志棟等，2000]，為有效解決構建本土化績效預測模式的困難與問題，計畫主持人與共同主持人(葛湘瑋博士)曾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，期望能深入探討LTPP資料庫之特性與適用限制、利用其構建鋪面績效預測模式、並探討其本土化之應用與系統整合。

雖然如此，在多年的資料分析經驗中亦不斷地發現，鋪面績效資料分析常常違反了傳統迴歸法對於隨機誤差所做的假設[李英豪、葛湘瑋，2005；2006；2007；吳佩樺，2006；林佳慧，2007]。鋪面績效資料屬於多層次資料(hierarchical or multilevel data)的一種，傳統迴歸方法不適合用來處理分析多層次資料。鑑於在執行前述計畫中亦發現，現地蒐集的LTPP長期鋪面績效資料變異性極大，且有效資料不足之問題仍舊存在[劉耀斌、吳炘達、顏少棠、李英豪，2002；Ker, Lee, & Wu, 2008]，更增添了利用多層線性模式(Hierarchical Linear Models, HLMs)或線性混合模式(Linear Mixed-Effects Models, LMEs)來分析LTPP長期鋪面績效資料庫的困難度。因此，本計畫擬以三年三期的方式，從事「美國最新鋪面暫行手冊之評估與應用」研究，除了將持續利用LTPP資料庫外，並將利用美國AASHO道路試驗的原始資料，配合線性混合模式與當代迴歸技術之分析與應用，深入探討AASHTO柔性鋪面與剛性鋪面設計公式與標準軸重當量(ESAL)觀念之適用性，以及暫行手冊之本土應用問題，主要的研究內容包括：(1)

國內外相關研究之文獻蒐集與整理；(2)美國最新鋪面暫行手冊(MEPDG)之評估；(3)LTPP DataPave Online交通資料之擷取與彙整；(4)軸重頻譜與標準軸重當量關係之研究；(5)AASHO道路試驗原始資料的擷取與彙整；(6)利用視覺圖法與線性混合模式來分析柔性與剛性鋪面道路試驗資料；(7)利用當代迴歸技術來分析柔性與剛性鋪面道路試驗資料；(8)檢視標準軸重當量之觀念並探討其適用性；(9)探討最新鋪面設計暫行手冊(MEPDG)之本土化應用問題；(10)我國現行鋪面交通荷重資料分析問題之研究；(11)LTPP柔性與剛性鋪面功能性指標(IRI)資料之擷取與分析；與(12)研究成果之彙整與應用。本年度(第二期)主要任務在執行前述第六至八項之工作。

利用美國AASHO道路試驗的原始資料來分析的主要優點在於該道路試驗所採用的材料、交通荷重、路基土壤、氣候環境、與維修記錄，因均受到實驗設計之最佳控制，資料的可信度較高，資料的隨機變異性受到相當程度的控制，預測模式構建後之可靠性亦較高。本研究希望能利用此成果，以有效解決最新暫行手冊(MEPDG)擬完全捨棄標準軸重當量(ESAL)的觀念，改採軸重頻譜的方式來分析交通荷重之爭議與延伸之問題。並期能協助解決採用美國長期鋪面績效資料庫(LTPP)分析時，因現地資料的缺失與登錄錯誤可能導致分析結果較不可靠的問題，以建立更有效且更可靠之鋪面設計與績效預測模式。

二、原始道路試驗資料的擷取

AASHO道路試驗在鋪面績效分析的歷史上佔有極重要的角色［Highway Research Board, 1962］，雖然因時空與經費之限制，該道路試驗僅限定於當地特定的鋪面材料、路基土壤、北伊利諾州的氣候條件、兩年的鋪面績效期間、特定的輪軸荷重組成、而且沒有混合的交通車流在任何的一個路段，所建立的預測模式之推論空間可能因此受到限制。然而，不可諱言地，AASHO道路試驗的原始資料畢竟是受到實驗設計控制，其可信度高、隨機變異性較低、較嚴謹、且較可靠。鑑於在過去研究中發現雖然美國長期鋪面績效LTPP資料庫中的資料範圍相當廣泛，然而在某些限制下使得某些路段對於鋪面的資料未能完整的蒐集，而且在長達將近二十年計畫期間某些路段經由一再的維修與養護、加鋪或重建等作業，在鋪面的特性上亦產生相當的變化與原始建造的資料已產生極大的差異。因此造成現地蒐集的LTPP長期鋪面績效資料變異性極大，嚴重地影響後續LTPP績效資料庫分析的可靠度。

因此，本研究在此階段利用 Visual Basic 與統計軟體程式完成 AASHO 道路試驗柔性鋪面原始資料(包含所有 1~55 個指標日的紀錄)的擷取與彙整工作，並與過去的研究成果相互驗証，以協助解決採用美國長期鋪面績效資料庫(LTPP)分析時，因現地資料的缺失與登錄錯誤導致分析結果較不可靠的問題。受限於現地試驗的特性，某些較弱的鋪面路段在兩年試驗完成期間前已完全破壞，因此被摒除在試驗之外。但是，有某些路段在整個試驗期間都保持非常好的鋪面狀況。為了確保每個路段最少會有五個績效資料，因此利用移動平均的技術將道路試驗的資料以下列兩種方式來登錄：(1)每隔 11, 22, 33, 44, 55 個指標日的資料(1 index day = 2 weeks)、或(2)PSI 值降低到 3.5, 3.0, 2.5, 2.0, 1.5 時的資料。研究中發現 AASHO 原始柔性鋪面設計公式係採用第二組資料建立而得的。此外，由於 AASHO 道路試驗年代久遠，其剛性鋪面所有原始 1~55 個指標日的資料不易取得，因此本研究在此僅擷取道路試驗報告［Highway Research Board, 1962］中所提供的資料作為後續分析之依據。

三、現有鋪面設計公式的分析與應用

在道路試驗中若所測得之鋪面狀況指標小於 1.5 時，則將其自試驗中剔除，並將該鋪面加鋪或重建，以利其他路段繼續進行試驗。且在道路試驗中發現柔性鋪面在春天融雪時較冬天結冰時有較高的損壞率，因此引進下列之季節性調整因子(q_t)之觀念與計算公式，來修正

原始交通荷重，以建立一個較佳的柔性鋪面設計公式。其中，$d_t, d_{t-1}, \bar{d}$ 各代表在指標日 t 與指標日 t-1 之撓度值、以及平均之撓度值。

$$q_t = \left[\frac{2d_t - d_{t-1}}{\bar{d}}\right]^2 \tag{1}$$

AASHO 並據此道路試驗的研究結果發展出鋪面設計手冊[Highway Research Board, 1962]，其柔性鋪面設計公式如下所示，其中，W = 各種不同輪軸荷重的次數；PSI = 現況服務能力指標(0-5)；ρ, β = 鋪面厚度、強度、輪軸荷重型態的函數；SN =柔性鋪面的結構數；L_1 = 輪軸荷重，kips；L_2 = 單軸荷重為 1、雙軸荷重為 2；D_1, D_2, D_3 為柔性鋪面面層、底層、與基層的厚度，in.。

$$\begin{aligned}
&\log W = \log\rho + \frac{\log\left(\frac{4.2 - PSI}{4.2 - 1.5}\right)}{\beta} \\
&\beta = 0.4 + \frac{0.081\left(L_1 + L_2\right)^{3.23}}{(SN+1)^{5.19}\, {L_2}^{3.23}} \\
&\rho = \frac{10^{5.93}(SN+1)^{9.36}\, {L_2}^{4.33}}{\left(L_1 + L_2\right)^{4.79}} \\
&SN = 0.44D_1 + 0.14D_2 + 0.11D_3
\end{aligned} \tag{2}$$

柔性鋪面設計公式(或公式 2)除了被應用在軸重當量之換算外，在鋪面分析與設計之應用亦相當廣泛。例如，鋪面工程師常常利用其預測對某個特定路段在到達某個特定的鋪面狀況下預期之交通量(或累加軸重當量數 W)；或者將上述公式重新編排後，工程師也常用它來預測在某個特定的鋪面厚度與交通荷重下的鋪面狀況預測(PSI)。可是，當我們利用與上述柔性鋪面設計公式相同的迴歸係數與道路試驗資料來預測工程師最想知道的 log(W), W, and PSI 的數值時，發現其最終統計迴歸結果為：

1. 預測 log(W)： $R^2 = 0.729$, SEE = 0.285, N = 1171
2. 預測 W： $R^2 = 0.615$, SEE = 155.3, N = 1171
3. 預測 PSI： $R^2 = 0.212$, SEE = 0.622, N = 1083

其中，R^2 為判定係數、SEE 為標準差的估計值、N 為資料點數。從上述分析中，雖然發現預測 log(W)之判定係數 R^2 與道路試驗的報告有些許差異，但我們相信這很有可能僅是計算的些微誤差。圖 1 顯示的是原始 AASHO 道路試驗柔性鋪面設計公式的預測結果，很顯然地雖然預測 log(W)的趨勢尚稱合理。但是，若利用同樣的公式來預測交通荷重的次數(W)時則發現實際試驗資料與預測的結果也會如扇形的方式向外發散，代表當 W 增加時估計誤差的變異數也會增加，明顯違反了統計迴歸的假設。圖 1 亦顯示若利用上述迴歸係數來預測 PSI 時，其預測結果將極為不穩定，其判定係數將降至 $R^2 = 0.212$，在分析中因某些資料使預測的 PSI 值為負值而被刪除，因此僅有 1083 筆資料點。

因此，AASHO 道路試驗所建立的柔性鋪面設計公式雖然可以合理的預測 log(W)，卻不見得可以確保對 W 與 PSI 的預測精度。因為迴歸模式的應用與數學公式的應用是截然不同的。數學公式可以經過不同的轉換仍然不會喪失其一般性；相反地，經過轉換或重新編排過的統計迴歸公式將未必與原來的公式有同樣的預測精度。統計迴歸模式必須被嚴格限制在同樣的變數形式下才可以使用，若是想要預測經過重新編排後或轉換過的新變數時，則必須要重新再作進一步的統計迴歸分析。由本次分析可發現，柔性鋪面設計公式的原始發展過程中，係採用傳統迴歸分析法，而其所獲得之結論亦隱含了非常高的變異性。尤其是所估算而得之軸重當量因子(LEFs)或軸重當量(ESALs)的觀念，亦隱含了非常高的變異性，將軸重當量因子設定為某個特定值的方式並不完全適用在後續的鋪面設計上，因此有必要做更進一步的分析與驗證。

