國立台灣科技大學
營 建 工 程 系
博士學位論文

校舍耐震資料庫之資料探勘

Data Mining on Aseismic School Building Database

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中文摘要

　　台灣國家實驗研究院地震工程研究中心（NCREE）在九二一大地震後，與教育部合作評估全台灣的各級學校校舍之耐震能力，在此計畫執行的過程中產生了大量的評估與調查資料，因此 NCREE 便建立了一個校舍耐震能力資料庫來收集各種相關的資料，收集了包括校舍的各種設計參數、材料強度、校舍現況及年齡、技師的評估與補強建議方案、實際補強的金額與補強方法等。收集的校舍資料數量龐大，除了當初設計的目的之外，應該還潛藏難以由人直接判斷取得的知識（knowledge）、模式（pattern）。資料探勘（Data Mining）就是用來分析這種數量龐大的資料，從中找出潛藏的知識的相關技術的統稱，本研究之目的即為利用資料探勘技術來發掘潛藏於此校舍耐震資料庫中的知識，本研究從資料探勘的四種主要分析方法：回歸、分類、分群、關聯出發，分別探討各種方法在此資料庫中有何可能的分析方向，有哪些可能的潛藏知識，並進行分析，最後得到了三個有用的預測模型，分別為校舍耐震能力預測模型、校舍破壞模式預測模型以及校舍補強經費預估模型。

ABSTRACT

　　台灣國家實驗研究院地震工程研究中心（NCREE）在九二一大地震後，與教育部合作評估全台灣的各級學校校舍之耐震能力，在此計畫執行的過程中產生了大量的評估與調查資料，因此 NCREE 便建立了一個校舍耐震能力資料庫來收集各種相關的資料，收集了包括校舍的各種設計參數、材料強度、校舍現況及年齡、技師的評估與補強建議方案、實際補強的金額與補強方法等。收集的校舍資料數量龐大，除了當初設計的目的之外，應該還潛藏難以由人直接判斷取得的知識（knowledge）、模式（pattern）。資料探勘（Data Mining）就是用來分析這種數量龐大的資料，從中找出潛藏的知識的相關技術的統稱，本研究之目的即為利用資料探勘技術來發掘潛藏於此校舍耐震資料庫中的知識，本研究從資料探勘的四種主要分析方法：回歸、分類、分群、關聯出發，分別探討各種方法在此資料庫中有何可能的分析方向，有哪些可能的潛藏知識，並進行分析，最後得到了三個有用的預測模型，分別為校舍耐震能力預測模型、校舍破壞模式預測模型以及校舍補強經費預估模型。

　　In general, the aseismic ability of buildings is analyzed using nonlinear models. To obtain buildings' aseismic abilities, numerical models are constructed based on the structural configuration and material properties of buildings, and their stress responses and behaviors are simulated. This method is complex, time-consuming, and should only be conducted by professionals. In the past, soft computing techniques have been applied in the construction field to predict the particular stress responses and behaviors; however, only a few studies have been made to predict specific properties of entire buildings. In this study, a Weighted Genetic Programming system is developed to construct the relation models between the aseismic capacity of school buildings, and their basic design parameters. This is based on information from the database of school buildings, as well as information regarding the aseismic capacity of school buildings analyzed using complete nonlinear methods. This system can be further applied to predict the aseismic capacity of the school buildings.

誌　　　　謝

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第 1 章　　緒論

1.1　　動機與目的

中小學校舍是使用人數密度極高的建築，且在國家防災的規劃上，許多的學校都是災害發生時，用來收容與暫時安置災民的重要場所，因此其建築物之可靠度相當重要，應比一般建築物有更高的要求，然而一九九九年九月二十一日發生的南投集集大地震，造成台灣將近半數校舍受損，讓學校校舍耐震能力不足的隱憂浮現，根據統計，中小學遭到損壞者共計 656 所，約佔全國學校總數的五分之一，其中南投地區更是有多數的校舍半毀或全毀，所幸地震發生時間為半夜，校舍並未在使用時間，並沒有因為校舍的受損而造成學生的傷亡。

現在中小學學校校舍的耐震性不足其問題最主要在於有很大比例的校舍屋齡已經很大，建造時使用的是建造當時的建築規範，其對於耐震能力的要求以現今的建築法規來看已經顯得不足，二來老舊校舍也會因為長期的使用以及經過數次天災、地震的影響，而使的其可靠度下降，因此教育部國教司在九二一大地震後，便開始了校舍耐震能力補強計畫，並與國家實驗研究院國家地震工程研究中心 (NCREE) 合作執行，目的在找出所有耐震能力有疑慮的學校校舍，請專業人士來評估現有校舍建築的耐震能力，根據評估結果來判斷是否有安全疑慮需要補強，抑或是需要拆除重建。

現有結構非線性分析模擬技術之發展已經能掌握結構系統於地震力作用下之整體反應與其細部構件之行為，使的非線性分析成為評估結構耐震力最詳細可靠的方法，美國 FEMA-273 [1] 之規範已建議使用非線性推垮分析來評估結構物於不同程度地震力作用下之破壞形式與可靠度，然而非線性推垮分析非常的耗時且非常昂貴，因其分析之正確性仰賴完整且詳細的數值模型以及專業人士的操作與結果判讀，模型的建立則同樣也是高度仰賴專業人力的耗時工作，要對全國所有校舍都進行專業的詳細評估實在是有所困難，且耗時長久，在即時地震威脅不會消失的情況下，要對全國所有的學校校舍都進行非線性推垮分析，實在是緩不濟急。

因此校舍耐震能力補強計畫是用三階段的篩選機制來快速的篩選出耐震能力有疑慮的校舍，進行詳細的耐震能力評估並進入後續的處理，這個篩選流程的第

一階段為全國中小學校校舍之普查與建檔，且同時調查校舍的基本資訊，第二階段則是初步評估，是委託各個地方的專業人士，如土木、結構技師、建築師等，到各學校透過 NCREE 所設計之初步評估表格，快速的推算出校舍的耐震能力參考值，藉以判斷該校舍是否有安全疑慮，如有安全疑慮則需要進入下一個階段的評估流程。第三個階段是詳細評估，這個階段使用的評估方法就是非線性推垮分析，由專業人士去現地調查，建立出完整詳細的數值模型，之後使用非線性推垮分析方法來模擬校舍受到地震力之行為，評估校舍的耐震能力，最後才根據評估結果決定校舍是否需要補強，如果需要補強，則進入到之後的補強流程。

在這個計畫執行的過程中，不同階段的評估都會產生大量的校舍相關資料，例如初步評估會有校舍的基本結構參數：長度、深度、樓層數、梁柱之尺寸及數量、樓地板面積以及校舍現狀等等資料，詳細評估則會有更詳細的如材料強度、優先破壞的構件、破壞地表加速度等等，後續的補強流程還會產生如補強工法、不同工法的補強量、補強經費等等資料，數量龐大，因此國家地震工程研究院便建置了一個校舍耐震資料庫，收集此計畫執行間產生的各種校舍資料，目前資料庫收集有全台灣兩萬多棟校舍的設計、評估與工程相關資料，其主要用途雖為輔助校舍耐震能力補強計畫，然而此一大量的資料，應當還可以從中挖掘出難以由人工觀察判讀的隱含知識。

資料探勘 (Data mining) 此一研究領域的發展是為了因應資料庫系統以及資料倉儲系統的發展、資料量的急遽成長以及越來越複雜的資料性質，因而越來越難從收集的資料中獲取有用的知識的情形。資料探勘的方法包括統計、線上分析處理 (OLAP、on-line analytical processing)、情報檢索 (information retrieval)、機器學習 (machine learning)、模式識別 (pattern recognition) 等，由前段敘述可以得知，校舍耐震資料庫內的資料量非常多，不只校舍數量旁大，收集的資料屬性也非常多，其中隱含的知識難以直接由人眼觀察取得，如果可以使用資料探勘技術，從其各種分析方法的特性出發，配合各種實務上的需求，應當可以從此資料庫中找出部分隱含的校舍建物知識，不過資料探勘分析需要每筆資料都能夠用相同的形式，並且用固定數量且有限的資料屬性來描述資料實體的特性。由於不同建築物的結構差異可能很大，沒有一個標準的形式可以只使用有限的資料屬性就描述所有的建築物，因此以往的研究均難以對大量的建築物資料進行資料探勘分析，不過校舍建築中，有很大的比例有相似的結構形式，這些校舍都為一字形，隔間為一間

一間連著，外面有走廊，樓梯間、廁所通常在末端，樓層數不超過五層樓，有些校舍雖然非一字形，較為複雜可能是 L 字形或是ㄇ字形，但是也可拆分為數個一字形形式的校舍，而由於有這些常見的形式，可以把校舍建築的資料屬性特徵化，用少量的資料屬性就可以正確的描述這種常見形式的校舍建築，資料屬性數量不會隨著建築物規模的擴大而增加，這樣的資料形式讓大量校舍建築物的資料探勘分析成為可能，而 NCREE 所建立的校舍耐震資料庫中收集的校舍資料即為使用這種形式來描述校舍設計參數之資料，因此本研究之研究目的即為基於校舍的建築形式以及已經收集大量校舍資料的校舍耐震資料庫，利用各種資料探勘方法來分析並尋找此意資料庫中，難以人工觀察判讀的隱含知識。

