8-2000

Formulation and Assessment of a Customizable Procedure for Pavement Distress Index

Zongren Wang
University of Tennessee - Knoxville

To the Graduate Council:

I am submitting herewith a dissertation written by Zongren Wang entitled "Formulation and Assessment of a Customizable Procedure for Pavement Distress Index." I have examined the final electronic copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Civil Engineering.

Lee D. Han, Major Professor

We have read this dissertation and recommend its acceptance:

Michael D. Vose, Robert E. Ford, Stephen Richards

Accepted for the Council:

Carolyn R. Hodges

Vice Provost and Dean of the Graduate School

(Original signatures are on file with official student records.)

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Dr. Anne Mayhew

Interim Vice Provost and
Dean of The Graduate School

(Original signatures are on file in the Graduate Admissions and Records Office.)

FORMULATION AND ASSESSMENT OF A
CUSTOMIZABLE PROCEDURE FOR
PAVEMENT DISTRESS INDEX

A Dissertation
Presented for the
Doctor of Philosophy
Degree
The University of Tennessee, Knoxville

Zhongren Wang
August 2000

DEDICATION

To the memory of my beloved mother Shubin Huang, 1949-1999. Born in Changtu County, Liaoning Province, China, mother devoted her whole life to the goodness of the family. She will always be remembered by those, whose lives have been touched and brightened by her wisdom, perseverance, and zest for life.

ACKNOWLEDGMENTS

There are many people to whom I am grateful for making my time at The University of Tennessee so rewarding. Particularly, I feel indebted to my research advisor, Dr. Lee D. Han, for his endless encouragement, guidance, and financial support. I am also grateful to my Dissertation Committee, Drs. Stephen Richards, Michael Vose, and Robert Ford for their support. They have all made a number of suggestions of the dissertation and the merit of this work is due in no small part to their guidance.

I would like to thank Dr. N. Mike Jackson, my advisor in the minor area, at the Department of Civil and Environmental Engineering for his understanding, encouragement, and financial support. Help from my classmates, Sherry Livengood, Mohammad Qureshi, and Hui Wang are acknowledged with gratitude. Their kind discussions, to-the-point corrections and enthusiasm in helping me out have greatly impressed me. Thanks also go to Mr. David Janish, the State Pavement Management Engineer at the Minnesota Department of Transportation (MnDOT). David provided me with all the necessary distress survey data from MnDOT.

My greatest debt is owed to my wife, Weili. Without her help, care, and companionship, I would never have tided over so many mishaps, and reached for this moment. The support and encouragement from my father Qingfang, and my parents-in-law, Xueli and Xinrong, can never be overemphasized for the successful completion of my study in the United States.

ABSTRACT

A customizable procedure for the formulation of Pavement Distress Index (PDI) based on human rating behavior is presented in this dissertation. This procedure formulates PDI as the maximum PDI value in a user-defined scale minus the Total Deduct Value (TDV), which is the sum of the product of each individual Deduct-Value (DV) and its corresponding weight. These weights, defined as a function of corresponding DV-percentages, i.e. individual DV over TDV, are identified using data simulated according to the studies by Sun and Yao (1991) and PAVER, a Pavement Management System (PMS) developed by the U. S. Army Corps of Engineers. Because these functions, called weight-curves captured from the two independent studies are quite similar, the rating behavior of pavement experts can be concluded to be reasonably stable, and therefore PDI may be formulated by fixing the weight-curve and customizing individual DVs only.

Non-linear programming techniques are employed in this study. DVs for user-defined distresses are determined when the total squared sum of the difference between user-rated PDI and that computed by the proposed formulation for a series of samples is minimized. Initially, simulated data from PAVER was used to establish and illustrate this procedure. Field data was later on used for validation purposes. The proposed methodology caters to user-defined PDI scales and distress definitions, and determines DVs for user-defined distresses so that the user-rated PDIs can be reproduced when similar pavement conditions happen. This procedure simplified the iterative PDI formulation process to the automated customization of deduct-values, it would thus greatly facilitate the formulation of a PDI for agencies that are implementing a PMS.