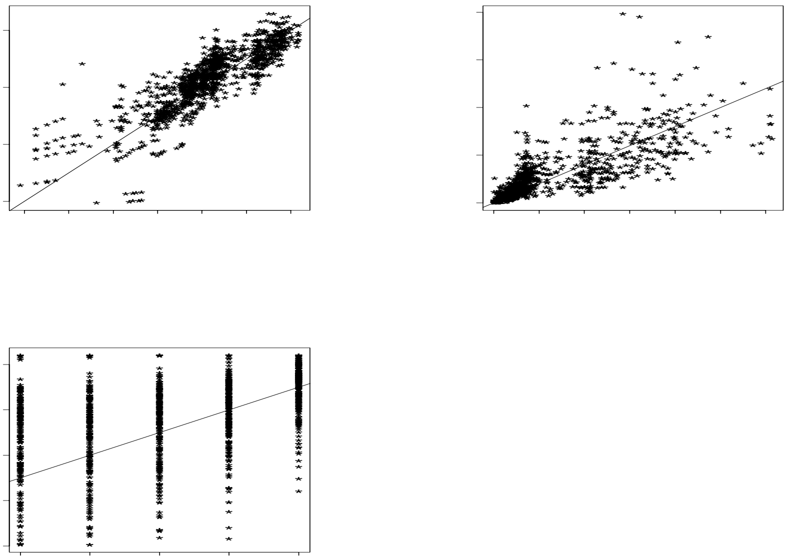

圖 1 AASHO 道路試驗柔性鋪面設計公式的預測結果

在道路試驗報告中亦指出，若是柔性鋪面不採用季節性調整因子來修正原始交通荷重時，原公式(2)應改為如公式(3)所示之預測模式。雖然如此，世界各國(包括美國在內)長久以來仍舊採用 AASHTO 所建議的柔性鋪面設計公式(或公式 2)，但是由於季節性調整因子並不容易估算，因此在設計鋪面時不曾對交通荷重做任何之修正。

$$\log W = \log\rho + \frac{\log\left(\frac{4.2 - PSI}{4.2 - 1.5}\right)}{\beta}$$

$$\beta = 0.4 + \frac{0.083\left(L_1 + L_2\right)^{4.87}}{(SN+1)^{8.73}\, L_2^{\ 4.87}} \tag{3}$$

$$\rho = \frac{10^{6.16}(SN+1)^{8.94}\, L_2^{\ 4.17}}{\left(L_1 + L_2\right)^{4.54}}$$

$$SN = 0.37D_1 + 0.14D_2 + 0.10D_3$$

此外，道路試驗中亦發現剛性鋪面的損壞率則較不受季節變化的影響，因此不需要季節性調整因子來修正剛性鋪面的交通荷重。原始的 AASHO 剛性鋪面設計公式如下所示，其中，D = 鋪面版的厚度，in.；W, PSI, ρ, β, L_1, 與 L_2 之定義同上。

$$\log W = \log\rho + \frac{\log\left(\frac{4.5 - PSI}{4.5 - 1.5}\right)}{\beta}$$

$$\beta = 1.0 + \frac{3.63\left(L_1 + L_2\right)^{5.20}}{(D+1)^{8.46}\, L_2^{\ 3.52}} \tag{4}$$

$$\rho = \frac{10^{5.85}(D+1)^{7.35}\, L_2^{\ 3.28}}{\left(L_1 + L_2\right)^{4.62}}$$

當本研究利用與上述剛性鋪面設計公式(或公式 4)相同的迴歸係數與道路試驗資料來預測 log(W)的數值時，發現其統計迴歸結果僅約為：$R^2 = 0.16$, SEE = 0.22, N = 371。由於根據

剛性鋪面設計公式所估算而得之軸重當量因子(LEFs)或軸重當量(ESALs)的觀念亦緣起於AASHO 現地道路試驗，在其原始發展過程中根據傳統迴歸分析法所獲得之結論亦隱含了非常高的變異性，因此亦有必要做更進一步的分析與驗證。

四、利用視覺圖法來做道路試驗資料的探索分析

很明顯地，AASHO 道路試驗之資料並非完全不相關、且非固定變異數，其資料可能取自不同鋪面結構設計、不同軸重、及不同荷重形式（單軸或雙軸）等各種層次，因為該道路試驗資料的一致性與完整性，非常適合以視覺圖法來協助資料探索分析(Ker, 2002; Ker, Wardrop, & Anderson, 2003)。由於剛性鋪面的資料較少，因此本研究在此階段首先對柔性鋪面道路試驗資料相關的建造與養護歷史、以及分析報告進行詳盡的了解。

值得注意的是在道路試驗時，報告中指出柔性鋪面在春天融雪時較冬天結冰時有較高的損壞率，因此利用季節性調整因子來修正交通荷重以建立一個較佳的柔性鋪面設計公式。另外，第二迴圈第一車道的道路試驗資料因為分析結果非常差，因此被完全排除在柔性鋪面設計公式之外。本研究亦將根據過去之研究經驗[葛湘瑋，2003; 2004]，利用視覺圖法來協助資料探索分析。利用視覺圖方法來對多層次資料做深入的資料探索分析是統計分析的首要工作，然而卻常被研究者所忽略、簡化或省略[Pinherio, & Bates, 2000; Raudenbush, & Bryk, 2002; Yang, Goldstein, Browne, &Woodhouse, 2002; Verbeke & Molenberghs, 2000］。

本研究初步利用視覺圖法來協助資料探索分析，茲將部分分析結果顯示如下：圖 2 顯示柔性鋪面道路試驗資料之整體平均現況服務指標值趨勢、圖 3 顯示各迴圈與車道之平均現況服務指標值之整體比較、圖 4 顯示各迴圈與車道之平均現況服務指標值、圖 5 顯示各迴圈與車道之平均現況服務指標值之比較(以面層厚度來區分)、與圖 6 顯示各迴圈與車道與面層厚度之平均現況服務指標值等。如前述道路試驗資料之探索分析所代表之意義極為重要，因此需更進一步地進行後續分析工作，以獲致更有意義之研究成果。

五、利用當代迴歸技術來分析道路試驗資料

本研究在此亦將採用嶄新的統計迴歸技術，利用一套系統化的統計與工程分析程序[Lee, 1993; Lee, & Darter, 1995]、可靠的資料分析流程、與詳盡的逐步分析步驟及準則，來分析道路試驗資料。此系統化的分析方法將整合工程專業知識、專家經驗、經驗法則、統計資料分析與迴歸技術在同一個分析架構下。此系統化分析流程可協助鋪面研究人員分析各式現場蒐集的鋪面績效監測資料、與各種鋪面的理論結構反應值等資料，並可在分析過程中預先偵測出並排除可能因含有錯誤的資料而導致各種問題。本研究擬選用之當代迴歸技術包括投影追逐迴歸法(projection pursuit regression, PPR)、小區域迴歸法(locally weighted reression, LOESS)、與類神經網路(artificial neural network, ANN) [Lee, Liu, & Ker, 2007; Insightful, 2001]。

然而，由前述對試驗資料的初步分析結果可知，道路試驗資料並非完全不相關、且非固定變異數，明顯地違反了統計迴歸技術之最小平方法的假設。因此，當本研究嘗試利用當代迴歸技術來分析柔性鋪面道路試驗資料時，初步分析結果並無法顯著改善現有預測模式，因此不在此贅述[Venables & Ripley, 2002]。

六、利用視覺圖法與線性混合模式來分析道路試驗資料

本研究首先將透過利用一套系統性的視覺圖法與線性混合模式來從事柔性鋪面道路試驗資料(多層次資料)之分析工作，並將依資料的特性，配合視覺圖來作分析，再與現有文獻與研究成果互相比較，以驗證所建立績效預測模式的適切性。這部份的主要工作包括發展/整合/組織視覺圖法來分析多層次資料、訂出視覺圖在多層次資料的準則、進行多層次資料的探索

分析、協助模式建立、及模式評估，並與軸重當量(ESALs)的觀念相互分析比較。

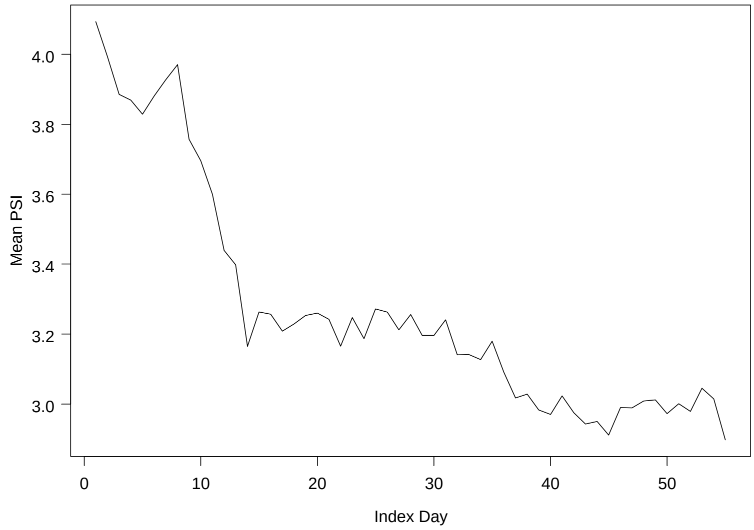

圖 2 柔性鋪面道路試驗資料之整體平均現況服務指標值

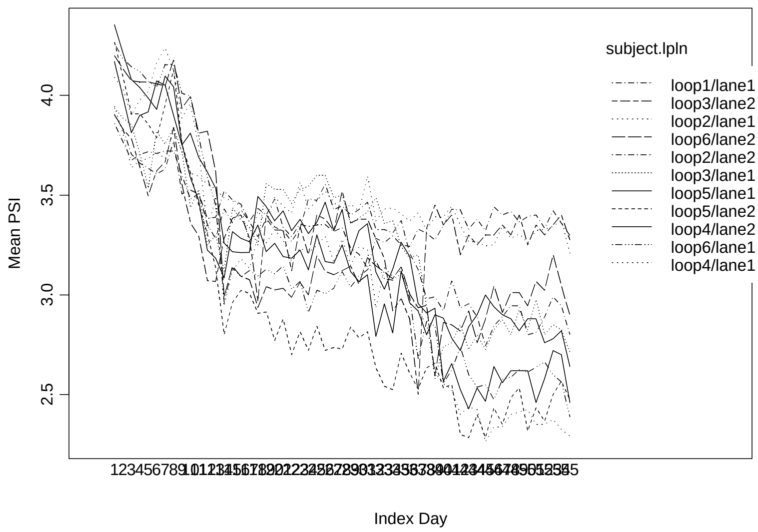

圖 3 各迴圈與車道之平均現況服務指標值之整體比較

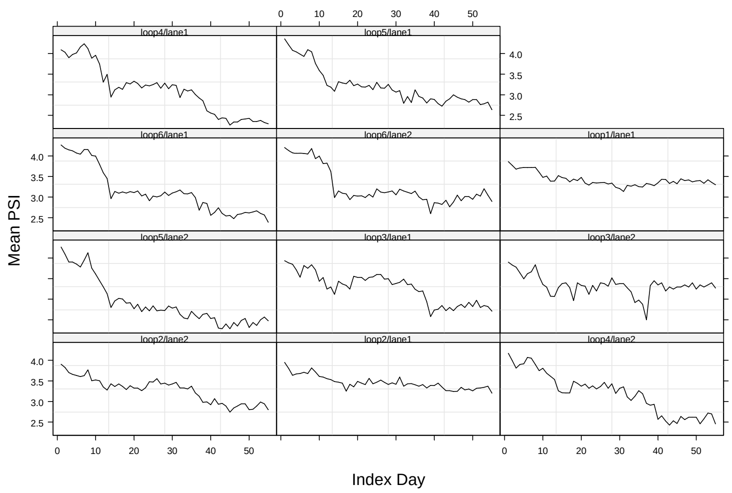

圖 4 各迴圈與車道之平均現況服務指標值

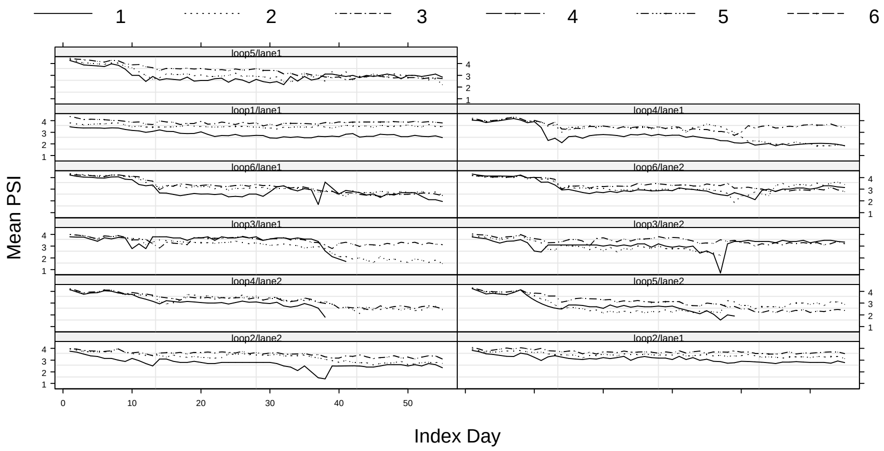

圖 5 各迴圈與車道之平均現況服務指標值之比較(以面層厚度來區分)