1.2 研究方法

本研究之研究方法可以分為三個階段，第一個階段為分析規劃階段，此一階段的主要目標為假設各種可能的隱含知識，並且定義出不同隱含知識的探勘方式，Fayyad [2] 依照不同資料探勘技術之特性，分出迴歸、分類、分群、關聯四大類，本研究的第一階段即根據此四種知識形式，以及校舍耐震補強計畫的執行流程與需求，假設並定出各種可能透過資料探勘技術取得的校舍耐震資料庫隱含的知識以及探勘方法，其中，迴歸形式的可能取得知識包括了校舍耐震能力預測、校舍破壞模式預測、校捨補強經費預測等，分類形式的可能知識包括了校舍是否需要補強的預測，分群形式的知識則是校舍的類型歸類條件，關聯式法則形式的可能知識則是校舍設計參數與其現狀的關連性。

第二階段則是根據假設的各種隱含知識和資料探勘規劃，實際進行資料探勘的分析和測試，最後的第三階段則是探勘結果的驗證和隱含知識的整理，基於此一流程，本研究最後得到了三個有一定可靠度的校舍耐震資料庫的隱含知識，分別為：

• 校舍資訊與校舍設計關係模型

• 校舍資訊與破壞構件之關係模型

• 校舍資訊與補強經費之關係模型

校舍耐震能力預測模型為本研究最主要的資料探勘目標，因為校舍耐震能力補強計畫當中，最重要的資訊就是校舍的耐震能力，傳統上，如果要取得可靠的校舍耐震能力，需要由專業的技師來評估，其過程需要先到現場調查，根據調查的資續建立完整的結構數值模型，並使用非線性推垮分析，其過程耗時且所費不貲，因此現在校舍耐震能力補強計畫是以分階段篩選的機制，先讓所有校舍進行一個較為簡單的初步評估，再根據初步評估的結果來決定哪些校舍的耐震能力可能比較不足夠，需要詳細的非線性分析，才真的對這些校舍進行詳細的非線性分析與耐震能力評估，然而這種方法有個缺點是其初步的評估方法無法完全反映出校舍的耐震能力，可能有校舍已經因為年代久遠造成耐震能力低落，然而卻無法在初步評估的結果中真實的反映出來，因此，如果有一個方法可以快速的得到更為可靠的評估數據，甚至可以當作詳細評估的參考，將可以大大的加速校舍耐震能力補強計畫的進行。

　　除了數值化的校舍耐震能力，本研究還建立一個模型，可以對校舍受到地震力時，優先破壞的構件進行預測，這個資訊可以幫助對校舍進行耐震能力評估的專業技師對目標的校舍弱點先有一些初步了解，不但可以協助詳細評估的進行，對於校舍補強設計的方式也有一定程度的幫助。

　　最後，由於校舍補強所需的經費龐大，因此校舍耐震能力補強計畫不可能在短期內就把所有耐震能力不足的校舍都完成補強，實務上會需要估算各個校舍補強所需的經費，排定預算，然後才知道不同預算年度能夠完成多少的校舍補強作業，因此校舍的補強經費在校舍補強計畫的決策中，是一個非常重要的數字，傳統的經費預估方法是由過往的經驗、數據和所欲補強校舍的規模作為依據，經由一些推估和統計所計算出來的，如果能夠建立一個預測模型，經由校舍的基本資料就可以得到準確的補強經費預測值，那便可以大大的加速校舍耐震能力補強計畫決策者的決策速度，也可以讓計畫執行人員能更快的了解補強作業的規模。

1.3　論文架構

　　本論文共分為八章，各章內容分別介紹如下：

1. 緒論：說明本研究之動機及目的。

2. 相關研究：回顧與本研究相關之文獻。

3. 校舍耐震資料庫：介紹校舍耐震資料庫之架構與其所收集資之資料。

4. 資料探勘：介紹資料探勘技術以及校舍耐震資料庫之資料探勘規劃，另外還介紹本研究使用到的各種演算法。

5. 耐震能力與校舍設計關係模型：詳述本研究第一個使用資料探勘方法找到的隱含知識，耐震能力與校舍設計參數間的關係模型。

6. 校舍設計、現況與破壞構件之關係模型：詳述使用資料探勘技術找出校舍現況、設計參屬等屬性與其遇到地震力時，可能先受力破壞構件之關係模型之方法與過程

7. 校舍設計、現況與補強經費之關係模型：詳述使用資料探勘技術找出校舍現況、設計參數等屬性與其可能需要之補強經費間關係模型之方法與過程

8. 結論：結果探討與未來展望。

第 2 章　相關研究

作業系統指紋辨識的方法，可分為主動式作業系統指紋辨識（Active OS Fingerprinting ）與被動式作業系統指紋辨識（Passive OS Fingerprinting ）。主動式作業系統指紋辨識，主動對目標主機送出自製的探測封包，並根據回傳的反應做判斷依據，軟體工具 Nmap 與 Xprobe2 即屬於此類。Nmap 主要控制 TCP 的參數值，做為探測用封包；Xprobe2 則是著重於送出 ICMP 封包，利用邏輯樹斷定作業系統的類型。被動式作業系統指紋辨識是監聽網路上目標主機的封包往來做為判斷的依據，P0f 即屬於被動式，相對於主動式作業系統指紋辨識較不易被人察覺。不論是主動式或被動式的作業系統指紋辨識，皆利用 TCP/IP 堆疊進行辨識，包括封包存活時間（time to live，TTL）、Window Size、最大分割大小（Maximum Segment Size）、不分段標記（Don't Fragment flag）、Window Scale Option 等，因為不同的作業系統的 fingerprint 有所不同，所以可做為判定作業系統的依據。如圖 2.1所示。
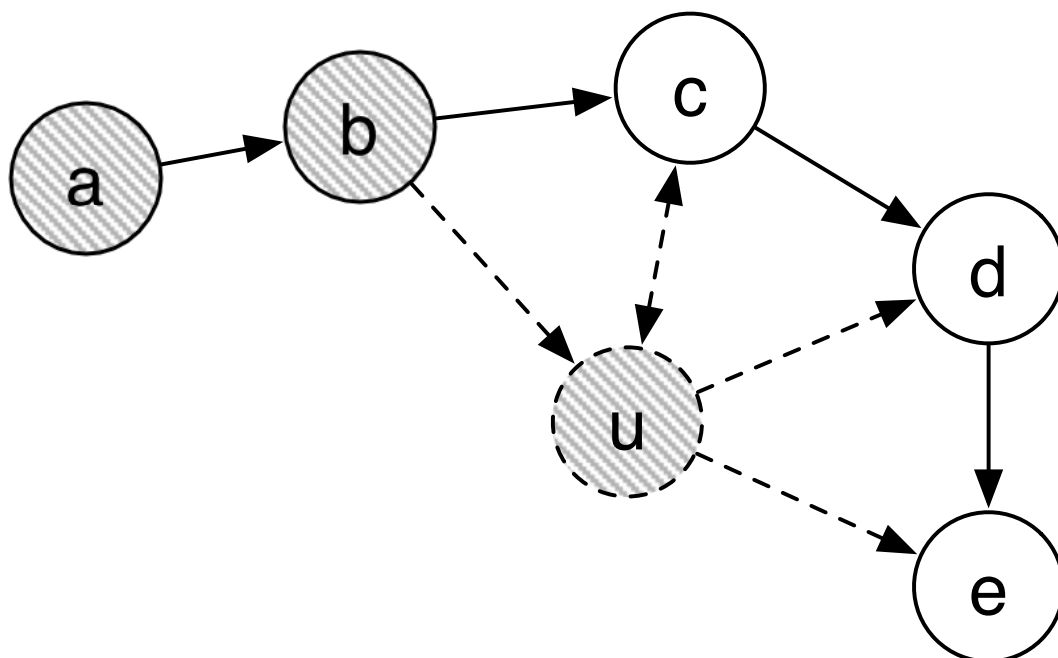
圖 2.1: The diagram of "prototypical PHI query"

網路發展興盛至今，小至個人，大至政府單位與各機關組織，都相當仰賴網路的使用，但許多人仍然對資安危機意識較低，針對資訊安全產品的投資也相對較少，加上對於資訊安全軟體工具缺乏有系統的整理，以致於未能有效運用。為此，本手冊蒐集整理相關開放源碼（Open Source）的資訊安全軟體工具，並透過專業人員實際操作演練，加以彙整並集結成冊，希冀透過本手冊的幫助，不僅能給予初學者對於資安工具軟體初步認識，也讓資訊從業人員在資訊安全工具上能有更多的選擇與應用。

　　資安開放源碼軟體的發展，往往會公開其發展技術及運用的原理，配合程式碼的開放，使得開放源碼軟體具有相當大的彈性，並根據個人使用情況所需，進行軟體的編修與整合，以求適應各種作業環境所需。使用開放源碼軟體所需負擔的金錢成本，遠低於商業付費軟體，可降低企業組織對資訊科技產品的部分支出，不需要過度仰賴軟體製造商的技術支援與更新，也能減少相對應的軟體開發時程。由於目前多數的資安開放源碼軟體的開發多為國外組織，因此較缺乏中文化介面，且部分軟體工具的使用，需要具備相當程度的專業知識，並非人人皆可輕易上手。本手冊擬透過中文化的工具介紹，減緩國內使用者入門的負擔。

　　由於現今網路環境日益複雜，遭受網路攻擊的事件層出不窮，網路安全越來越受到各界重視。網路掃描是網路安全的根本，也是攻擊者對目標主機進行攻擊的首要步驟，因此，了解網路掃描的攻擊與防禦，將有助於網路管理者提升網域的安全管理。此外，網路流量代表所有網路訊息的傳送，能提供管理者即時了解網路狀況，藉此檢視網路情況正常與否。本手冊將針對以上兩類的開放源碼軟體，逐一介紹其功能、安裝、操作與軟體評比，令讀者對相關的資訊軟體能有所了解，並進一步應用於資訊安全的監測與控管。以下即對網路掃描及流量監控兩大類軟體，進行整理與原理說明。