TABLE OF CONTENTS

LIST OF TABLES

TABLE PAGE

LIST OF FIGURES

Chapter 1 Introduction

1.1 Significance of Pavement Distress Information

Pavement distresses are visible imperfections on the surface of pavements. They are symptoms of the deterioration of pavement structures. Most, if not all, agencies that have implemented a Pavement Management System (PMS) collect periodic surface distress information on their pavements through distress surveys (Haas et al. 1994). Generally four categories of surface distress are collected: surface defects, permanent deformation or distortion, cracking, and patching, with each category including several specific types of distresses. Although an extremely wide variation exists in the manner in which the distress surveys are conducted, recorded, analyzed, summarized, and stored, information on distress type, severity, density, and sometimes location is usually gathered.

Pavement engineers have long recognized the importance of distress information in quantifying the quality of pavements. This information has been used to document present pavement condition, chart past performance history, and predict future pavement performance (Shahin et al. 1994). Pavement distress information is also broadly used as the only quality measure of pavements in many PMS. This is particularly true for systems used by local governments and in urban areas where roughness measurements are not performed because of a lack of equipment availability, high cost, or a lack of relative applicability.

1.2 Necessity for PDI Formulation

Pavement distress information can be used in a detailed manner for developing a demand-based localized maintenance program. However, in order to obtain an overall assessment of pavement conditions for a road network, it is often necessary to combine individual distress data to form one composite index, called Pavement Distress Index (PDI), which summarizes the condition of each pavement segment or project. This is particularly true when distress information is used for project selection purpose. Is it more important to repair a section with alligator cracking or rutting? What combinations of density and severity of the different distresses will indicate that one pavement section is in a worse state than another pavement with a different set of distresses (Haas et al. 1994)? In addition, the composite PDI is also easier to understand at the non-technical level within and outside of an agency.

1.3 Nature of the PDI

By definition, PDI is a subjective evaluation of pavement conditions by experienced pavement engineers, based on a user-defined scale, such as 0-5, 0-10, or 0-100. It summarizes the pavement condition in terms of individual distress, so that pavement performance may be evaluated, predicted, and improved using effective treatments. As Grivas et al. (1992) pointed out, the objective of developing a PDI is to (1) Combine distress data in a manner that reflects the maintenance practices of a specific agency and that is meaningful to field personnel and middle and upper management; and (2) Create a sufficiently responsive condition measure that can be used for network-level analysis.

Assessments of pavement conditions are usually obtained by means of organized experiments using expert panels. As such, it is impractical and expensive to perform pavement quality ratings on an entire pavement network. Consequently, considerable effort in PDI formulation has gone into correlating various objective, high speed and reliable mechanical measurements with the subjective ratings on samples of the network (Haas et al. 1994). Based on the established relationship, the necessity of repeated organized experiment is eliminated, and the expert-rated PDIs may be reproduced using the objective measures of individual pavement distress.

1.4 Methods for PDI Formulation

There are two major streams in the PDI formulation methods, i.e. the pure regression and the deduct-value method. Pure regression analysis is one of the most commonly adopted approaches, and its implementation may date back to the time of the AASHO Road Test, when the famous AASHO Present Serviceability Index (PSI) was formulated (Carey and Irick, 1960). In this method, each distress included is considered as an independent variable, and all the independent variables combined linearly or nonlinearly to reproduce the user-ratings based on pure data fitting. Similar analyses were also reported by Turner et al. (1986) and Wu (2000) in developing quantitative rating indexes in Alabama and North Carolina, respectively.

A more popular method involves the use of deduct-values. In this method, each type-severity-density distress on a pavement is considered a “deduct-value” from the rating of a perfect pavement. The magnitude of the deduct-value represents the impact of the distress on the pavement condition when it appears alone. The relative amount of the deduct-value implies that certain types of distress contribute more than others to the overall pavement damage. The PDI is hence the rating of a perfect pavement minus the total deduct-value, which is a nonlinear aggregation of all the individual deduct-values. Because of its clear physical meaning, the deduct-value method has received wide acceptance by many agencies, such as the Federal Aviation Administration, the U.S. Department of Defense, and the American Public Works Association (Shahin 1994). According to the author’s survey, many state highway agencies have also taken advantage of the deduct-value concept and use it in the development of their PMS. These states include Arkansas, Iowa, New York, North Carolina, South Carolina, South Dakota, Tennessee, Washington, the Province of Alberta and British Columbia in Canada (FHWA 1983, Jackson et al. 1996, StanTech 1999).