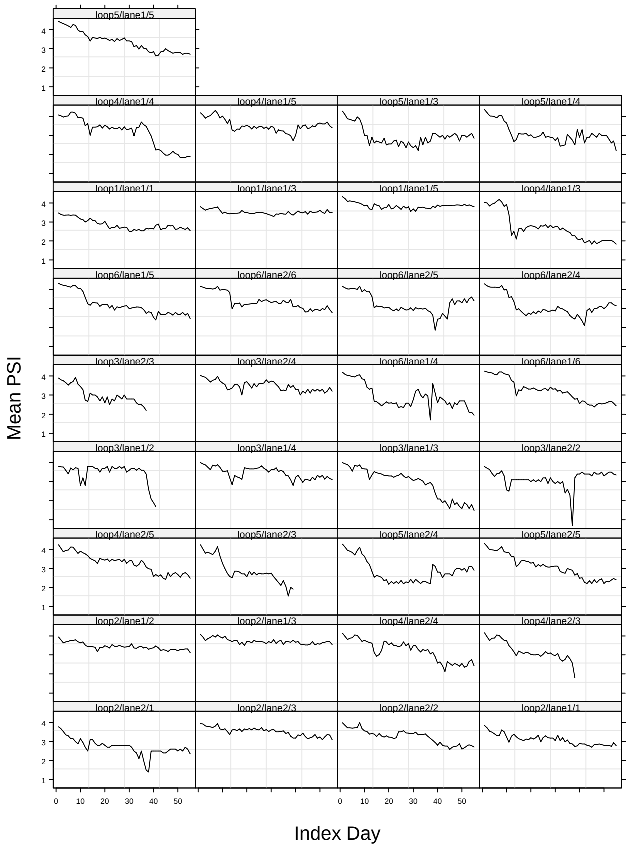

圖 6 各迴圈與車道與面層厚度之平均現況服務指標值

以視覺圖方法(visual-graphical methods) [Cleveland, 1993]來探索資料的特質、協助建立模式及模式評估非常有用，尤其在多層次資料的分析，更是有其不可忽視的功用。在建立模式時，如能先以視覺圖技巧來選擇合適的次模式，那麼就不必要每種次模式都嘗試。然而，傳統的視覺圖技巧，如餅狀圖、直方圖、散布圖、與盒鬚圖等，並不足以或不適用於多層次資料的分析。視覺圖若要使用多層次資料分析，必須至少能讓研究者看出是否有主體間(between-subject)的變異及主體本身(within-subject)的變異、資料特性、次模式及模式的曲線形式。因此，多層次資料的視覺圖技巧比單層次資料複雜。多層次資料的統計分析，如果只是以統計量來顯現並不容易窺得分析的全貌，必須輔以視覺圖方法才能獲得全象(Ker, 2002)。多

層次資料有其特性（主體本身及主體間的有變異的特性），因此視覺圖方法在多層次資料分析上須依循此項特性，針對資料探索分析、模式建立、及模式評估等方面來配合應用[Pinherio, & Bates, 2000; Raudenbush, & Bryk, 2002; Yang, Goldstein, Browne, &Woodhouse, 2002]。

多層線性模式(HLMs)或線性混合模式(LMEs)包含固定效果及隨機效果兩部分，模式的建立比一般標準複迴歸模式複雜。以 LMEs 來分析縱向資料的基本步驟包括選擇固定效果、隨機效果、以及殘差結構等三大部分，茲以柔性鋪面道路試驗資料分析為例，依序說明如下：

6.1 選擇初始的固定效果模式

共變異數結構適用於處理固定效果所不能解釋的變異，因此受平均結構的影響很大。建立模式的第一步是先移除隨機效果，先建立固定效果模式。因此，一個可能的初始平均結構可為如公式(5)（或模式一），數據包括：面層厚度(thick, in.)、底層厚度(basethk, in.)、基層厚度(subasthk, in.)、未修正過之原始交通荷重次數(uwtappl)、與月平均凍融次數(FT)等解釋變數。

$$\begin{aligned}\overline{PSI_{ij}} &= \beta_{0j} + \beta_{1j}(thick)_{ij} + \beta_{2j}(basethk)_{ij} + \beta_{3j}(subasthk)_{ij} + \beta_{4j}(uwtappl)_{ij} + \beta_{5j}(uwtappl)_{ij}^{2} \\ &+ \beta_{6j}(FT) + \text{two-way internaction terms of thick, basethk, subasthk, and uwtappl} \qquad (5) \\ &+ \text{three-way internaction terms of thick, basethk, subasthk, and uwtappl} + R_{ij}\end{aligned}$$

6.2 選擇一個初始的隨機效果結構

在縱向資料研究中，通常包含同一個受試者在不同時間點上重複地接受試驗的資料。而縱向資料主要特性為在主體內的殘差通常是具有異質性（即變異數不等於零）、相關或是兩者兼之。本節研究將包括選擇具有隨機效果的參數以及選擇隨機效果的共變異矩陣兩大部份。

6.2.1 選擇具有隨機效果的參數

通常會以最小平方法(ordinary least square, OLS)來去除從數據中之平均結構，以判斷是否需要使用線性混合效應模式，並決定隨時間變化的變異數是否須包含在隨機效果內。

圖 7 是每個迴圈/車道採用式模式一所得的殘差的盒鬚圖，此圖顯示出模式一對某些迴圈/車道較適當，但並非對所有的迴圈/車道均合宜。譬如受試者第四迴圈/第一車道、第六迴圈/第一車道和第六迴圈/第二車道三者區間較寬，而第三迴圈/第一車道第五迴圈/第一車道兩者區間較窄，因此模式一較適合解釋後者這兩個迴圈/車道的情形；同時迴圈/車道彼此間的殘差的區間有很大的差異，這指出了此組資料採用 HLMs/LMEs 較合適，因 HLMs/LMEs 為主要用於建立主體間有變異(between-subjects varability)的模式。

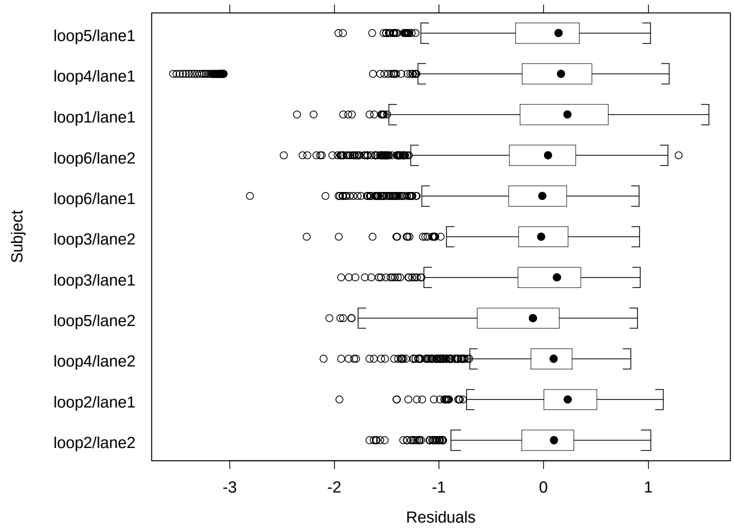

圖 7 各車道/迴圈採用模式一所得的殘差的盒鬚圖

6.2.2 選擇隨機效果的共變異矩陣

共變異數模式有多種形式，依據此視覺搜尋資料等的特性，三種合適的變異數-共變異數結構為一般正定 (general positive definite，或稱 unstructured)模式、對角(diagonal)模式、及區間對角(block-diagonal)模式。一般正定模式是一般的共變異數矩陣；對角共變異數矩陣是假設隨機效果彼此間是獨立的；區間對角模式則假設不同組(sets)的隨機效果有不同的變異數。在視覺搜尋資料中，隨機效果可為截距、時間、時間的平方。這三種共變異數的矩陣形式如下：

$$Unstructured = \begin{bmatrix} \sigma_1^2 & \sigma_{21} & \sigma_{31} \\ \sigma_{21} & \sigma_2^2 & \sigma_{32} \\ \sigma_{31} & \sigma_{32} & \sigma_3^2 \end{bmatrix} \qquad Diagonal = \begin{bmatrix} \sigma_1^2 & 0 & 0 \\ 0 & \sigma_2^2 & 0 \\ 0 & 0 & \sigma_3^2 \end{bmatrix} \tag{6}$$

$$Block-diagonal = \begin{bmatrix} \sigma_1^2 & 0 & 0 \\ 0 & \sigma_2^2 & 0 \\ 0 & 0 & \sigma_2^2 \end{bmatrix}$$

一般正定模式中，對角線的變異數σ_1^2、σ_2^2、σ_3^2分別為截距、時間、時間的平方的變異數，對角線外則為此三項變數倆倆之間的共變異數。對角模式假設變數間無共變異，而每個變數都有自己的變異數，因此，對角線外的值為零，對角線的變異數σ_1^2、σ_2^2、σ_3^2分別為截距、時間、時間的平方的變異數。區間對角矩陣為對角矩陣的特例，在區間對角矩陣中，只有兩種變異數，這是因為假設截距有自己的變異數（σ_1^2），時間及時間平方的變異數相同（同為σ_2^2）。因為對角模式為一般正定模式的特例，而區間對角矩陣為對角矩陣的特例，這三種共變異數的模式可以以概度比檢定來比較，比較結果如表 1 所示。LMEs 的模式比較通常參考對數概度統計量的絕對值、Akaike Information Criterion(AIC)、Bayesian Information Criterion(BIC)三種數值，模式的三種數值越小則適配性越佳【Pinherio & Bates, 2000】。然而因為 p-value＜0.0001 皆有顯著差異，此時需挑選各數比較多的模式，而概度比檢定結果顯示一般正定矩陣較合適，更適合解釋資料，因此本資料將採用一般正定矩陣。

表 1 三個變異數模式的比較

模式	參數個數	Akaike Information Criterion	Bayesian Information Criterion	Log-Likelihood	Test	L.Ratio	p-value
(1)一般正定	29	12910.29	13117.74	-6426.143			
(2)對角	21	12725.71	12875.94	-6341.856	1vs.2	168.5748	<0.0001
(3) 區間對角	20	12192.28	12335.35	-6076.140	2vs.3	531.4330	<0.0001

初始隨機效果的第二層模式包含截距(intercept)、uwtappl、uwtappl^2 和 FT。初始的第二層模式(preliminary level-2 modle)可表示為：

$$\begin{aligned} \text{Level-2:}\quad & \beta_{0j} = \gamma_{00} + u_{0j} \\ & \beta_{1j} = \gamma_{10} \\ & \beta_{2j} = \gamma_{20} \\ & \beta_{3j} = \gamma_{30} \\ & \beta_{4j} = \gamma_{40} + u_{4j} \\ & \beta_{5j} = \gamma_{50} + u_{5j} \\ & \beta_{6j} = \gamma_{60} + u_{6j} \end{aligned} \tag{7}$$