　　如表 2-1所示。

表 2-1: The relation of aggregation overhead between different techniques

	Space usage of root aggregator	Communication overhead	Query requirement
Traditional warehouse	n	$O(n)$	$O(n)$
AM-FM sketch technique	$\log a$	$O(\log n)$	$O(a \log n)$
"prototypical PHI query"	$\log a$	$O(\log n)$	$O(\log n)$

第 3 章　校舍耐震資料庫

　　學校是人才培育的場所，也是緊急災難時，居民避難的主要地方，但台灣地區學校建築在每次大地震來時之損壞卻非常嚴重，尤其是老舊校舍，因興建年代久遠，其設計所依據之規範較為老舊，耐震能力可能遠低於現今結構耐震安全上之要求，故教育部已委託國家地震工程研究中心進行全國學校校舍之耐震能力評估與補強研究，此計畫建立了校舍建築耐震能力評估補強機制及施行的流程與細節，並且已經對全國學校校舍耐震能力作了全面性的普查，篩選出耐震能力有疑慮之校舍，並儘速透過補強或拆除新建的手段來提昇校舍的耐震能力。而此計畫進行期間所產生之資料，均收集到此一校舍耐震資料庫中。

3.1　典型校舍

　　我國之校舍建築有極大比例在校舍的結構形式、幾何尺寸等都有相似的結構，其平面配置多如圖3.1，這類校舍為一字型的長形建築，教室一間一間排列，教室外有走廊，走廊多有柱，且樓層數多不超過五樓，此一類型之校舍統稱為典型校舍，典型校舍在受地震力時，通常破壞樓層都在一樓，而且是沿著長向破壞。而因為其結構形式單純，只需要少量的屬性便可以完整的描述建築物的結構，不用完整詳細的記錄所有的樑柱等構件之個別尺寸強度與位置。
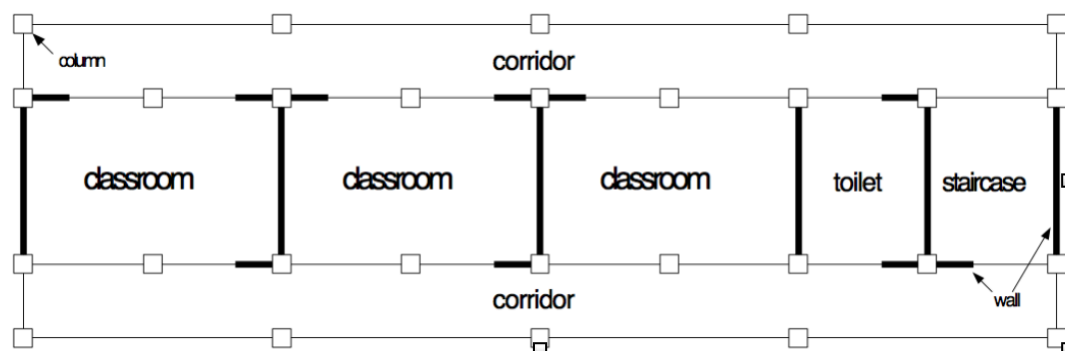

圖 3.1: 典型校舍

3.2　收集範圍

　　此一校舍耐震資料庫中收集有台灣各級學校，不同詳細程度的耐震能力相關的調查資料，此一資料庫乃是由國家地震工程研究中心（NCREE）在執行教育部委託之「全國各級學校舍耐震能力補強計畫」時所建。而除了耐震能力相關的結構評估資料，本資料庫還收集了評估階段之後的，包括補強設計、補強工程發包與結案的相關資料。

　　結構耐震能力評估的方法可分為兩類，第一類為初步評估 (preliminary evaluation)，其通常的方法是基於結構物之設計及現況填寫評估表，所填寫資料再依評估公式計算出結構物耐震能力之評分等級或指數，此類方法之評估速度快，但是結果可靠度較低，主要的目的是對大量結構物之耐震能力作排序與篩選，這類型評估方法所使用之評估表與評估公式通常是使用已經收集的其他結構物資訊，用數值統計的方法迴歸，或是根據基本的結構耐震能力供需比以及專業人士相關的經驗設計得到的，其所適用之結構物類型也有所限制，評估表並不能套用到各種類型的結構物上；另一類評估方法為詳細評估 (detailed evaluation)，此類方法為對結構物進行詳細的結構耐震分析，通常是使用結構分析程式以電腦數值模擬結構物遇到地震時的非現性行為，並根據模擬結果為依據，準確詳細的檢驗評估出結構物的耐震能力，這類方法的可靠度較高，但是花費相當昂貴，所需要的時間也比使用評估表要來的久很多。此二類耐震評估的方式通常相輔相成，結合成為標準的結構耐震能力評估程序，其即是先對所有需評估之結構物先以初步評估作耐震能力之評分與排序，以篩選出其中耐震能力有疑慮者，再對其以詳細評估的方式做詳細的檢驗。

　　由於中小學校舍數量龐大，若直接大量投入人力物力，可能造成大量之資源浪費，也無法快速的鎖定耐震能力不足之校舍建築，故針對有效達成此一校舍耐震評估標準需求以及基於上述標準耐震評估程序之精神，國家地震工程研究中心提出之解決程序為；經由學校總務人員之簡易調查及工程專業人員之初步評估，有效的將校舍結構之耐震能力排序，以縮小問題之規模，對於耐震堪慮之校舍，依嚴重程度，由工程專業人員，進行結構耐震之詳細評估，倘尚符合補強之經濟效益，即進一步作耐震補強之設計，若不符合補強之經濟效益，則將之列為拆除重建。在此過程中會產生的校舍資料最重要的為：初步評估、詳細評估、補強設

計、補強工程等四組資料。

3.2.1　初步評估

ask 趙哥 for text

　　初步評估相較於詳細評估的模擬運算而言，是簡化許多的耐震能力評估方式，評估的方式是使用地震中心根據過往資料與相關規範所設計而得，其設計的基礎與詳細評估的 CDR 值相同，皆為校舍的耐震能力與耐震需求的比值，主要的對象為典型校舍，假設校舍之破壞位置為長向的一樓，耐震需求為則為建築物需要能承受其所在地所可能發生的的 475 年週期最大地震之地震力，由推估的校舍載重以及地震之地表加速度推估而得。而耐震能力則是根據校舍之柱、牆等尺寸，並根據實驗數據推估所得到的等效強度，兩者相除後再乘上調查人員根據校舍現況所填入之調整參數 Q，所得到的 Is 即為使用初步評估表格所評估之校舍耐震能力。

3.2.2　詳細評估

　　美國針對鋼筋混凝土 (RC) 建築物之耐震能力規範 ATC-40 [3] 中，建議用來評估建築物耐震能力之方法稱為容量震譜法 (capacity spectrum method)，此一評估方法可以分為兩個部分，第一部分是進行側推分析 (pushover analysis) 取得容量震譜 (capacity spectrum)，流程如 Figure 1 所示，第二部分是根據建築物所在地的各種相關資訊和規範取得需求震譜 (demand spectrum)，接著使用容量震譜法 (capacity spectrum method) 以取得建築物性能點，根據性能點 (performance point) 座標帶入公式計算可以得到建築物的破壞地表加速度 (collapse ground acceleration) 以及耐震能力指標 (aseismic ability index)，如 Figure 2 所示。

　　求取容量震譜的側推分析 (pushover analysis) 需要先建立建築物完整的非線性分析模型 (nonlinear structure model)，此模型要由進行評估的專業人士根據建築物的幾何尺寸資訊來建立基本的建築物框架。接著根據建築物的材質計算建築物自身重量以及需要承載的人員和配設物件之重量，並將其附加到柱、牆等承載元件上。接著最重要的是設定建築物各構成元件如樑、柱、牆受力時的非線性行為，

這些力與變形的關係多為實驗得到或是利用其他分析模擬方法得到的。至此，側推分析 (pushover analysis) 要用的數值模型才算建立完成。而側推分析 (pushover analysis) 其程序是依照規範，使用建議之側力，逐步地給結構模型施加增量外力，將結構物向某一方向推動，每次增量即進行一次結構分析計算每一構件之應力 (stress) 與變位 (strain)，之後與上一次的分析結果累加即可得到每一個構件於此受力階段之反應，並判斷構件是否破壞，例如開裂 (crack)、降伏 (yield)，甚至達到極限強度 (ultimate force) 等，之後各構件依其破壞程度更新其行為，例如改變其勁度，或者將已發生破壞的構件從結構模型中抽離，如此重複分析直到結構不穩定而崩垮為止，側推分析完成後可以得到建築物之容量震譜 (capacity spectrum)。

需求震譜 (demand spectrum) 是根據建築物環境現況，參考規範製成之地震需求頻譜。參考的環境狀況如土層種類，堅硬的土層可以讓建築物有較好的抗震能力。另外靠近斷層的建築物在地震發生時往往會因為斷層於地震時產生的反應而受到嚴重的損害，因此建築物與斷層的距離也納入參考的資料之一，稱為近斷層效應 (special effects of near-source earthquakes)，其他還需要的資料有地層資料、地震震區等，綜合這些資料並參考規範即可得到該建築物所需符合之需求震譜。

容量震譜法 (capacity spectrum method) 最後是將需求震譜 (demand spectrum) 以及容量震譜 (capacity spectrum) 轉換格式後相疊，求取建築物之性能點 (performance point)，性能點之物理意義為該建築物在特定水準地震下所能承受之最大變位 (strain) 及剪力 (shear force)，但是由於結構物受地震力作用進入非線性行為時，結構物的阻尼效應會產生消能的作用，因此還要視情況對需求曲線進行折減，此為一個迭帶運算的過程，可能需要不斷折減需求曲線，並進行性能點 (performance point) 正確性的檢核，直到檢核通過，才能得到建築物真正之性能點 (performance point) 如 Figure 2 (d)，由建築物性能點 (performance point) 之座標帶入公式可以求得建築物的破壞地表加速度 (collapse ground acceleration)AC，詳細評估所使用的耐震能力值為 CDR，其定義如下：

$$CDR = \frac{AC}{AD} \tag{3-1}$$

AD 為根據建築物所在地的並依據規範所得到的，建築物所需要能承受的 475 年週期最大地震所產生之地表加速度，CDR 大於 1 代表此一棟建築物能夠承受該

地區 475 年一遇的最大地震。

3.2.3　補強設計

如果校舍經過詳細評估過後，負責的專業人士認為此棟校舍確實有安全疑慮，但尚可以補強，不需要拆除重建時，則該棟校舍需要進入補強設計，補強設計階段中，負責的專業人士需要依據詳細評估的結果，設計出兩種不同的補強方案，並且對不同的補強方案進行詳細的耐震能力評估，因此這個階段的資料包括兩組補強設計的資料，以及兩組補強後的耐震能力詳細評估資料。補強設計收集的資料主要為使用的補強工法以及補強量，主要收集的補強工法包括了：擴柱、剪力牆等，

3.2.4　補強工程

補強工程部分的資料則包括了實際補強工程的相關資料，其中包括了採用的補強設計，工程發包的相關資料，例如工程經費、發包時間、驗收報告等等。

第 4 章 資料探勘

資料探勘技術方法繁多，Fayyad [2] 根據其處理的問題形式，將資料探勘的方法分為分類、分群、迴歸尋找關聯等四種主要的問題類型，分類方法處理的問題是在用來判斷資料的類別，而且這些類別是已知的類別，例如將所有的校舍資料分類成有安全疑慮和沒有安全疑慮的就是屬於分類問題。分群問題和分類問題有點相似，一樣是將資料分成數個群組，最主要的差異是分群問題的各個群組特性一開始並不清楚，分群方法是將資料根據其屬性數值為依據，把相似的放在同一個群組，不同群組的特性是要在分出群組後進行分析才會得到。迴歸問題就是要用迴歸方法來從資料的屬性中，找出特定屬性與其他屬性間的關係模型，這些屬性間的關係可能是非線性的，而且沒有解析解的關係模型，因此常見的方法是用統計迴歸的方式，用現有的資料來迴歸得到，又或著是用像類神經網路之類的機器學習方式，拿現有的資料下去學習已得到關係模型，以校舍耐震資料庫來說，校舍耐震能力指標的預測就是一種迴歸問題，因為校舍耐震能力指標與其校舍的設計參數間的關係就是一個非線性關係，要得到兩者之間的非線性模型就需要用到迴歸問題的處理方法，迴歸問題也是最常見的資料探勘問題種類。最後一種是尋找屬性間的關聯，這種問題的主要目標在尋找不同筆資料屬性間所存在的關係，舉例來說，使用校舍耐震資料庫的資料來作關聯分析，可能可以去尋找像是：五層樓的校舍的校舍長度深度有什麼趨勢，或是民國八十到九十年之間的校舍的校舍走廊設計是否偏好有走廊柱等。

本研究後期確定主要的探勘目標後，使用的資料探勘方式為迴歸為主，分類分群為輔助，以下分別介紹各種使用的的分析方法：

4.1 Generalized Linear Model

廣義線性模型是由 Nelder and Wedderburn [4] 所提出，比起迴歸分析 (simple regression) 更為彈性，此模型是假設資料點的分佈有一分佈模式，且 X 與 Y 之間的關係是由一連結函數 (Link Function) 建立，如 log function、power function 等，

其定義之 XY 關係模型如下：

$$g(E(y)) = x\beta + O, y\ F \qquad (4\text{-}1)$$

$g(.)$ 是為所選的鏈結函數，O 是偏移 (offset) 變數，F 則是 y 的分佈模型，其是用牛頓法 (Newton-Raphson Method) 不斷的調整 β 使的 $x\beta + O$ 逼近 $g(E(y))$，最後最接近的方程式即為 XY 兩者的關系式。比起迴歸分析，此方法還需要了解 Y 值分佈狀況，選擇出最適合的分佈函數，並假設 XY 間的鏈結函數形式，雖然越多的參數選擇代表了更多的模型不確定性，但廣義線性模型卻能夠提供比迴歸分析更廣的應用範圍，也可能得到更接近真實的關係模型。

4.2   Support Vector Machine

SVM 最早是 BOSER [5] 等人，在 1992 年的 COLT (Computational Learning Theory) 所提出，SVM 是一個基於統計學習理論的分類方法，用來處理二元分割的問題，其原理是將原本無法線性分割的問題轉換到一個不同維度的空間 (kernel) 後，假設該空間存在一超平面 (hyperplane)，可以正確的將資料分開，並將尋找此一超平面的問題轉換為一最佳化問題，求解後即可得到二元分割邊界的方程式。而後 Harris Drucker, et. al.,[9] 將此二元分割問題轉換為迴歸分析問題，故 SVM 也可以處理迴歸問題。

4.3   Artificial Neural Networks

其是希望能模擬建構出人腦內的神經網路，以處理各種複雜的問題，人類大腦是由大約千兆個神經元 (Neuron) 所構成，而每個神經元又會和其他約一萬個神經元連結，構成一個龐大且複雜的神經網路，這樣複雜的一個神經網路讓人類可以學習並了解各種事物與知識。McCulloch and Pitts [6] 所提出的模型為後續類神經網路發展的雛形，一個標準的類神經網路可以分為輸入層 (input layer)、隱藏層 (hidden layer)、輸出層 (output layer)，輸入層 (input layer) 負責接受各種求解問題需要的量化數據和資料，經由隱藏層 (hidden layer) 的不斷自我更新學習的模型處

理過後，在輸出層 (output layer) 就可以得到想要的解答，類神經網路可以處理的問題種類多樣，其模型的品質多數也都不錯，缺點是學習時間長，且得到的模型為一個黑盒子，難以解釋其物理或是數學模型上的意義。

4.4 Genetic Programming

4.5 Weighted Genetic Programming

4.6 K-means

As proposed by MacQueen [7], K-means is one of the most common clustering methods and has a wide application scope. Notably, it is a machine learning method; its principal steps are as follows.

1. A user indicates that data should be grouped into K clusters.

2. Data are divided randomly and equally into K groups and the center of each cluster are calculated.

3. Each bit of data should find the proximal center of a cluster and update its cluster label that it belongs to.

4. Recalculate the new cluster center.

5. Repeat steps 3 to 4 until the cluster centers of all data do not change.

4.7 Two-Step Classification

Based on of the massive volume of basic data for school build- ings in the database, this study chooses two-step clustering method. The basic concept was first proposed by Zhang, Ramakrishnan and Livny [8] for handling large amounts of data. This method

has two major steps. The first step sequences data and pre-clusters sequences into small subclusters based on the similarity of adjacent data, thereby reducing the amount of data. The second step divides several small subclusters into the desired number of clusters using a hierarchical clustering method. The hierarchical clustering method then combines close subclusters slowly until the stop condition is met. The computing speed of this method is influenced slightly by the volume of data.

第 5 章　　校舍資訊與耐震能力之關係模型

在校舍耐震資料庫中，不同階段的調查資料有不同的校舍耐震能力指標，這些指標都是以數值形式來量化校舍建築物的耐震能力，有了此一數值後，可以快速找出有安全疑慮的校舍，根據耐震能力排序，甚至推算會需要多少預算來補強多少棟校舍等等，都可以使用此數值作為依據來達成，可以說是非常重要的校舍特性，然而要取得此一數值非常耗時耗力，如果有其他快速便宜的方法可以取得此一數值，那便可以大幅度的減少校舍耐震能力補強作業的所需要的時間與經費，因此本研究的第一個資料探勘目標，便是找出預測耐震能力索引的預測模型，得到此一預測模型後，便可以根據校舍的設計參數與現況作為輸入參數，快速的得到該校舍的耐震能力索引參考值。

初步評估階段資料的耐震能力指標是 Is 值，此一數值為專業人士於現場良策、調查後，使用國家地震中心的專家根據過往的實驗數據統計分析後，所設計出的一個評估表計算而得到的，為一初步的評估值，較詳細評估所計算的耐震能力指標可靠度來的低，但仍是校舍補強計畫初期的篩選工作中非常重要的數值。詳細評估和補強設計階段的耐震能力指標則是 CDR 值，CDR 值是由專業人士根據校舍的設計與實際狀況建製結構模型，並進行非線性的推垮分析所得到的，此數值與建築物之設計參數為高度非線性的關係，也是最接近校舍建築物實際耐震能力的量化指標。

而除了數值量化的耐震能力指標外，本研究還將「校舍是否需要補強」（D_isR）這個二元指標作為耐震能力來作為校舍耐震資料庫中的第三個耐震能力指標，Is、CDR、D_isR 這三個耐震能力指標的預測模型，即為本研究所取得的第一個校舍耐震資料庫隱含知識，以下便針對不同指標的預測模型的資料探勘流程與結果詳細介紹。

5.1　Is 值與校舍設計之關係模型

校舍耐震資料庫中的初步評估資料表的耐震能力索引是為 Is 值，初步評估是校舍耐震能力補強作業中，很重要的篩選過程，因為建築物的詳細評估所需要的

金額極高，評估需要的時間也很長久，因此需要一個速度、價錢和可靠度都可以接受的評估方法，用比較短的時間找出耐震能力有疑慮的校舍，盡早處理。而地震中心所設計的初步評估表即為一個速度、價錢和可靠度都可以接受的評估方法，只要根據建築物的設計參數，像是樓層數、長度、深度、柱子尺寸以及校舍現況等，就可以快速的得到一個極具參考價值的耐震能力指標，而其計算的原理也與詳細評估的耐震能力指標索引 CDR 值一樣，為耐震容量與耐震需求的比。找出 Is 值與校舍設計參數之間的關係模型，可以進一步分析初步評估表中各種數據的重要性，並將結果回饋到此一初步評估表，將初步評估表調整的更為精簡，負責評估的人員也可以更快速的完成此意評估表格。

The proposed prediction model, based on data-mining technology, has six steps – business understanding, data understanding, data preparation, modeling, evaluation, and deployment – as recommended in the cross industry standard process for data mining (CRISP-DM) proposed by Chapman et al. (2000) (Fig. 9). The objective of this work is to construct a prediction model for the aseismic ability indices of school buildings and collect complete data. Hence, the major tasks are data preparation, modeling, and evaluation. Fig. 10 shows the procedural plan based on needs and the methods chosen.