將初始的第二層模式代入初始的第一層模式，獲得初始的線性混合效應模式如公式(8)所示，沒有進行殘差結構分析之前，此模式可稱為均質模式。

$$
\begin{aligned}
\overline{PSI_{ij}} = {} & \gamma_{00} + \gamma_{10}(thick)_{ij} + \gamma_{20}(basethk)_{ij} + \gamma_{30}(subasthk)_{ij} + \gamma_{40}(uwtappl)_{ij} + \gamma_{50}(uwtappl)_{ij}^{2} \\
& + \gamma_{60}(FT)_{ij} + \gamma_{70}(thick*basethk)_{ij} + \gamma_{80}(thick*subasthk)_{ij} + \gamma_{90}(basethk*uwtappl)_{ij} \\
& + \gamma_{100}(subasthk*uwtappl)_{ij} + \gamma_{110}(basethk*subasthk*uwtappl)_{ij} \\
& + \gamma_{120}(thick*basethk*subasthk*uwtappl)_{ij} \\
& + U_{0j} + U_{4j}(uwtappl)_{ij} + U_{5j}(uwtappl)_{ij}^{2} + U_{6j}(FT)_{ij} + R_{ij}
\end{aligned} \tag{8}
$$

6.3 建立殘差結構

殘差結構分成變異結構(variance structure)及相關結構(correlation structure)兩部分。變異結構主要處理殘差的異質性，相關結構主要處理殘差的相依性。Goldstein、Healy 與 Rasbash(1994)建議在進行相依模式建立之前，先將所有其他變異結構建置完成。因此，本研究在建立殘差模式的順序時，先處理其異質性再處理其相依性。均質模式與異質模式的概度比統計量(likelihood ratio statistic)為 6273.29 且 p＜0.0001 達顯著水準，顯示異質模式比均質模式更適合解是資料(如表 2 所示)。

表 2 均質模式與異質模式的比較

模式	參數個數	AIC	BIC	Log-Likelihood	L.Ratio	p-value
均質模式	29	12910.29	13117.74	-6426.14		
異質模式	34	12614.57	12857.79	-6273.29	305.71	＜0.0001

在處理個體內殘差的相依性時，可先用異質模式殘差標準差的經驗自我相關函數(empirical autocorrelation function) 圖作解釋。因研究發現自我相關(autocorrelation)隨時差(lag)的增加而呈幾何性的減低，因此可採用自我迴歸模式階次 1（簡稱 AR(1)）納入異質模式中來處理主體內殘差的變異，此時此模式可稱為異質自我迴歸階次 1 模式（另稱為異質相依模式）。表 3 顯示異質模式與異質相依模式的概度比統計量達顯著水準（概度比統計量為 132.10, p <0.0001），因此異質相依模式比異質模式更適合解釋此資料，亦即殘差模式同時具異質性與相依性。

表 3 異質模式與異質相依模式的比較

模式	參數個數	AIC	BIC	Log-Likelihood	L.Ratio	p-value
異質模式	34	12614.57	12857.79	-6273.29		
異質相依模式	35	12484.47	12734.85	-6207.24	132.10	＜0.0001

6.4 模式簡化

在建立主體內殘差節構模式之後，下一個步驟是檢查整個異質自我回歸階次 1 的模式是否可再簡化，以符合模式精簡的基本原則。在模式簡化過程中，須先簡化隨機效果再簡化固定效果。此模式包含四個隨機效果(截距、uwtappl、$uwtappl^2$ 以及 FT)。此模式可和兩個隨機效果(截距、uwtappl) 的模式互相比較，以決定 $uwtappl^2$ 和 FT 是否須具隨機效果。假設 1（模式 1 與 2）是檢定是否 $uwtappl^2$ 須具隨機效果，假設 2（模式 1 與 3）是檢定 FT 是否須具隨機效果，兩項檢定結果均顯示此兩種二次函數均須具隨機效果，表 4 為三種隨機效果模式的比較。依 Morrel、Pearson 與 Brant（1997）的建議，如果一個 n 階的變數具隨機效果，此變數低於 n 階的乘冪均須具隨機效果。在異質相依模式中，既然 $uwtappl^2$ 具隨機效果，那麼截

距、uwtappl 以及 FT 亦須具隨機效果，因此共變異矩陣須含截距、uwtappl、$uwtappl^2$與 FT。固定效果的簡化則是移除一些未達顯著水準的參數估計值。

表 4 三種隨機效果模式的比較

隨機效果模式	參數個數	Log-likelihood	Test	L.Ratio	p-value
截距、uwtappl、 $uwtappl^2$、FT	35	-6207.24			
截距、 uwtappl、 FT	31	-6333.81	1 vs. 2	253.1457	＜0.0001
截距、uwtappl、 $uwtappl^2$	31	-6255.73	1 vs. 3	96.98533	＜0.0001

表 5 是固定效果簡化之後的結果，所有參數的估計值均達道顯著水準，因此為所建議的二次線性混合效果模式。其中對數概度估計值的絕對值為 6208.89，具隨機效果的參數為截距、uwtappl、$uwtappl^2$ 以及 FT，標準差依序各為 0.170、1.679、0.765、0.00722。主體內殘差的標準差為 0.448，自我迴歸的參數估計值為 0.126。固定模式可表示為：

$$\begin{aligned}\overline{PSI}_{ij} &= 2.4969 + 0.2629(thick)_{ij} + 0.059(basethk)_{ij} + 0.0386(subasthk)_{ij} \\ &-3.6191(uwtappl)_{ij} + 1.1524(uwtappl)_{ij}^2 + 0.0148(FT)_{ij} - 0.0062(thick*basethk)_{ij} \\ &-0.0082(thick*subasthk)_{ij} + 0.1275(basethk*uwtappl)_{ij} + 0.1355(subasthk*uwtappl)_{ij} \\ &-0.0291(basethk*subasthk*uwtappl)_{ij} + 0.0073(thick*basethk*subasthk*uwtappl)_{ij}\end{aligned} \quad (9)$$

表 5 建議的二次線性混合效果模式

隨機效果					
	截距	uwtappl	$uwtappl^2$	FT	殘差
標準差	0.170	1.679	0.765	0.00722	0.448
固定效果					
參數	估計值	標準誤	自由度	t-value	p-value
(Intercept)	2.4969	0.0703	9423	35.51	< 0.0001
thick	0.2629	0.0122	9423	21.48	< 0.0001
basethk	0.0590	0.0066	9423	8.91	< 0.0001
subasthk	0.0386	0.0041	9423	9.37	< 0.0001
uwtappl	-3.6191	0.5254	9423	-6.89	< 0.0001
uwtappl^2	1.1524	0.2481	9423	4.65	< 0.0001
FT	0.0148	0.0023	9423	6.39	< 0.0001
thick*basethk	-0.0062	0.0016	9423	-3.81	< 0.0001
thick*subasthk	-0.0082	0.0010	9423	-8.07	< 0.0001
basethk*uwtappl	0.1275	0.0172	9423	7.40	< 0.0001
subasthk*uwtappl	0.1355	0.0181	9423	7.50	< 0.0001
thick*basethk*uwtappl	-0.0155	0.0045	9423	-3.43	0.0006
thick*subasthk*uwtappl	-0.0077	0.0036	9423	-2.16	0.0307
basethk*subasthk*uwtappl	-0.0291	0.0029	9423	-9.87	< 0.0001
thick*basethk*subasthk*uwtappl	0.0073	0.0006	9423	11.53	< 0.0001

Note. (a) Model fit: AIC=12481.77, BIC=12710.69, logLik=-6208.89. (b) Correlation structure: AR(1); parameter estimate(s): Phi= 0.126. (c) Variance function structure: for different standard deviations per stratum (thick= 2, 1, 3, 4, 5, 6 in.), the parameter estimates are: 1, 1.479, 0.935, 1.199, 0.982, 0.959.

固定效果模式將隨機效果設定為零，用於獲得母體預測值或配適值。混合效果模式則加入隨機效果，用於獲得主體預測值或配適值。這也是線性混合模式的特點之一，它除了提供整體平均成長曲線外（固定效果），加上隨機效果之後，每個受試者可依自己的特性，有自己的成長曲線，可與母體整體平均互相比較，了解自己的相對地位。從表 5 可知，所有的主效果包括 thick、basethk、subasthk、uwtappl、uwtappl^2、FT 以及二因子、三因子和四因子交互作用參數均達顯著水準。thick、basethk、subasthk 的參數估計值為正，指出當鋪面厚度更厚時則平均 PSI 值也會跟著變大。而 uwtappl 的參數估計值為負則指出平均現況服務能力指標值會較低。由以上分析可知，使用 HLMs/LMEs 來分析縱向資料的優點為 HLMs/LMEs 能提出正確的模式形式，在建立共變異模式時較有彈性，並且能將殘差的異質性及相依性納入模式中。

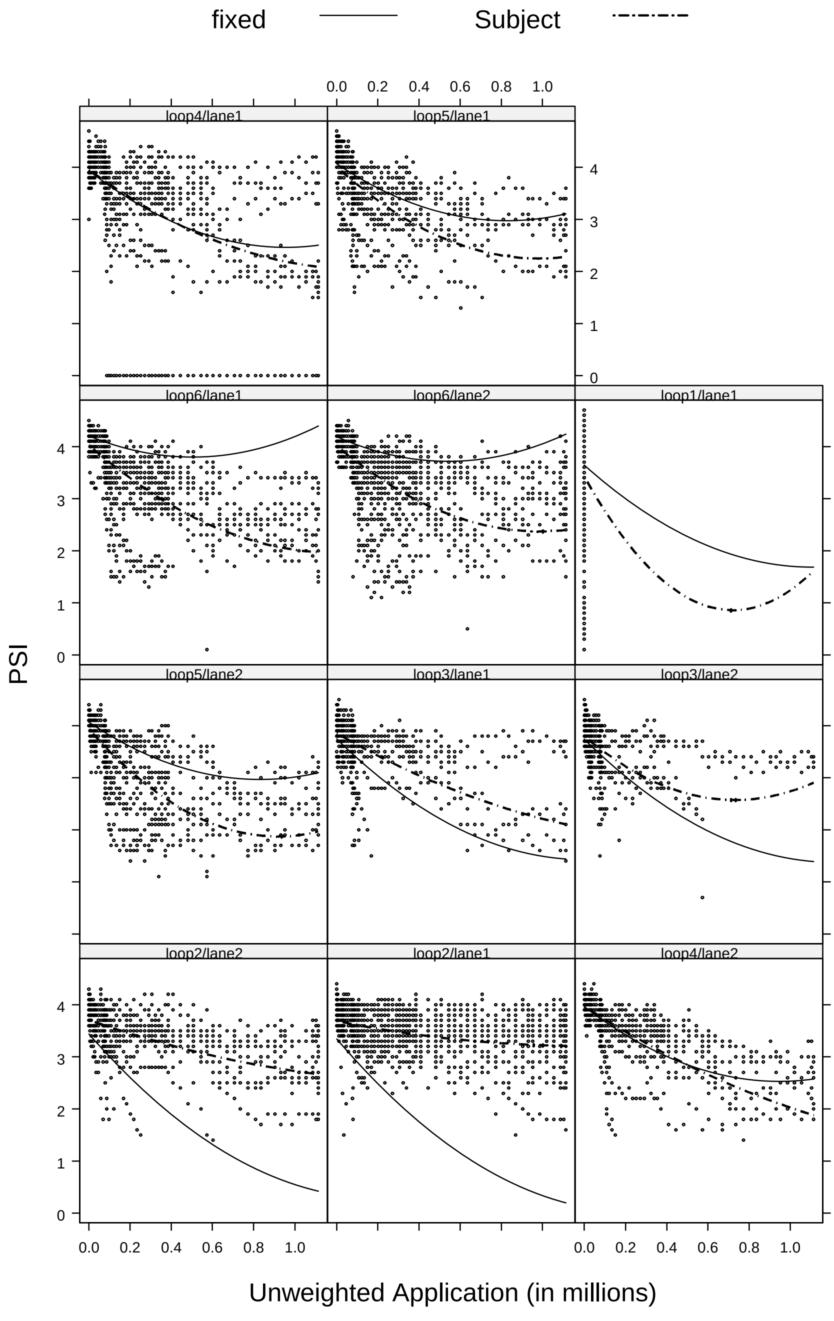

圖 8 二次混合效果模式各個迴圈/車道的母體預測曲線、主體預測曲線及觀察值

圖 8 為此二次混合效果模式每個迴圈/車道的母體預測曲線(fixed)、主體預測曲線(subject)以及觀察值圖。對每個迴圈/車道而言，由於設計鋪面厚度不同，因此母體預測曲線也會不一樣。圖 8 也提供了母體預測曲線和主體預測曲線的相關資訊，這種資訊有助於了解各個迴圈/車道的平均現況服務能力指標值與整體平均現況服務能力指標值的相關情形。從圖 8 可看出第五迴圈/第一車道、第五迴圈/第二車道、第六迴圈/第一車道和第六迴圈/第二車道第五迴圈/第一車道會低於整體平均現況服務能力指標值，第二迴圈/第一車道、第二迴圈/第二車道、第三迴圈/第一車道、第三迴圈/第二車道和第四迴圈/第一車道的平均現況服務能力指標值則會高於整體平均現況服務能力指標值。