5.1.1　資料前處理

首先，從國震中心的校舍耐震資料庫中，將各棟校舍的 Is 值與其校舍的相關資料挑出並整合在一起，第一步是過濾掉明顯不合理的錯誤資料，這些資料通常是人為的錯誤造成的，而過濾的方法則是使用國陣中心建議的過濾條件：

- 校舍總長或總深度超過兩百公尺

- 有任意牆厚度超過五十公分

- 有任意柱的長或寬超過一百公分

- 柱間垮距超過八公尺或小於兩公尺

大約有八百筆資料符合這組基本的過濾條件，而在初步的過濾之後，前處理的第二個步驟則是減少資料屬性的維度，主成分分析（Principal component

analysis）是很常使用的資料前處理方法，這個分析方法可以找出所有資料屬性中，重要度較高的屬性，它是把原始的多個資料屬性，透過向量轉換的方式，線性組合出主要的資料屬性。

Roughly 800 bits of valid data are obtained. After filtering using these conditions. Principal component analysis (PCA) is then used to reduce the dimensionality of data attributes. Notably, PCA, a very common data preparation method, can identify very important attributes among various attributes. The goal is to convert the original variables through vector transition into mutually independent variables of a linear combination. The ideal situation is that principal components obtained from linear combination retain most of the information of original variables.

校舍的分群則是基於校舍的設計模式，目標是要找出校舍建築物的幾種特定設計模式，也就是要分析校舍的幾何設計參數、柱量、牆量等等，經過不斷的測試及調整，最後找出了五個主要成分屬性：

- 走廊柱資訊

- 教室柱資訊

- 強設計資訊

- 牆量資訊

- 柱量資訊

Clustering analysis of school buildings is based on the design patterns of school buildings; the goal is to find several design patterns. Hence, the attributes for analysis are the geometric information of school buildings, such as dimensions and quantity of walls and columns, and width and height of school buildings. Other attributes, such as year of construction and locale, may not be incorporated into PCA analysis. After continuous testing and adjustment, five major attributes are obtained and the importance of constitutional fields is considered as the basis for naming. The five attributes are as follows: corridor column information; classroom column design information; wall design information; data for number of walls; and, data for number of classroom columns.

在前面的處理完成後，還使用分群分析將校舍分群，以幫助後續的 Is 值關係模型的建立，分群的目標是將校舍依照不同的設計模式特性區分開來，將相近設計的校舍放在同一群集，分群的依據是主成分分析法所找出的五種主要校舍設計相關屬性，圖十一是使用 SPSS Clemitine 進行此一分群分析時的節點設計圖，分別使用的 K-means 和 Two-Step 兩種分群演算法，其參數設定如下：

After data preparation, clustering analysis is utilized to find hidden design patterns of school buildings. This study uses the K-means and two-step clustering methods. Fig. 11 shows the node deployment for clustering using the SPSS Clementine (2007) software. The parameter choices for the two methods are as follows.

K-means

此一分群方法最重要的設定參數是初始的群集數 k，雖然有許多研究都在研究如何找出最佳的 k 值，但是目前仍沒有一個方法可以宣稱它找到 k 值是最佳的，唯有對該領域的專業了解以及詳細的測試才能得到最佳的 k 值，在本分析案例中，K-means 分群的停止條件是設定為 20 次迭代，如果 k 太大，那會造成分群結果無法在 20 次迭代內收斂，如果 k 小於 6，則分群的結果就可以在 20 次迭代內完整的收斂，每筆資料都會故底定在所屬的群集內，不在變動，最後挑選的 k 值是 5，而根據此意參數的分群結果可以找出三個主要的校舍群集，分別的比例是 28%、56% 和 16%。

The most important parameter with this clustering method is the initial group, k. Although many researchers have developed methods for choosing the initial K value, no method can confirm that it has found the best K value. The best K can be found only based on researcher understanding and problem testing. In this study, K-means clustering is set to stop after 20 iterations. If the K value is too large and cannot be completely converged after 20 operations, some data points will continue to change the clusters to which they belong. When the K value is reduced to <6, Clustering models can be completely converged after 20 iterations, become stable, and no longer change cluster label of all data bit. The K value chosen is 5, and three major clusters are obtained. The remaining two clusters have few data and are considered outliers. The distribution of three major clusters are 28%, 56%,

and 16%.

Two-Step

　　Two-Step 分群有兩個優點，一是複雜度不高，運算時間與資料數量間之關係為線性關係，第二個優點就是不需要由人工決定分群的群數，演算法即可自己根據資料狀況決定，操作人員只需給予上下限，在本分析中，上下限的設定為最少兩個群集，最多八個群集，而最後的分析結果是所有的資料都被分到兩個群集中，分別佔了 54% 和 45%。

　　This clustering method has two features. The first is enhanced scalability. The algorithm has low complexity. Computing time does not grow nonlinearly as data volume increases. The other feature is that it can determine the number of clusters, unlike K-means clustering, which requires manual designation of parameters. However, this work can designate the upper and lower limits for the number of clusters. This work sets the limit to 2–8 clusters based on experience with K-means clustering. Consequently, all data are divided into two clusters, accounting for 54% and 45% of all data.

　　此資料探勘分析還用了十群交叉驗證來驗證結果的可靠度，因此資料前處理的最後一個步驟就是將整理好的資料隨機分為十組。

　　This work uses 10-fold cross validation to validate the prediction model. After preparation, data are grouped by first dividing data randomly and equally into 10 clusters. One cluster is then chosen as a dataset for validation and the remaining nine clusters are combined into one training dataset.

5.1.2　資料探勘

　　完成資料前處理，將校舍的群集分好之後，才開始建立 Is 值與校舍設計參數的關係模型，本分析使用了廣義線性模型、線性回歸和類神經網路三種分析方法，每種方法都有三種分析資料群，分別為先經過 K-means 分群的資料、先經過 Two-step 分群的資料及沒有先經過分群的資料。圖 12 為使用 SPSS Clemitine 分析時的節點設計圖。以下分別對三種分析方法的參數設定作說明。

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The prediction model is built only after clustering is completed. This work uses a GLM, simple regression, and ANNs to build the prediction model based on three groups of data – not clustered in advance, clustered by K-means, and clustered by the two-step method in advance. In total, nine prediction models are generated. Fig. 12 shows the node configuration within SPSS Clementine. Below are the parameters chosen for the three methods.

Generalized linear model

廣義線性模型是假設在輸入參數和預測目邊之間有一個可以用連結函數表達的關係，這個連結函數可能是指數函數、對數函數、Logistic 函數等，經由一些測試資料的測試，我們選擇使用對數函數作為連結函數，並且根據實際的資料分布選擇了常態分布作為輸入參數的分布函數，而關係模型的分布也選擇常態分布，因其表現教其他分布形式較好。

The GLM assumes a relationship between input variables and a predictor; this relationship can be built by a link function such as identity function, log function, logit function, or power function. After available link functions testing on some data, the prediction model performs best when using log function as the link function; hence, this work chose the log function. The distribution function of the predictor is based on the actual distribution of data. This work chose the normal distribution, which is close to the real data distribution. The prediction model constructed using the normal distribution performed better than those with other distribution types.

Simple regression

線性回歸是選擇使用最小平方根法來建立校舍建築物的設計參數與其耐震能力 Is 之間的關係，這也是最常使用的回歸方法之一。

Simple regression in this work uses the least square method by adopting the building design parameters as independent variables X and the aseismic ability of buildings as dependant variables Y. The linear equation between regressed design parameters and

aseismic indices serve as the model for predicting aseismic ability Y based on building design parameters X.

Artificial neural networks

　　類神經網路需要決定的參數包括隱藏層的數量、每層的神經元數量、學習率、停止條件等，除了直接設定神經網路的參數，還有一些方法可以使用，例如 dynamic、multiple 或是 prune method 可以用來調整並找出最佳的神經網路大小和結構，dynamic method 是從一個小型的神經網路開始（兩個隱藏層、每層兩個神經元），慢慢成長，並且比較成長前後的神經網路效能與結果，Multiple method 則是同時產生各種不同的神經網路，並且一起訓練到達停止條件，然後在從中挑選出表現最好的一個，而 Prune Method 則是從一個大的類神經網路開始，慢慢的把重要度低的神經元節點拿掉。本分析最後挑選的是 Exhaustive Prune Method，是 Prune Method 的一種修改形式，對於節點的篩選要求較高，是所有方法中最花時間的，但是通常也可以找到最好的結果。其他的類神經網路設定參數為：初始的神經網路為兩層隱藏層，其中一層有 30 個神經元、一層有 20 個神經元，停止條件為 250 個訓練循環，在這個設定下，Exhaustive Prune Method 是表現最好的方法。

　　Generally, ANNs must decide on such parameters as number of hidden layers, number of neurons in each layer, learning rate, and stop condition. Aside from directly setting these parameters, methods such as dynamic, multiple, and Prune methods are available for adjusting and finding the optimal size and structure of the neural network. The dynamic method starts with a small neural network (two hidden layers with two neurons for each layer), expands network size gradually, and decides on the further expansion based on model performance before and after expansion. The multiple methods constructs multiple neural networks simultaneously, trains all neural networks to reach the "stop condition," and then selects the group with the best performance. In contrast with the dynamic method, which slowly builds a large neural network from a small one, the Prune method first builds a large network and then removes neurons with low importance based on training. This work chooses the exhaustive Prune method, a special application of the Prune method. The

initial neural network has two hidden layers, one with 30 neurons and the other with 20 neurons. The stop condition is set to 250 training cycles. Under this limit, the prediction model built by the exhaustive Prune method performs best.