七、檢視標準軸重當量之觀念並探討其適用性

前述鋪面績效預測模式的構建過程中，必需反覆地進行驗證與調整。本研究除了將 AASHO 道路試驗作為驗證的資料外，研究中亦擬將依前述各種統計迴歸方法（包括線性混合模式與當代迴歸技術）所建立的績效預測模式與 AASHTO 現有之柔性鋪面與剛性鋪面設計公式相互比較，並深入探討其適用性。研究中亦擬針對模式中可能需要的鋪面輸入參數進行敏感度分析，以作為後續鋪面績效分析之用。本研究並將進一步地探討軸重當量因子(LEFs)、以及將各種不同輪軸荷重轉化為 18,000 磅單軸軸重當量數(或軸重軸次)(ESALs)的可靠性與適用性。根據過去的研究結果顯示，應用 LTPP 計畫所蒐集之鋪面資料與各種現有的績效預測模式的預測結果並不吻合。本研究將適時地將所建立的績效預測模式與 LTPP 資料庫中的荷重頻譜資料進行驗證，以探討進一步地改善 ESAL 觀念的可能性。

八、結論與建議

本研究除了持續利用LTPP資料庫外[FHWA, 1998; 2004; Hajek & Selezeva, 2000; Simpson *et al.*, 1993]，並利用美國AASHO道路試驗的原始資料，配合線性混合模式與當代迴歸技術之分析與應用，深入探討AASHTO柔性鋪面與剛性鋪面設計公式與標準軸重當量(ESAL)觀念之適用性，以及暫行手冊之本土應用問題。研究中發現，在分析AASHO現地道路試驗資料、與軸重當量因子或ESAL概念的原始發展過程中，亦隱含了非常高的變異性。這次分析亦指出利用將軸重當量因子設定為某個特定值的方式並沒有辦法完全適用在後續的鋪面設計上。在利用美國長程鋪面績效(LTPP)資料庫來建立或驗證各種鋪面設計與績效預測模式時，若是僅要對於AASHO原始模式做任何的修正，而無法同時完全捨棄或進一步的分析ESAL概念時，其成效將會是非常值得商榷的。

九、參考文獻

李英豪、張德文 (2002)。台灣地區鋪面工程之研究與展望，*鋪面工程，中華鋪面工程學會會刊*, 第一卷第三期, 第 80-101 頁.

李英豪、葛湘瑋(2005)。*鋪面績效預測模式之構建與應用(一)*(Development and Applications of Pavement Performance Prediction Models, Phase I)，精簡報告，國科會計畫編號 NSC93-2211-E-032-016，淡江大學，民國九十四年七月三十一日。

李英豪、葛湘瑋(2006)。*鋪面績效預測模式之構建與應用(二)*(Development and Applications of Pavement Performance Prediction Models, Phase II)，精簡報告，國科會計畫編號 NSC94-2211-E-032-014，淡江大學，民國九十五年九月三十日。

李英豪、葛湘瑋(2007)。*鋪面績效預測模式之構建與應用(三)*(Development and Applications of Pavement Performance Prediction Models, Phase III)，精簡報告，國科會計畫編號 NSC95-2211-E-032-061，淡江大學。

葛湘瑋(2003)。應用線性混合效果模式於建立多層縱向資料的模式之實例研究。*教育與心理研究期刊, 27,* 第 399-419 頁。

葛湘瑋(2004)。*多層線性模式/線性混合模式之統計實務: 以視覺圖方法來輔助多層線性模式/線性混合模式建立與分析之研究*，精簡報告，國科會計畫編號 NSC93-2118-M-263-001，致理技術學院。

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。

林佳慧(2007)。*剛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 96 年 1 月。

周家蓓等(1994)。*台北市道路鋪面養護管理資料庫系統電腦程式建立之研究*，台灣大學土木工程學研究所，民國 83 年 7 月。

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。

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。

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。

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.

Cleveland, W. S. (1993). *Visualizing Data*. NJ: Hobart Press.

FHWA (1998). *Mechanistic Evaluation of Test Data from LTPP Flexible Pavement Test Sections*, Final Report, Vol. 1, Publication No. FHWA-RD-98-020.

FHWA (2004). *Long-Term Pavement Performance Information Management System: Pavement Performance Database Users Reference Guide*. Publication No. FHWA-RD-03-088.

Hajek, J. J., and O. Selezeva (2000). *Estimaing Cumulative Traffic Loads.* Final Report for Phase 1, Federal Highway Administration, Publication No. FHWA-RD-00-054.

Highway Research Board (1962). *The AASHO Road Test, Report 5, Pavement Research, Special Report 61E*. Publication No. 954, Highway Research Board, National Academy of Science, National Research Council, Washington, D.C.

Insightful (2001). *S-Plus 6.1 User's Guide* and *Guide to Statistics*, Seattle, Washington.

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

Ker, H. W, J. Wardrop, and C. Anderson (2003). Application of linear mixed-effects models in longitudinal data: A case study. *Proceedings, Hawaii International Conference on Education*, January 7-10.

Ker, H. W., Y. H. Lee, and P. H. Wu (2008). Development of Fatigue Cracking Performance Prediction Models for Flexible Pavements Using LTPP Database. *Journal of Transportation Engineering, ASCE, Vol. 134, No. 11*, pp. 477-482.

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

Lee, Y. H., and M. I. Darter (1995). Development of performance prediction models for Illinois continuously reinforced concrete pavements, *Transportation Research Record 1505*, Transportation Research Board, Washington, D.C., 1995, pp.75-84.

Lee, Y. H., Y. B. Liu, and H. W. Ker (2007). Application of Modern Regression Techniques and Artificial Neural Networks on Pavement Prediction Modeling. *CD-ROM, Presented at the 86th Annual Meeting of the Transportation Research Board*, Washington, D.C., January 21~25.

Pinherio, J. C., and D. M. Bates (2000). *Mixed-Effects Models in S and S-Plus*. New York: Springer-Verlag.

Raudenbush, S. W., and A. S. Bryk (2002). *Hierarchical Linear Models: Applications and Data Analysis Methods* (2nd ed.). Newbury Park, CA: Sage. 2

Simpson, A. L., J. B. Rauhut, P. R. Jordahl, E. Owusu-Antwi, M. I. Darter, R. Ahmad, O. J. Pendleton, and 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.

Venables, W. N., and B. D. Ripley (2002). *Modern Applied Statistics with S* (4th ed.). New York: Springer-Verlag.

Verbeke, G., and G. Molenberghs (2000). *Linear Mixed Models for Longitudinal Data*. New York: Springer-Verlag.

Yang, M., H. Goldstein, W. Browne, and G. Woodhouse (2002). Multivariate Multilevel Analyses of Examination Results. *Journal of the Royal Statistical Society, A, 165*, 137-153.

出席國際會議報告
國際瀝青鋪面與環境學術研討會

李英豪
淡江大學土木工程學系

一、前言

國際瀝青鋪面與環境學術研討會(International ISAP Symposium on Asphalt Pavements and Environment)係由國際瀝青鋪面學會(International Society of Asphalt Pavement, ISAP)委託瑞士國家材料試驗與研究實驗室(EMPA)主辦，瑞士國家道路局(Swiss Federal Road Office, FEDRO)、瑞士道路與交通專家協會(Swiss Association of Road and Traffic Experts, VSS)、與法國國際營建材料暨系統與結構實驗室與專家聯盟(RILEM, International Union of Laboratories and Experts in Construction Materials, Systems and Structures)共同協辦。會議地點被安排在瑞士蘇黎世(Zurich, Switzerland) Swissotel 旅館舉行，會期由二OO八年八月十八日至二十日，共計三天。

二、會議主題

國際瀝青鋪面學會(ISAP)成立的主要宗旨在促進世界瀝青鋪面技術的發展與交流。本屆國際瀝青鋪面與環境學術研討會目的在探討瀝青鋪面在環境保護、永續發展、與資源保存等議題上之最新發展與應用。本次會議分成環境衝擊與資源管理、與耐環境性與耐久性兩大主題來進行。其中，環境衝擊與資源管理包括環境永續新材料、再生再再生與材料資源、節能與生產、減少排放與噪音等子題；而耐環境性與耐久性則包括創新設計、排水與水敏感性、耐久性與老化等子題，以供世界各國產官學研界相互交流與研討。依據大會資料顯示，大會共收到 21 個國家的百餘篇論文摘要，經技術委員會嚴格審查後，僅接受其中的 70 餘篇論文來發表，與會人員超過百餘人。筆者很高興能通過本屆研討會論文審查，並獲得行政院國家科學委員會之經費補助，有充分的時間與機會與世界各國專家學者研討、交換研究心得。

三、參加會議經過

為了順利參加本屆研討會，筆者自到達蘇黎世後，於會議開始前第一天(八月十七日)即至議場報到，並參加主辦單位所安排之歡迎茶會。

翌日上午九時舉行開幕儀式後，研討會正式開始，大會並邀請瑞士國家道路局(FEDRO)局長 Rudolf Dieterle 先生致開幕辭暨發

表專題演講，在短暫的中場休息後，大會另邀請加拿大滑鐵盧大學(University of Waterloo) Gerhard J. A. Kennepohl 教授發表專題演講，演講題目為瀝青鋪面與環境，亦受到與會人員的熱烈迴響。

午餐後，大會隨即進行環境永續新材料(2a, 3a)、以及創新設計(2b)、排水與水敏感性(3b)等共四個場次的論文發表會。根據大會安排，每篇論文的發表時間約為二十分鐘，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。筆者的論文「利用美國 LTPP 資料庫構建柔性鋪面車轍預測模式之研究」(Development of Rutting Prediction Models for Flexible Pavements Using LTPP Database)亦被安排在創新設計(2b)子題下來發表，有機會與世界各國知名的專家學者分享由我國行政院國科會專題計畫補助的研究成果，並獲得與會人員的熱烈迴響。會後，與會人員共同乘坐交通車至瑞士國家科技院(Swiss Federal Institute of Technology in Zurich, ETHZ)主建築之屋頂參加歡迎酒會，與會人員有相當多之時間交談，並可遠眺蘇黎世市各區之夕陽美景。

十九日(星期二)上午，會議繼續進行，主要的議題包括再生再再生與材料資源(4a)、節能與生產(5a)、排水與水敏感性(4b, 5b) 等四個子題進行論文發表。下午的議程則包括節能與生產(6a)、減少排放與噪音(7a)、耐久性與老化(6b, 7b) 等四個論文發表會。本屆研討會之晚宴被安排在晚上七時三十分舉行，大會並安排有瑞士傳統樂器現場表演，與會人員並有機會暢談研究經驗與未來可能合作方向。

研討會最後一日(二十日)，上午大會安排有減少排放與噪音(8a, 9a)、耐久性與老化(8b, 9b)等四個子題之論文發表會。下午，在進行閉幕典禮之前另有兩場論文發表會，主要延續上午之議題，包括減少排放與噪音(10a)、與耐久性與老化(10b)。

四、與會心得與建議

在大會精心安排的議程下，有機會與世界各國之專家學者交流研討，並據此得知世界鋪面技術的最新發展與知識，以及現在與未來之挑戰，乃是參加此次國際學術研討會的最大收獲。筆者很慶幸能獲得行政院國家科學委員會之經費補助，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

參加本屆國際瀝青鋪面與環境學術研討會攜回資料包括：本屆會議論文集與議程各一份。

Development of Rutting Prediction Models for Flexible Pavements Using LTPP Database

Hsiang-Wei Ker, Chihlee Institute of Technology, Taiwan
Ying-Haur Lee, Tamkang University, Taiwan
Pei-Hwa Wu, Tamkang University, Taiwan

ABSTRACT: This study strives to develop improved rutting prediction models for flexible pavements using the Long-Term Pavement Performance (LTPP) database. The prediction accuracy of the existing prediction models implemented in the recommended Mechanistic-Empirical Pavement Design Guide was found to be inadequate. Exploratory data analysis indicated that the normality assumption with random errors and constant variance using conventional regression techniques might not be appropriate. Therefore, generalized linear model (GLM) along with several distribution functions were adopted for the modeling process. After considerable amount of trails, the quasi family with the same link and variance functions from Poisson family appeared to be the best choice. To further enhance the model fits, generalized additive model (GAM) techniques were adopted. Box-Cox power transformation technique was utilized to estimate a proper, monotonic transformation for each variable based on the preliminary GAM model. The LTPP pavement performance data was refitted with these transformed predictors using GLM techniques. Consequently, the resulting mechanistic-empirical models included several variables such as yearly KESALs, pavement age, annual precipitation, annual temperature, critical compressive strain on top of subgrade layer, freezing-index, and freeze-thaw cycle. The goodness of fits appeared to better agree with the performance data although their further enhancements are possible and recommended.

1. Introduction

Performance predictive models have been used in various pavement design, evaluation, rehabilitation, and network management activities. Since rutting is one of the major flexible pavement distress types primarily caused by the accumulated traffic loads. Extensive research has been conducted to predict the occurrence of this distress type using various empirical and mechanistic-empirical approaches. Conventional predictive models usually correlate rutting damage to the critical compressive strain of the subgrade and the allowable number of load repetitions. As pavement design evolves from traditional empirically based methods toward mechanistic-empirical, the equivalent single axle load (ESAL) concept used for traffic loads estimation is no longer adopted in the recommended Mechanistic-Empirical Pavement Design Guide (MEPDG) (NCHRP Project 1-37A) (1, 2). The success of the new design guide considerably depends upon the accuracy of pavement performance predictions. Thus, this study will first investigate its goodness of fit and strive to develop improved rutting prediction models for flexible pavements using the Long-Term Pavement Performance (LTPP) database (http://www.datapave.com or LTPP DataPave Online) (3, 4, 5).

2. Brief review of existing mechanistic-empirical prediction models

Since rutting is primarily caused by accumulated traffic loads, various predictive models as shown in Table 1 based on the following expressions have been proposed to estimate the maximum allowable number of repetitions (N_d) using the critical compression strain (ε_c) on top of the subgrade (6-9):

$$N_d = k_4 (\varepsilon_c)^{-k_5} \tag{1}$$

In which, k_4, and k_5 are regression coefficients. Cumulative rutting damage (D_d) is then calculated by adding the damage caused by each individual load application based on Miner's hypothesis, where, k is the number of axle load type, n_i is the number of axle applications, and N_{di} is the corresponding maximum allowable number of repetitions.

$$D_d = \sum_{i=1}^{k} \frac{n_i}{N_{di}} \le 1.0 \tag{2}$$

Table 1: Coefficients for predicting allowable load repetitions

Organization (Year)	k_4	k_5
AI (1982)	1.365×10^{-9}	4.477
Shell (1994)	6.15×10^{-7}	4.0
Indian model (1999)	2.56×10^{-8}	4.533
Mn/ROAD (2003)	7.0×10^{15}	3.909

Starting from 1987, the LTPP program has been collecting a national pavement database in a factorial format with wider ranges of pavement designs, materials, and climatic zones. More than 2,400 asphalt and Portland cement concrete pavement test sections across the North America have been monitored. Very detailed information about original construction, pavement inventory data, materials and testing, historical traffic counts, performance data, maintenance and rehabilitation records, and climatic information have been collected. In the NCHRP project P-020 (10), an early sensitivity analysis study of the LTPP database was conducted and the following models were developed for rutting prediction:

$$\text{Rut Depth} = \text{N}^{B} 10^{C} \tag{3}$$

in which, Rut Depth is in hiches; N is the accumulated 18-kip equivalent single axle load (ESAL, in thousands), $B = b_o + b_1x_1 + b_2x_2 + \cdots\cdots + b_nx_n$ and $C = c_o + c_1x_1 + c_2x_2 + \cdots\cdots + c_nx_n$. The regression coefficients are given in Table 2. Separate models for different climatic zones (dry-freeze, dry-nonfreeze, wet-freeze, and wet-nonfreeze) are also available.

Table 2: Regression coefficients of the P-020 rutting model

Parameters x_i	Unit	Regression Coefficients	
		b_i	c_i
(Intercept)	—	0.151	-0.00475
Log（HMAC percent passing #4 shieve）	Weight %	0	-0.596
Log（HMAC air content）	Voulme %	-0.0726	0
Log（base thickness）	in.	0	0.190
Subgrade (percent passing #200 shieve)	Weight %	0	0.00582
Freezing Index (FI)	Degree F-Days	$8.49*10^{-6}$	0
Log（AC thickness）× Log（base thickness）	in.	0	-0.161

In the recommended MEPDG (2), the rutting damage is determined in an incremental manner based on more complicated Axle Load Spectra (ALS) concept. The damage is estimated for each subseason of each sublayer. To estimate the permanent deformation (or rut depth) of each sublayer, the plastic strain accumulated at the end of each subseason was computed. The overall permanent deformation is briefly expressed as follows:

$$RD = \sum_{i=1}^{k} \varepsilon_p^i h^i \tag{4}$$

In which, RD is the rut depth (in.); ε_p^i is total plastic strain in sublayer i; h^i is the thickness of sublayer i; and k is the number of sublayers. The process is repeated for each load level, subseason, and month of the analysis period. Permanent deformation is only estimated for asphalt bound and unbound layers. To estimate the permanent deformanent of asphalt layer the following model was proposed:

$$\frac{\varepsilon_p}{\varepsilon_r} = k_1 * 10^{-3.4488} T^{1.5606} N^{0.479244} \tag{5}$$

where, ε_p is the accumulated plastic strain at N load repetitions; ε_r is the resilient strain of the asphalt material as a function of mix properties, temperature and time rate of loading; N is the numver of load repetitions; T is temperature (degress F); k_1 is a function of total asphalt layer thickness (h_{ac}, in.) and depth (in.) to correct for the confinine pressure at different depths as follows:

$$\begin{aligned} k_1 &= (C_1 + C_2 * depth) * 0.328196^{depth} \\ C_1 &= -0.1039 * h_{ac}^2 + 2.4868 * h_{ac} - 17.342 \\ C_2 &= 0.0172 * h_{ac}^2 - 1.7331 * h_{ac} + 27.428 \end{aligned} \tag{6}$$

More detailed information is available in the literature (2). The prediction accuracy of the proposed models implemented in the recommended MEPDG (2) will be further investigated. To avoid undesirable misunderstanding of the new guide's prediction algorithm due to the complexity involved, it was decided to directly use the MEPDG software for the prediction of rutting. The beta version of the software could be downloaded from http://www.trb.org/mepdg/software.htm.

3. Database preparation

Initially, the DataPave 3.0 program was used to prepare a database for this study. However, in order to obtain additional variables and the latest updates of the data, the Long-Term Pavement Performance database retrieved from http://www.datapave.com (or LTPP DataPave Online, Release 18.0) (4) became the main source for this study. There are 8 general pavement studies (GPS) and 9 specific pavement studies (SPS) in the LTPP program. Of which, only asphalt concrete (AC) pavements on granular base (GPS1) and on bound base (GPS2) was used for this study.

This database is currently implemented in an information management system (IMS) which is a relational database structure using the Microsoft Access program. Automatic summary reports of the pavement information may be generated from different IMS modules, tables, and data elements. The thickness of pavement layers was obtained from the IMS Testing module rather than the IMS Inventory module to be consistent with the results of Section Presentation module in the DataPave 3.0 program. Several material properties were queried from the Inventory module. Detailed traffic counts and equivalent single axle load (ESAL) were obtained from the Traffic module. The cumulated ESAL during the performance analysis period was calculated by multiplying pavement age with mean yearly ESAL (or kesal) which could be easily estimated from the database. Environmental data were retrieved from the IMS Climate module and the associated Virtual Weather Station (VWS) link. The rutting data used in this study was obtained from MON_T_PROF_INDEX_SECTION table in the IMS Monitoring module. Maintenance and rehabilitation activities could effectively reduce the distress quantities. Thus, the records in both Maintenance and Rehabilitation modules were used to assure that this study only chose the performance data of those sections without or before major improvements.

For the purpose of this study, a Microsoft Excel summary table containing the pavement inventory, material and testing, traffic, climatic, and distress data was created using the relational database features of the Access program. The Excel table was then stored as S-Plus datasets for subsequent analysis. The summary, table, cor, plot, pairs, and coplot functions were heavily utilized to summarize the information of interest and to provide more reliable data for this study. To estimate the critical compressive strain (ε_c) of the subgrade layer, a systematic approach was utilized and implemented in a Visual Basic software package to automatically read in the pavement inventory data from the summary table, generate the BISAR input files, conduct the batch runs, as well as summarize the results (5). In which, the static (or laboratory tested) elastic modulus data recorded in the IMS Testing module and a single wheel load of 40 kN (9,000 lbs) with a tire pressure of 0.482 MPa (70 psi) were used for the analysis.

Furthermore, the aforementioned mechanistic-empirical models also require the dynamic Young's modulus of AC surface layer. LTPP program utilized the MODCOMP4 program to (11-12) backcalculate the dynamic modulus of each pavement layer which could be retrieved from the IMS Monitoring module. Thus, it would be interesting to compare the laboratory tested layer moduli versus the backcalculated dynamic Young's moduli so as to have a better understanding of their associated variability. As shown in Figure 1, the variability of the relationship between the dynamic and the static (or laboratory tested) moduli could not be ignored. The average ratios of which are approximately 2.6, 2.7, 7.3, and 3.4 by eliminating some apparent outliers for AC surface, base, subbase, and subgrade layers, respectively (5).

A data cleaning process must be conducted before any preliminary analysis or regression analysis can be performed. With the help of graphical representation, some rutting data were plotted against surveyed years for each section in the database with additional information displayed. Each section was carefully examined. Two additional codes were assigned to each section to indicate the findings of the examination, i.e., whether the rutting is reasonable according to the distress history, or which year of data is questionable and could be deleted if necessary.

4. Preliminary analysis of the rutting database

Univariate data analysis consists of statistical methods for describing the distribution and spread of each individual variable. Some basic descriptive statistics regarding the data range, its variation, and the number of missing values for each individual variable were conducted. Univariate data analysis procedure is often used to investigate the possibility of data errors and potential distribution problem for each variable considered in a regression analysis. A few extreme (or unusual) data points may be identified or deleted from the analysis.