5.1.3　驗證

驗證有兩個主要的目的，一是確保資料探勘找到的關係模型的可靠度，而不會找到只適用於該組訓練資料集的關係模型，第二個目的是可以用來作為比較不同分析方法的指標數據，本分析使用的驗證方式是十群交叉驗證，這個方法將所有的資料等分成十份，每次挑選九組出來作為訓練資料集，留下一組作為驗證資料集，如此可以得到十組模型以及其可靠度的指標，求此十組指標平均值即可得到代表此關係模型的可靠度代表值，而本分析所選擇的指標有三個，線性關係、絕對平均誤差（Mean Absolute Prediction Error, MAPE）以及 hit rate。

Validation work has two purposes. The first is to ensure model reliability instead of to generate only good performance during data training. The second is to serve as a benchmark for comparing the performance of different prediction models. This work uses 10-fold cross validation to assess and compare the performance of prediction models. This method divides a fixed amount of data into 10 groups, conducts 10 rounds of model building and validation, chooses a different group of data for testing, trains the model with remaining nine groups of data, and uses test group data to validate model accuracy. After validation for 10 times, the accuracy of the 10 models is obtained and their average is taken as the accuracy of this algorithm. This study uses linear correlation, mean absolute prediction error (MAPE), and hit rate as the indices for comparing the prediction model performance.

5.1.4　結果

此資料探勘分析會產生九個校舍耐震能力與校舍建築設計資訊間的關係模型，包括直接使用 GLM、線性回歸和類神經網路的三組，混合使用 K-means 或是 Two-Step 分群的六組，要比較其優劣我們使用了線性關係 R、MAPE 和 hit rate 三

個指標，並配合十群交叉驗證，其中線性關係 R 之公式為：

This work constructed nine prediction models; three are directly generated by the GLM, simple regression, and ANNs. The mixed model of K-means and two-step clustering generated three prediction models. Hence, nine models were obtained and 10-fold cross validation is used to compare the performance of the three reference indices – R2, MAPE, and hit rate. Notably, R2, the linear correlation is

$$R = \frac{\sum (\hat{y}_i - \tilde{y})^2}{\sum (y_i - \tilde{y})^2} \tag{5-1}$$

其中 y_i 是校舍的實際耐震能力指標 Is 值，$\hat{y}_i$ 則是透過此關係模型的到的推估耐震能力指標值，$\tilde{y}$ 則是所有資料的 Is 值之平均，透過此一公式即可得到實際的 Is 值與透過關係模型得到的推估值之間的線性關係，線性關係越高表示兩者之間越接近，也代表著關係模型的正確性。MAPE 的公式為：

where yi is the aseismic CDR of school buildings obtained using nonlinear analysis of the database, yi is the CDR obtained from the prediction model, and y is the average aseismic CDR of school 651 buildings obtained using nonlinear analysis. The correlation between aseismic CDR of school buildings obtained via the prediction model and nonlinear analysis can be determined based on linear correlation. A high CDR indicates a strong correlation and many opportunities to make correct predictions. The MAPE is derived as

$$MAPE = \frac{\sum \dfrac{y_i - \hat{y}_i}{y_i}}{N} \tag{5-2}$$

其中 N 是資料總數，MAPE 的是用來表示關係模型誤差之數值，由於關係模型不可能完全沒有誤差，即使有非常高的線性關係也是會有誤差，因此會使用 MAPE 作為判斷其誤差程度的參考。hit rate 的定義是：

where N is the number of samples. The MAPE is used to judge the degree of error of prediction models as the prediction result always has errors, although the prediction mode

has an adequately high R2. The hit rate is derived as hit rate

$$hit\ rate = \frac{\sum I\{(1-\alpha)y_i \leq \hat{y}_i \leq (1+\alpha)y_i\}}{N} \tag{5-3}$$

其中 $0 \leq \alpha \leq 1$，且 $I\{L\} = 1$。hit rate 是用來判斷關係模型的正確率的。在本分析中，我們設定了兩個 α 值作為 hit rate 指標用，分別是 0.1 和 0.2，表 5-1 列出了這九個關係模型使用這三個指標配合十群交叉驗證所得到的數值，表現最好的關係模型是先使用 K-means 分群再使用 GLM 所建立的，第二好的則是先使用 Two-step 分群再使用 GLM 所建立的，圖 13 是先使用 K-means 分群再使用 GLM 所建立模型的實際 Is 值與使用模型得到的 $\hat{Is}$ 值的比較圖，資料點的回歸取現的斜率非常接近 1，可以看得出來兩者之間的相關度非常高。如果單看模型的線性關係表現，類神經網路的表現比 GLM 和線性回歸都要來的好，這也可以驗證校舍的耐震能力與其設計參數之機善一個非線性的關係，而雖然 GLM 整體的排名較 ANN 來的好，但是 hit rate 卻是 ANN 表現的比較好，但是看到 MAPE 又會發現 ANN 的 MAPE 較大，因此我們建議在 Is 值的關係模型的挑選，可以依據應用的需求來決定，如果需要較高準確率的時候，建議使用 ANN，如果是需要降低整體的誤差，則建議使用 GLM。如果先使用分群方法將校舍資料根據設計參數分出不同群集後，再對不同群集分別探勘其耐震能力與設計參數的關係模型，結果會比沒有先分群要來的好一些，探討其原因，是因為典型校舍已經是校舍建築物的一個子集合，而此子集合的特性已經非常接近，因此再進行分群也不會有顯著的改善。

表 5-1: Cross-validation result of the prediction model

	K-means ANNs	Two-step ANNs	ANNs	K-means Regression	Two-step Regression	Regression	K-means GLM	Two-Step GLM	GLM
R	80.21%	81.78%	80.76%	72.16%	72.16%	72.15%	87.41%	87.11%	87.05%
MAPE	28.69%	26.64%	26.51%	46.06%	46.05%	46.05%	24.68%	24.70%	24.71%
hit_rate(0.2)	53.12%	54.29%	54.31%	40.16%	40.17%	40.21%	48.82%	48.64%	48.52%
hit_rate(0.1)	27.71%	28.72%	28.75%	21.13%	20.98%	21.09%	25.05%	25.16%	25.16%
Rank	6	4	3	9	7	8	1	2	4

When 0<a<1 and IL = 1, hit rate is utilized to determine the percentage of data predicted correctly by the prediction model, that is, prediction model accuracy. In this work,

the hit rate is ranked by setting a equal to 0.1 and 0.2, which are utilized as two assessment indices that average and rank the performance of accuracy. Table 1 lists the assessment indices of the nine prediction models. The prediction model that performs best is that built using the GLM with K-means clustering. The second best prediction model is that built via the GLM with two-step clustering. Fig. 13 compares the actual CDR and CDR obtained using the K-means and GLM prediction models. The slope of the regression curve equation approaches 1, indicating a strong correlation between school building design data and aseismic ability of building. However, the scattered distribution of actual data points corresponds to a high R2 and high MAPE. After a thorough comparison of the nonlinear analysis by ANNs, the GLM, and linear analysis by simple regression, the ANNs perform better than the GLM and linear analysis by simple regression all aspects, confirming that the design parameters of school buildings have a nonlinear relationship with aseismic ability, which conforms to the fact that the aseismic CDR in this work is obtained using nonlinear analysis. Although the GLM ranks high in comprehensive assessment, its hitate is worse than that of ANNs; ANNs also have a higher MAPE. Hence, it is possible to determine which prediction method is suitable based on actual needs when predicting the aseismic ability of school buildings. We recommend using ANNs for accurate prediction of the aseismic abilities of school buildings; however, the drawback in using ANNs is that the prediction model generated is a black box. We recommend using the GLM to minimize total error. When building prediction models by clustering first and then comparing the performance of the three assessment methods, the prediction model built with clustered data performs slightly better than those built directly, indicating that traditional school buildings are already a subcluster of various architectural patterns. One feature of subclusters is their weak correlation with the aseismic ability of school buildings. Hence, information added to the cluster will not markedly improve prediction model quality.

　　由於校舍補強預算和時間有限，因此其執行的優先順序就會依照評估得到的耐震能力作為參考排序，因此本分析還用此實際的應用作為另一個評量關係模型優劣的指標，此指標將所有的校舍依照其 Is 值排序後，照順序等分成 10 群，另外在用關係模型得到的 $\hat{Is}$ 排序，一樣照順序等分為 10 群，接著比較每筆校舍所分配到的群集，如果實際所屬的群集編號和關係模型得到的群集編號一樣，則誤

差（error）為 0，如果差了一號，則誤差為 1，差了兩號則誤差為 2，表 5-2 即為九組關係模型的排序誤差結果。可以發現表現最好的一組仍然為先使用 K-means 分群再用 GLM 探勘所得到的關係模型，其誤差小於 1 的資料比例為 70.8%，誤差小於 2 的資料比例則有 88.9%。

The budgets and priorities for reinforcing school buildings are based on the aseismic abilities of school buildings. This work analyzed the sequencing result of aseismic ability of school buildings by sequencing school buildings based on CDR values, dividing them into 10 equal zones, and comparing the zone number of actual and predicted values. Table 2 shows the zoning result. When Error = 0, the predicted and actual values have the same zone number; when Error = 1, predicted and actual values are in adjacent zones; when Error = 2, predicted and actual values are separated by one zone. The prediction model built by the GLM with K-means clustering performs best. The zoning error of this prediction model <1 is 70.8%, and the zoning error <2 is 88.9%, indicating that the prediction model already has sufficient accuracy when sequencing is used.

表 5-2: Sequencing analysis of prediction of aseismic ability

Error	K-means ANNs	Two-step ANNs	ANNs	K-means Regression	Two-step Regression	Regression	K-means GLM	Two-Step GLM	GLM
0	32.8%	35.0%	33.9%	33.4%	34.1%	33.3%	35.6%	34.9%	35.0%
1	36.0%	35.2%	36.5%	35.4%	34.2%	35.5%	35.2%	35.9%	35.7%
2	17.5%	15.2%	16.2%	16.6%	17.1%	16.4%	18.1%	17.3%	17.5%
>2	13.7%	14.6%	13.5%	14.6%	14.7%	14.8%	11.1%	11.9%	11.8%
Rank	5	5	4	7	9	8	1	2	2

5.2 CDR 值與校舍設計之關係模型

校舍耐震資料庫中，詳細評估表的耐震能力索引 CDR 值是用來評估校舍是否需要補強、甚至是拆除的最重要依據，此數值的取得非常耗時耗力，且與校舍結構材料、設計與現況等參數之間為高度非線性的關係，如果能夠取的此一關係模型，對於校舍耐震能力補強計畫的進行，可以有很大的幫助。

5.2.1 資料前處理

　　人工輸入的資料很容易發生單位錯誤或是格式不正確的資料，而資料的品質對於資料探勘的結果優劣影響很大，因此需要在資料前處理時把這些問題都處理過，資料前處理的最主要目標是讓處理過的資料能夠很確實的反映出分析問題所要尋找的資料特性，使用的方法包括資料過濾、屬性過濾、新屬性的生成等，首先，本分析中第一個前處理工作就是資料過濾，要把有問題的資料，不合理的資料都過濾掉，過濾的條件則是依照國震中心所建議的典型校舍特性的過濾條件：

　　Manually inputting data may result in incorrect units or formats because controlling data quality in the real world is difficult. Hence, it is necessary to pre-process data before building the relational model. Quality, as an important part of soft computing and data analysis, has considerable influence on subsequent analytic results or even on the reliability of the generated model. Apart from the actual data, the researcher also refers to expert advice from NCREE for data pre-processing. The main target of data pre-processing is to ensure the accuracy and adjustment of the data in a format that clearly reflects the target of analysis. Pre-processing includes data screening, property screening, and new property synthesis. Data screening is divided into two stages. The first stage is the rationality screening of the data. Pre-existing mistakes are unavoidable because the data in the School Building Database were entered manually; the obligation is to identify such mistakes. Most of the school buildings were I-type shaped buildings; a very common design. . With regard to the properties of these school buildings, the NCREE (2005) suggests the following screening conditions:

- 校舍深度介於六到二十公尺之間

- 校舍垮距介於二到八公尺之間

- 每間教室至少有一個垮、兩個柱

-

- 校舍的破壞地表加速度是長向較小

- Total depth of the school building should exceed 20 meters or is less than 6 meters

- The span exceeds 8 meters or is less than 2 meters

- The number of spans for a single classroom is less than 1

- The number of columns in the classroom is low

- The collapse ground acceleration of the major direction is greater than that of the minor direction

由於並不是所有的校舍都有進行過詳細評估，因此第二個步驟就是要挑選出同時有基本設計資料以及詳細評估的 CDR 值的資料，接著，由於校舍資料庫中的原始資料，每棟校舍都有上百個資料屬性，因此接著要對屬性進行篩選與合併，與國震中心之專家討論過後，挑選過濾掉大部分的屬性，但是仍然有約三十多個屬性，因此為了能夠繼續減少資料屬性，本分析接著還繼續對這些資料的屬性進行分類，根據其屬性分布挑選出一組典型校舍子集來分析，這個挑選出來的子集其特性為：

In the second stage, choosing school buildings with both basic design parameters and minimum destruction ground acceleration is necessary because not all school buildings have detailed information. According to the raw data in the seismic assessment database for school buildings, each data set contains hundreds of properties. Based on our judgment with expert which are non-structural and low importance, and synthesize some properties with similarity. There are still more than 30 properties left after this reduction process. This study further classifies school building records into subsets based on similarities in property values, and chooses one subset with major population as the data set for further studying. After the classification of school buildings, we try to do further reduction and finally determine a set of key properties which is optimal to represent the seismic characteristics of individual school buildings. The choice is based on data distribution, and a subset that correctly represents I-shaped school buildings. The features of this subset adopted in this study are listed below:

- 沒有走廊柱

- 只有一種教室柱

- 校舍沒有 RC 牆

- 沒有四面圍束磚牆

- 沒有三面圍束磚牆

- No corridor columns

- Only use one type of classroom column

- School buildings have no RC walls

- School buildings have no brick walls with four-side confinement

- School buildings have no brick walls with three-side confinement

最後前處理完成的資料總共有 107 筆。總共有十二種屬性

After finalizing the data for the first and second stages, 107 datasets conform to the above condition. Twelve properties are then chosen for the screened data with reference to expert advice, displayed as P1 to P12 in Table 1. In addition to the screening based on existing properties, this study synthesizes two new properties, P13 and P14. They represent the number of classrooms and number of spans for a single classroom, respectively, based on expert advice and existing data. In P11, SDS stands for design spectral response accelerations at short-periods, and in P12, SD1 stands for design spectral response accelerations at 1 sec. These two parameters represent the magnitude of the seismic force at the building＇s location, and are very important parameters for analyzing the aseismic ability of buildings by non-linear analysis.

The last step of data preprocessing is normalization. The purpose of normalization is to balance the impacts of the parameters in different scales. If an input parameter has small values of mean and standard deviation, but is of high importance and if the result is also sensitive to this parameter, then it is necessary to use data normalization to prevent its influence from being overshadowed by other larger scale parameters. Normalization methods include converting the data into the range of 0 to 1, using the maximum and minimum values, and converting data to the standard deviation of its mean. The normalization

principle adopted in this paper is to retain the original values as far as possible, so only a few parameters with large values, such as P2, P3, P7, P9 and P10, are divided by 1000 to make their scale comparable to other parameters. ▯OBJ▯OBJ▯OBJ▯OBJ▯OBJ▯OBJ▯OBJ▯OBJ▯OBJ▯OBJ▯ After the three pre-processing steps, 107 datasets and 14 properties were obtained. The subsequent analysis was based on this dataset.

5.2.2 資料探勘

Genetic Programming

An AC model was built for this study to represent the relationship between the basic design parameters of school buildings, and minimum destruction ground acceleration. GP was the first model to be used, and based on a preset number of tiers for different operation trees; it can result in relational equations with different degrees of complexity. In this case, several operation trees with different number of tiers were tested, and it was found that the most suitable number is either four or five. Having a low number of tiers leads to reduced complexity of the relation model and hence, poor performance. Conversely, large numbers result in many difficulties, such as convergence problems, time-consuming progressive computation, and a very complicated relationship model. The optimum setting is 200 populations of 5000 progressive iterations, a crossover rate of 0.8, and a mutation rate of 0.1. The crossover function used in this paper is the scattered function. The mutation function is the adaptive feasible function. Both these functions can be applied to solve many different problems. The scattered function diversifies the child layer after crossover. The adaptive feasible function is suitable for the constrained minimization problem. This setting was chosen after the analysis was conducted 30 times. Table 2 shows the root mean square (RMSE) of the model generated.

RMSE is the index used in the current study to judge the quality of models, and is defined as the equation below:

$$RMSE = \sqrt{\frac{\sum (y_i - \hat{y}_i)^2}{N}} \tag{5-4}$$

where n is the number of datasets, y is the estimated value obtained from the equation, and $\hat{y}$ is the actual unit-less deviation index value (the smaller the better). The ground acceleration of the minimum destruction obtained from the nonlinear analysis was distributed between 0.04 and 0.5, and therefore, the relationship model has a sufficient recognition rate. Experts from NCREE recommend that the RMSE must be below 0.04. The control group is the relationship model obtained from the artificial neural network. In applying the relationship model constructed by SPSS Clementine and choosing the Exhaustive Prune method to adjust the number of tiers and nodes, the initial neural network has two hidden tiers with 30 and 20 neurons, respectively. The neurons have been trained for 250 iterations, and those with a low degree of importance are removed during the training period based on the situation. The resulting RMSE is 0.041, which is close to the target of 0.04. In this paper we use WGP to create an aseismic ability prediction model for real school buildings. The quality of our model is similar to models built using Artificial Neural Networks. However, Artificial Neural Network based models are complicated; their mechanism is in a black box. The WGP model, on the other hand, is just an equation of the building's design parameters and its aseismic ability. Thus, it can easily be ported to other platforms and programming languages for use in many applications. The optimum model obtained from the GP pattern is represented by the relationship equation below. Function nodes in a tree topology, displayed in Figure 8, uses several symbols and text to represent the F of that node.

"+" represents $f = x_1 + x_2$; "-" represents $f = x_1 - x_2$; "×" represents $f = x_1 \times x_2$; "÷" represents $f = x_1/x_2$; and "pow" represents the power function, $f = x_1{}^{x_2}$.