A graph is always far more perceptible than thousands of numbers. A single plot which well describes the spread of the data was created by combining these univariate statistics with a histogram. A correlation matrix of these variables and trimmed correlation matrices show the variable correlations after eliminating a certain portion of influential data points or possible outliers such that more reliable indices of the correlations were conducted. A scatter plot matrix can graphically represent their relationships and scatters. Applying a data smoothing technique (lowess) on the same scatter plot matrix (13-14), the pairwise relationships become clearer and possible data errors may also be easily identified.

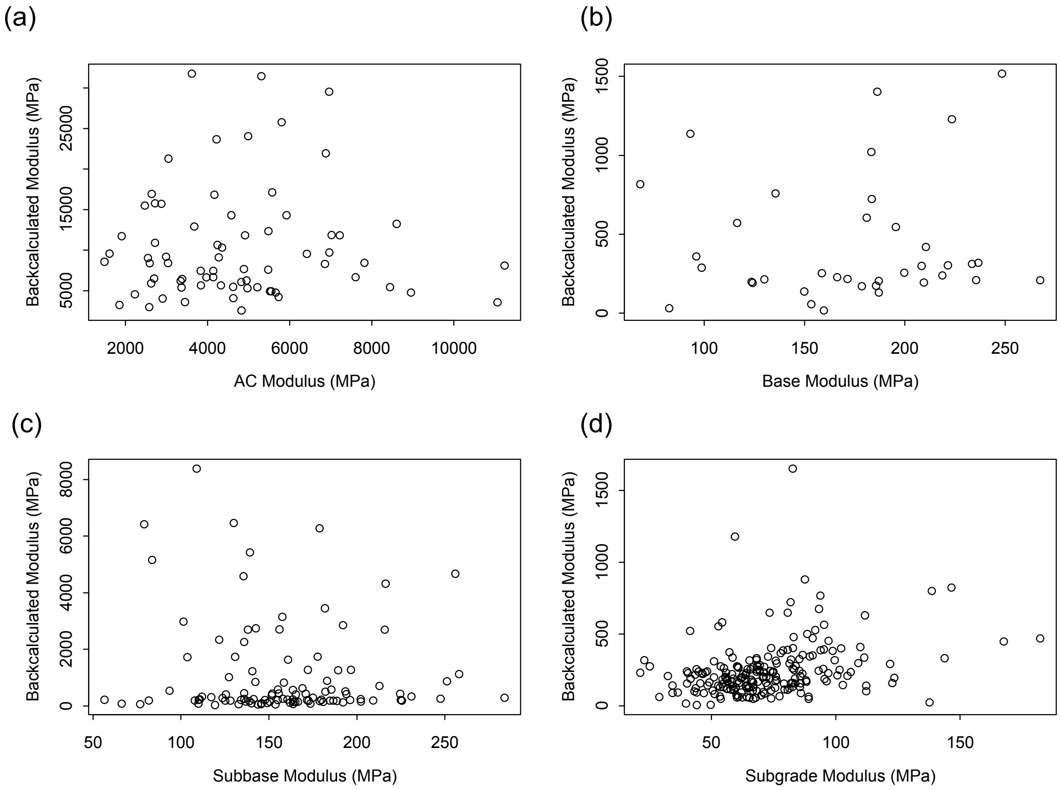

Figure 1: Comparison of layer moduli of (a) AC surface layer; (b) base layer; (c) subbase layer; and (d) subgrade obtained from laboratory testing (x axis, MPa) and backcalculation program (y axis, MPa)

5. Goodness of prediction of the existing models

To investigate the goodness of prediction, cumulative rutting damage (D_d) was calculated and plotted against the actual rutting equations (1) and (2) and the coefficients given in Table 1 for AI and Shell Oil models as shown in Figure 2. In addition, the goodness of prediction using the NCHRP P-020 model and the recommended MEPDG model was given in Figure 3. Unfortunately, the prediction accuracy of the existing prediction models was found to be inadequate.

6. Development of improved rutting models

The occurrence of rutting in field depends on various factors namely traffic, environment, structure, construction, maintenance and rehabilitation. Even though the use of an incremental approach and more complicated Axle Load Spectra (ALS) concept seems to be a very logical approach, the integration of which with monthly or seasonal environmental factors and several assumed parameters often resulted in more variations in the predictions of rutting due to many uncertainties involved. To develop a more reliable predictive model for practical engineering problems, Lee and Darter (15-16) proposed a predictive modeling approach to incorporate robust (least median squared) regression, alternating conditional expectations, and additivity and variance stabilization algorithms into the modeling process. The robust regression is proposed due to its favorable feature of analyzing highly contaminated data by detecting outliers from both dependent variable and independent variables. Through the iterative use of the combination of these outlier detection and nonparametric transformation techniques, it is believed that some potential outliers and proper functional forms may be identified. Subsequently, traditional regression techniques can be more easily utilized to develop the final predictive model. Nevertheless, many preliminary trials using these regression techniques have shown extreme difficulty to achieve a satisfactory predictive model for this set of data.

(a) (b)

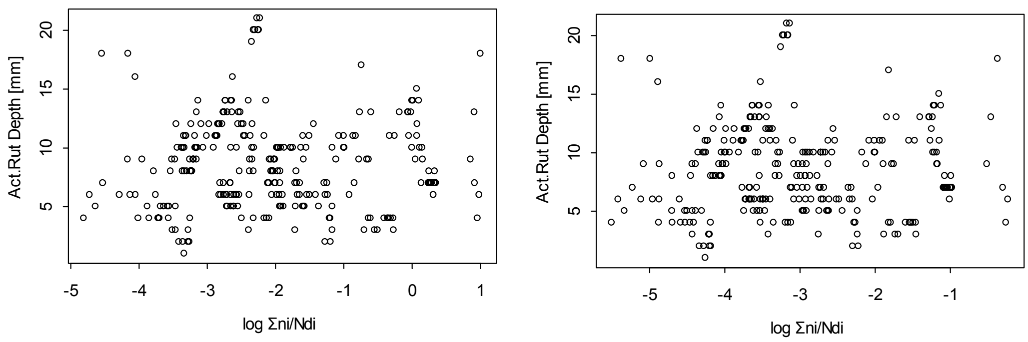

Figure 2: Comparison of prediction results using (a) AI model; and (b) Shell Oil model

(a) (b)

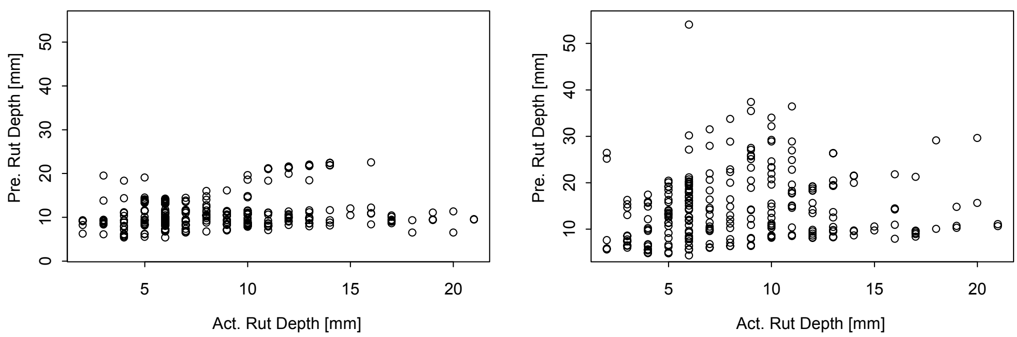

Figure 3: Goodness of prediciton using (a) SHRP P-020 model; and (b) MEPDG model

6.1 Preliminary analysis using linear model

Preliminary analysis using many explanatory parameters in a linear model form was first conducted. The resulting regression statistics are given in Table 3. In which, age stands for pavement age (years); cumulated ESALs (cesal, millions); kesal is the yearly ESALs (thousands); fi is freezing-index (^{o}C-days); temp is mean annual temperature (^{o}C); h1 is the thickness of AC surface layer (cm); base thickness (h2, cm); subgrade resilient modulus (e4, MPa); viscosity of AC binder (visco, poise); precip is mean annual precipitation (mm); L.Damage is the logarithm of rutting damage; epsilon.c (ε_c) is critical compressive strain of the subgrade; and act.rut is actual rutting (mm). To improve the model fits, it is possible to develop separate models for different climatic zones to account for other factors not considered in the above model implicitly. Due to the unbalanced data structure, of which 80, 114, 194, 71, 141, and 124 data points were obtained from Wet-Freeze, Wet-NonFreeze, Wet, Dry, Freeze, and NonFreeze zones, respectively. A summary report of such analyses is given in Table 4 showing that desireable high coefficient of derermination (R^2) might be obtained. Nevertheless, it was also noted that the physical interpretations of many parameters in the model were inappropriate, in which, SEE is the standard error of estimate.

Table 3: Regression coefficients of a linear model trail

Parameters	Value	Std. Error	t value	Pr(>|t|)	Parameters	Value	Std. Error	t value	Pr(>|t|)
(Intercept)	13.4420	2.7023	4.9743	0.0000	visco	0.0007	0.0007	0.9741	0.3310
age	0.0191	0.0574	0.3333	0.7392	fi	-0.0052	0.0011	-4.8267	0.0000
cesal	0.8254	0.2251	3.2357	0.0014	temp	-0.3344	0.0802	-4.1722	0.0000
kesal	-0.0127	0.0042	-3.0422	0.0026	L.Damage	0.1480	0.4436	0.3337	0.7389
h1	0.1385	0.0418	3.3162	0.0010	epsilon.c	-504.971	1264.44	-0.3994	0.6900
h2	0.0579	0.0193	3.0103	0.0029	precip	-0.0019	0.0009	-2.1050	0.0363
e4	-0.0176	0.0103	-1.7189	0.0869					
Residual standard error: 3.493 on 252 degrees of freedom									
Multiple R-Squared: 0.2245									

Table 4: Summary report of the results of several linear models by different climatic zones

Zones / Variables	All	Wet-Freeze	Wet-Nonfreeze	Wet	Dry	Freeze	Nonfreeze
age	---	P	---	P	---	P	---
cesal	P	---	P	P	---	---	---
kesal	N*	---	N*	N*	N*	---	---
h1	P*	P*	P*	P*	---	P*	P*
h2	P*	P*	P*	P*	P*	P*	P*
e4	N	N	---	N	N	---	---
vicso	---	N	P*	P*	P*	N	P*
fi	N	---	---	---	N	N	---
temp	N*	---	N*	---	N*	---	---
L.Damage	---	---	---	N*	P	P	---
epsilon.c	---	---	P	P	---	N*	P
Precip	N*	---	N*	N*	P	---	---
No. of Obs.	265	80	114	194	71	141	124
SEE	3.493	2.689	2.399	3.259	1.381	2.344	3.215
R^2	0.2245	0.705	0.659	0.427	0.784	0.673	0.337

---: Insignificant; P: Positive correlation; N: Negative correlation; *: Inappropriate.

6.2 Proposed models using modern regression techniques

Exploratory data analysis of the response variable indicated that the normality assumption with random errors and constant variance using conventional regression techniques might not be appropriate for prediction modeling. The Shapiro-Wilk W-statistic for testing for departures from normality was also used to test the distribution of rutting data (13-14). Thus, generalized linear model (GLM) along with several distribution functions including normal/Gaussian, gamma, Poisson, and quasi were adopted for the modeling process. Without fully knowing the error distribution of the response variable, the quasi family with the same link and variance functions from Poisson family was found to be the best choice. After many trails in eliminating insignificant and inappropriate parameters, the resulting mechanistic-empirical model included several variables such as pavement age, yearly ESALs, freezing index, mean annual temperature, and critical compressive strain of the subgrade for rutting prediction.