The performance of this model is not ideal because the RMSE can only reach 0.056. Based on Figure 9, the relationship model generated did not correctly build the relationship between the design parameters of school buildings, and ground acceleration of the minimum destruction. As only three input parameters were used, it resulted in the minimum equation as the linear equation. This can be attributed to the fact that this seismic ability model for school buildings has high complexity, and the application of GP pattern alone cannot obtain the relationship between them.

The WGP pattern was then used to build the relationship equation between the de-

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sign parameters of school buildings, and ground acceleration of the minimum destruction because it could be used for relationships that are more complex than with the GP pattern.

$$AC = \frac{P_3}{P_{11}} + P_3 P_{12} - P_3 P_{12}{}^3 \qquad (5\text{-}5)$$

Weighted Genetic Programming

WGP was used as the second model, which also chose five tiers of the operation tree. The optimum setting of GA is the same with GP: 200 populations of 5000 progressive iterations, a crossover rate of 0.8, and a mutation rate of 0.1. The best group was chosen after the analysis was conducted 30 times. Contrary to GP, the weight was set from +10 to -10 within the weighted (w) range. Table 2 shows the RMSE of the model generated, and the four-tier optimum equation is shown as Equation (9). The tree topology generated is displayed in Figure 10, and uses the same symbol as the GP tree topology to represent the same operator. The other symbol that was used is a black solid dot, which represents f=w1x1.

$$AC = \left(165 P_{10}{}^{8.86 P_6} P_4{}^{4.86} + \frac{22.5 P_8 + 39.5 P_{10}}{P_{10}}\right)^{-98.6 P_4 P_8{}^{-1.3} - 133 P_{10} - 0.05 P_7{}^{1.38 P_{10}}} \qquad (5\text{-}6)$$

Table 2 shows the RMSE of the optimum relationship equations generated from the two patterns. The RMSE reached 0.039, which is better than the performance of the model built by the artificial neural networks in the contrast group. Figure 12 displays the comparison between the estimated, and the actual values of the model. By comparing the results, the model constructed by the WGP pattern is superior to the model constructed by the GP pattern.

The parameters entered are analyzed based on the equation obtained from WGP, and Table 3 shows the input parameters obtained from the optimum relationship equations. SDS and SD1 were not used, as both are relevant to the demand of the CDR. For this study, the target is to estimate the Capacity (Aseismic Ability Index), which is irrelevant to Demand. Hence, this result conforms to the expectations. As all of the remaining input

parameters were used, this indicates that the parameters chosen at the data processing stage are important.

Capacity Index Formulation Tuning

Similar with the CDR obtained from the detailed estimation, the aseismic capacity index of school buildings is the demand ratio of the aseismic capacity, excluding the ability unit and measure. CDR is directly compared to the ground acceleration, and IS is the estimated force ratio. If CDR is greater than 1, then the building has sufficient aseismic capacity. If CDR is 1, the building has an aseismic capacity equal to the demand. However, it should be noted that IS is a hundred-mark system, and 100 indicates that the capacity is equal to the demand. IS also needs to consider the usage coefficient I, of buildings. When IS equals 1.25, CDR is 1 and IS is 80. This relationship can be described by a formula that converts IS into CE, which has the same meaning as the ground acceleration of the minimum destruction.
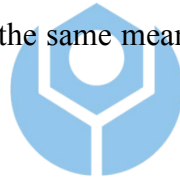
$$C_E = f(Is) = \frac{Is \times Demand \times I}{80} \tag{5-7}$$

I is the usage coefficient that intends to keep the seismic design at the conservative side, and prevents miscalculations caused by the insufficient estimation of the earthquake destruction. For this study, I is set to a constant of 1.25 for school buildings. Demand is set to different recommended values based on the positions of the school buildings. It represents the minimum ground acceleration that the buildings can withstand in the area. The School Building Database contains the demand data that was determined by engineers, based on the actual situations. This study adds T to CE as a revised formula, such that it is closer to the minimum destruction ground acceleration AC, of school buildings obtained from nonlinear analysis.

$$AC = C_E + T \tag{5-8}$$

Based on the analysis above, this study only uses the WGP pattern to build the model,

and this can be applied to complicated situations. Parameters chosen are: the operation tree has four to five tiers, 200 populations of 5000 progressive iterations, crossover rate of 0.8, mutation rate of 0.1, and choosing the best group after the analysis was conducted 30 times. The optimum T generated from the four-tier operation tree is shown in the equation below, and the tree topology is displayed in Figure 11.

$$AC = C_E + 0.54\frac{P_3}{P_2} - 24.86\frac{P_6^{0.36P_3}}{P_5^{2.6P_9}} - (37.84\frac{P_5}{0.67P_2 + 5.52P_7})^{\left[(-0.67P_{12})^{1.23P_7/P_{13}}\right]} \quad (5\text{-}9)$$

5.2.3 結果

Table 2 shows the RMSE after the revision. The RMSE of the IS formula used by NCREE in the preliminary appraisal is 0.067. Although there is still a gap between the target of 0.04 and this value, the emphasis is on the degree of relationship between them, and the main target is to screen out the school buildings with degrees of higher risk. Figure 13 shows the comparison between the CE converted from IS of NCREE, and the destructive ground acceleration obtained through linear analysis. Even though the data have the correct directional tendency, the model obtained from the GP method is better because of higher deviation, and a linear relationship. Subsequent to adding T to the revised formula, RMSE is reduced to 0.045. Figure 13 shows the comparison, and it can be seen that the directional tendency is quite close, thus reducing the deviation. A good revision effect is observed, making the screening result of the preliminary appraisal more accurate.

Table 3 shows the input parameters used by the equation obtained from the WGP method, and by the optimum relationship equations with four to five tiers. The number of floors (P1), total floorage (P10), and number of spans in a single classroom (P13) were not used because the number of floors and total floorage, which are highly important, were already used in the IS formula. Hence, IS has been correctly included in the two properties above, and the number of spans in a single classroom can be inferred as hidden in the formula. Hence, T in the revised formula will not use this input parameter. However, the input parameter is still used to directly construct the relationship equation in the previous case, and has a certain degree of importance.

In order to estimate the aseismic ability of a building, we need to obtained detailed information about its geometric dimensions, the properties of materials used, etc. and we may need to perform sampling and other experiments to obtain certain information e.g. the properties of materials used. Based on this information, a structural model of the building has to be constructed and then non-linear pushover analysis is used to perform estimation. This process is time-consuming, and technicians are required. It usually takes about one months to estimate the aseismic ability of a building.

In this study, we adopted the WGP method to construct a relation model, which uses the basic design parameters of school buildings to estimate their aseismic ability. The pre-processing efforts carried out for the proposed prediction model can be divided into two parts. The first part is a data filter for selecting out data sets which are reasonable as typical school buildings. The selection conditions of this data filter is proposed based on judgment with expertise in structural engineering. The second part is the determination of the key properties used in the proposed model. We first eliminate some properties which are non-structural and low importance, and synthesize some properties with similarity. We further classifies school building records into subsets based on similarities in property values, and chooses one subset with major population as the data set for further studying. Based on this subset, we try to do further reduction and finally determine 14 properties which are optimal to represent the seismic characteristics of individual school buildings. In comparison with hundreds of properties in the original data, a very high reduction ratio is reached.

Same as GP, a key characteristic of WGP is the resulting model is in the form of mathematic equation, which is very easy and convenient to be applied in engineering practice, and thus is more practical than other soft computing methods. This study also applies GP on the same set of school building data for predicting the building's collapse ground acceleration. Compared to the prediction results by using GP, the accuracy of WGP model is much better. This case shows WGP can handle problems with more complexities than GP. Regarding the application of WGP method, this study performs 5000 iterations of revolutions for test models with operation tree from two to five levels respectively, and determines the optimized values of model parameters, such as the crossover rate and mu-

tation rate, for this application case through repeated tests. The RMSE of the resulting model achieves less than 0.04. This accuracy in prediction is comparable with the model using Artificial Neural Networks (ANNs). In addition, the graph compared the actual values with predict values shows the distribution trend of the data points are consistent with the expected direction. The result verification indicates the proposed WGP-based model successfully establishes the relation between the 14 input properties and the output property, building's collapse ground acceleration. In practice, the proposed model can be applied directly and efficiently for preliminary assessment of school buildings for seismic capacities.

In addition to directly inferring the aseismic capacity of school buildings from the design parameters, the current study revised the aseismic capacity index formula of school buildings designed by NCREE using GPS. The formula was to provide greater accuracy with a smaller deviation. This model can help decision makers with issues that are related to the aseismic capacity of school buildings, as well as estimating the disaster loss, during a disaster in a timely manner. These applications require that the estimation of the aseismic capacity of many school buildings be generated rapidly, and this would be impossible if traditional non-linear structural analysis were applied.

5.3　D_isR 值與校舍設計之關係模型

　　「校舍是否需要補強」此一指標其數值之基礎即為詳細評估的耐震能力指標 CDR 值，CDR 值超過 1 表示其耐震能力尚符合安全規範，反之，則是有安全疑慮，需要進一步補強或是拆除。而 D_isR 則是標記各校設耐震能力是否足夠的二元指標，也是教育部的校舍耐震能力補強計畫中，前期篩選工作的最主要目標。找到這個指標與校舍設計、現況等參數的關係模型，與 Is 值和 CDR 值關係模型一樣，此一關係模型對於校舍耐震能力補強計畫中，初期的篩選工作可以有很大的助益，也可以輔助決策者編定預算、快速的根據狀況決定不同計畫年度補強的規模等。

5.3.1 資料前處理

5.3.2 資料探勘

5.3.3 結果

第 6 章　校舍資訊與破壞構件之關係模型

第 7 章　校舍資訊與補強經費之關係模型

第 **8** 章　　結論與討論

8.1　結論

8.2　討論

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