Since the primary assumption of the above preliminary GLM models is that a linear function of the parameters was used in the model. Generalized additive model (GAM) extends GLM by fitting nonparametric functions using data smoothing techniques to estimate the relationship between the response and the predictors (13). To further enhance the model fits, generalized additive model (GAM) techniques were adopted in this analysis. Box-Cox power transformation technique was routinely utilized to estimate a proper, monotonic transformation for each variable based on the resulting preliminary GAM model. The rutting data was refitted with these transformed predictors using generalized linear model (GLM) techniques. Again, after going through several trails in eliminating insignificant and/or inappropriate parameters, the following model was obtained:

$$\ln(Rut) = -0.9998 + 0.1370 * \sqrt{age} + 0.3224 * \log(kesal) + 0.3812 * \log(1 + fi) + 0.3521 * \sqrt{temp} + 0.08288 * (epsilon.c * 1000)^2 \quad (7)$$

$$\text{Statistics}: \mathrm{R}^2 = 0.164, \mathrm{SEE} = 1.22, \mathrm{N} = 265$$

in which, dispersion parameter for Poisson family taken to be 1; null deviance = 460.866 on 264 degrees of freedom; residual deviance = 385.5342 on 259 degrees of freedom; *age* stands for pavement age (years); *kesal* is the yearly ESALs (thousands); *fi* stands for annual freezing index (^{o}C-days); temp stands for mean annual temperature (^{o}C); epsilon.c (ε_c) is the critical compressive strain of the subgrade; Rut is the predicted rutting (mm); and N is the number of observations

Figure 4 shows two diagnosing plots of the above model. The plot of the response versus fitted values also showed that the proposed model has substantial improvements over the existing models in an attempt to uncover the underlying relationships. A normal probability plot or a quantitle-quantile plot of the residuals can be used to check the adequacy of the model. As shown in Figure 4(b), an approximately straight-line relationship was observed indicating that the residuals distribution is close to normal. Since the main objective is to predict the amount of rutting, it is desirable to rearrange the above equation into the following expression and obtain new regression summary statistics:

$$Rut = \exp[-0.99 + 0.137 * \sqrt{age} + 0.322 * \log(kesal) + 0.38 * \log(1 + fi) + 0.352 * \sqrt{temp} + 0.083 * (epsilon.c * 1000)^2] \quad (8)$$

$$\text{Statistics}: \mathrm{R}^2 = 0.155, \mathrm{SEE} = 3.568, \mathrm{N} = 265$$

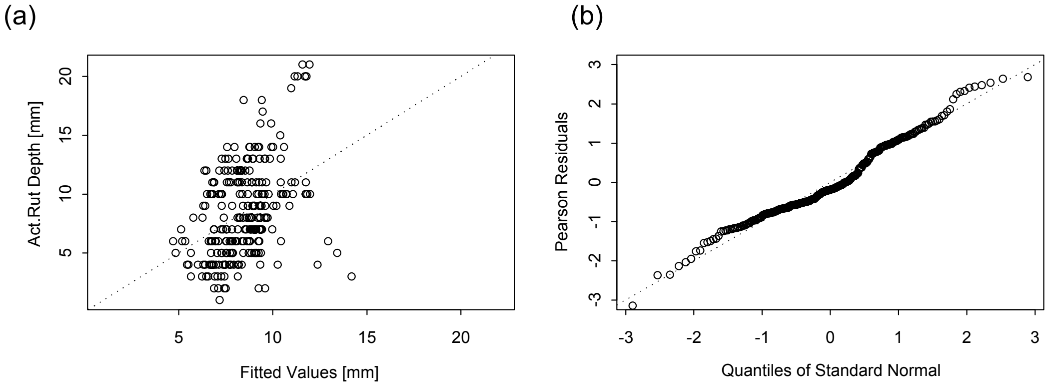

Figure 4: Diagnosis plots of the proposed model: (a) response against fitted values; and (b) a normal probability plot of the residuals

To improve the model fits, the following models were subsequently developed for wet and nonfreeze climatic zones, respectively:

$$(Rut)_{wet} = \exp[-1.489 + 0.25 * \sqrt{age} + 0.6 * \log(kesal) + 0.24 * \log(1 + fi) \\ + 0.256 * \sqrt{temp} + 0.288 * (epsilon.c * 1000)^2] \quad (9)$$

$$\text{Statistics}: \mathrm{R}^2 = 0.338, \mathrm{SEE} = 3.401, \mathrm{N} = 194$$

$$(Rut)_{nonfreeze} = \exp[0.253 + 0.065 * \sqrt{age} + 0.486 * \log(kesal) + 0.187 * \log(1 + fi) \\ + 0.06 * \sqrt{temp} + 0.288 * (epsilon.c * 1000)^2] \quad (10)$$

$$\text{Statistics}: \mathrm{R}^2 = 0.282, \mathrm{SEE} = 3.193, \mathrm{N} = 124$$

7. Sensitivity analysis of the proposed model

The goodness of the model fit was further examined through the significant testing and various sensitivity analyses of pertinent explanatory parameters. Some plots showing the sensitivity of the various factors in the proposed model are presented in Figure 5. These plots were prepared based on the range of the actual data while setting the remaining parameters to the corresponding mean values. The plots show the relationships among yearly ESAL (kesal, thousands), pavement age (age, years), the critical compressive strain of the subgrade (epsilon.c), mean annual tmperature (^{o}C), yearly freezing index (fi, ^{o}C-days), and the predicted rutting (pre.rut, mm). The general trends of these effects seem to be fairly reasonable.

8. Conclusions

The prediction accuracy of the existing rutting models for flexible pavements using the Long-Term Pavement Performance (LTPP) database was found to be inadequate and greatly in need for improvement. Normality assumption using conventional regression techniques might not be appropriate for this study. Thus, generalized linear model (GLM) and generalized additive model (GAM) along with the assumption of Poisson distribution and quasi-likelihood estimation method were adopted for the modeling process.

After many trails in eliminating insignificant and inappropriate parameters, the resulting proposed model included several variables such as yearly KESALs, pavement age, annual temperature, critical compressive strain on top of the subgrade, and freezing index for rutting prediction. The goodness of the model fit was further examined. The residual plot and the plot of the response versus fitted values all indicated that the proposed model has substantial improvements over the existing models. Sensitivity analysis of the explanatory variables indicated their general trends seem to be fairly reasonable. The tentatively proposed predictive models appeared to reasonably agree with the pavement performance data although their further enhancements are possible and recommended.

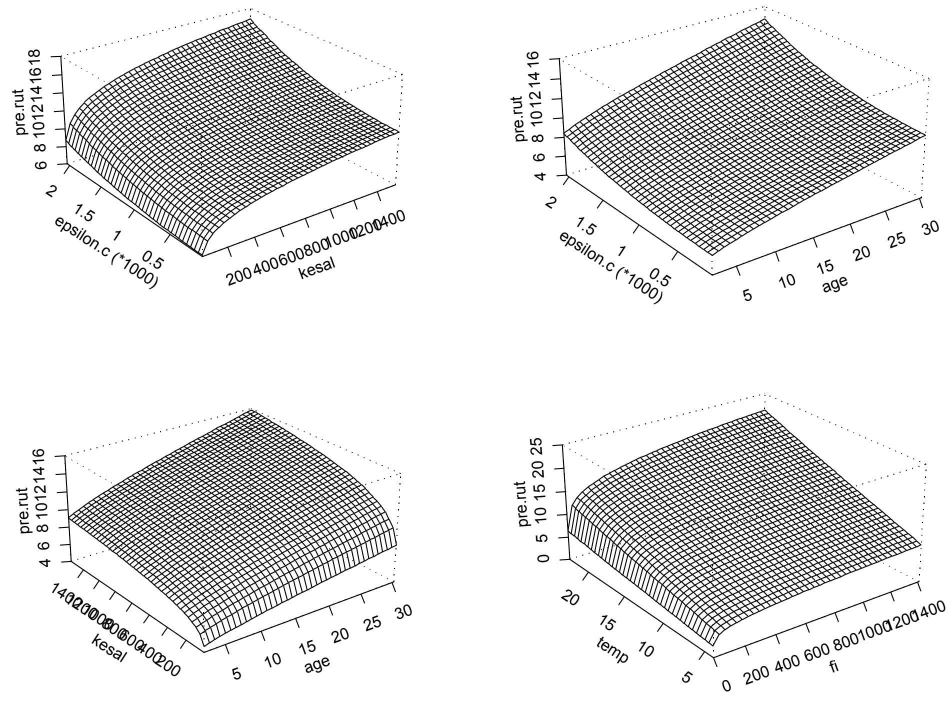

Figure 5: Sensitivity analysis of the proposed model

9. Acknowledgments

This study was sponsored by National Science Council, Taiwan, under the project titled "Development and Applications of Pavement Performance Prediction Models," Phase I (NSC 93-2211-E-032-016) and Phase II (NSC94-2211-E032-014). Technical guidance provided by Dr. Ming-Jen Liu and Dr. Shao-Tang Yen is gratefully acknowledged.

10. References

1. Ayres, M. and Witczak, M., "Mechanistic Probabilistic System to Evaluate Flexible Pavement Performance" ,Transportation Research Record 1629, (1998) 137-148.
2. ARA, Inc., "Guide for Mechanistic-Empirical Design of New and Rehabilitated Pavement Structure", ERES Consultants Division, NCHRP Research 1-37A Report, TRB, National Research Council, Washington, D.C., (2004).
3. FHWA, "Distress Identification Manual for the Long-Term Pavement Performance Program", Publication No. FHWA-RD-03-031, (2003).
4. FHWA, "Long-Term Pavement Performance Information Management System: Pavement Performance Database Users Reference Guide", Publication No. FHWA-RD-03-088, (2004).
5. Wu, P.H., "Development of Performance Prediction Models for Flexible Pavements", Master Thesis, Tamkang University, Tamsui, Taipei, Taiwan, (2006). (In Chinese)

6. Asphalt Institute, “Research and Development of the Asphalt Institute’s Thickness Design Manual MS-1“, 9th Ed., College Park, Md., (1982).
7. Shell International Petroleum Company, “Shell Pavement Design Method for Use on a Personal Computer User Manual,” Shell, London, (1994).
8. Das, A., and Pandey, B.B., “Mechanistic-empirical design of bituminous roads: an Indian perspective,” J. Transportation Engrg., ASCE, 125(5), (1999) 463-471.
9. Timm, D.H., and Newcomb, D.E., “Calibration of flexible pavement performance equations for Mn/ROAD,” TRB Paper #03-2012, Transportation Research Board 82nd Annual Meeting, Washington, D.C. (2003).
10. Simpson, A.L., Rauhut, J.B., Jordahl, P.R., Owusu-Antwi, E., Darter, M.I., Ahmad, R., Pendleton, O.J., and Lee, Y.H., “Early Analyses of LTPP General Pavement Studies Data, Volume 3, Sensitivity Analyses for Selected Pavement Distresses”, Contract No. P-020, Report No. SHRP-P-393, Strategic Highway Research Program, National Research Council, Washington, D.C. (1993).
11. FHWA, “Mechanistic Evaluation of Test Data from LTPP Flexible Pavement Test Sections”, Final Report, Vol. 1, Publication No. FHWA-RD-98-020 (1998).
12. FHWA, “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 (2002).
13. Venables, W.N., and Ripley, B.D., “Modern Applied Statistics with S”, 4th Ed., New York: Springer-Verlag (2002).
14. Insightful Corp., “S-Plus 6.2 for Windows: User’s Manual, Language Reference” (2003).
15. Lee Y.H., “Development of Pavement Prediction Models”, Ph.D. Dissertation, University of Illinois, Urbana, Illinois (1993).
16. Lee, Y.H., and Darter, M.I., “Development of Performance Prediction Models for Illinois Continuously Reinforced Concrete Pavements.” Transportation Research Record, No. 1505, TRB, National Research Council, Washington, D.C. (1995) 75-84.