Both of the aforementioned methods for PDI formulation are not perfect. First, they are both very costly and time-consuming to develop. Each individual distress type contributes in a distinct manner toward the aggregate pavement condition: The formulation of a PDI must accommodate the relative significance of each distress type and magnitude (severity and density) (Grivas et al. 1992). Since there are several types of distress, several possible degrees of severity for each type, and a wide range of density for each type, combining the effects of these three characteristics to form one index is a large-scale regression problem, and hence entails great effort. For the deduct-value method, the large-scale regression is replaced by an inevitable and painstaking iterative process, because both the individual deduct-values and how they should be "non-linearly" combined are unknown. As evidenced by the two previous studies (Shahin and Kohn 1979, Sun and Yao 1991), a common loop for such an iterative process is to assume the individual deduct-values and the combination schemes first, and then adjust them according to field-tests and user-rated PDIs.

In addition, the painstakingly established relationships or models are applicable only to a selected distress definition. Once there is a change in the distress definition, the original PDI model would be rendered meaningless and un-usable. This is extremely undesirable because every agency is free to select the distresses to be included in its PDI formulation; it is not uncommon for an agency to update its distress definitions, either. For example, some agencies may introduce new data collection methods or equipment, which may well alter some or all of the existing distress definitions. In order to update the deduct-values for the newly included distress definitions, the iterative formulation process has to be started again.

1.5 The Desired Procedure

In some sense, existing procedures did not solve the PDI formulation problem satisfactorily, and, in fact, brought about a dilemma. On the one hand, PDI formulation has to allow for the free choice of distress definitions; on the other hand, the costly formulation process just produces a definition-specific model. The fact that distress definitions may change aggravates the situation. In order to avoid such a dilemma, a customizable procedure that is flexible enough to accommodate a wide range of distress definitions without undergoing the conventional iterative formulation process may be more appropriate.

In the study of Sun and Yao (1991), the idea of such a customizable procedure was first proposed. They reported that human rating behavior might be used as the basis for PDI formulation because it was found to be reasonably stable across China. This study will further explore the concept of such a customizable procedure based on human rating behavior, and it will construct and automate a more generic PDI formulation procedure that is customizable to any distress definition.

1.6 Objectives and Scope

The primary objective of this research is to develop a customizable procedure for PDI formulation based on human rating behavior. Specifically, this study will: (1) Propose a generic PDI formulation as the maximum PDI value in a user-defined scale minus the sum of the product of each individual deduct-value and its corresponding weight; (2) Identify the human rating behavior, i.e. the relationship between the individual deduct-value and its corresponding weight (the so-called weight-curve) by approaching the PAVER and China method using the proposed formulation, and analyze the stability of the rating behavior; (3) Automate the extraction of deduct-values based on a reasonably stable weight-curve and user distress survey data; (4) Verify whether the extracted deduct-values would reproduce the user-rated PDI reliably.

Chapter 2 Literature Review

2.1 Introduction

Several PDI formulation methods based on the deduct-value concept are reviewed in this Chapter. These include the original and modified PAVER PCI method, the China method (Sun and Yao 1991), and the Baladi's method (Baladi 1991). Each of these methods is a complete start-from-scratch PDI formulation process. The PAVER and China methods are the forerunners of the method proposed in this dissertation. It is the objective of this Chapter to review the common formulation process of a deduct-value method, i.e. the distress definition, PDI formulation, iterative solution of the formulation, and validation.

2.2 The PAVER PCI Method

PCI is the abbreviation for Pavement Condition Index. It was initially developed for the pavement maintenance of the army airports by the U. S. Army Corps of Engineers. It is a numerical index, ranging from 0 for a failed pavement to 100 for a pavement in perfect condition. It measures pavement structural integrity and surface operational condition. The essential concept behind PCI is to consider each given distress severity and amount as a negative deduct on pavement condition. Once these deduct-values are determined, the relationship between PCI, the subjective rating and objective measurements may be established. PCI, the user rating, may be reproduced when similar conditions occur on the road in the future.

According to Shahin and Kohn (1979), there are several essential steps in developing the PCI. The first step is to select a rating scale as a standard for comparing different pavements. The next step is to clearly and exactly describe and define each pavement distress types, severity levels, and the measurement criteria. In PAVER system, deduct-value curves, such as those shown on Figure 2-1 for alligator cracking, were developed for each of the distress types in the third step. The abscissa of the graph is the extent or density of distress. Each graph contains three curves corresponding to the severity of the distress. The ordinate is the deduct-value. Because each deduct-value represents its negative effect on pavement structural integrity and operational surface condition, these deduct-values should be adjusted based on distress surveys by using samples with single type-severity-density distressed samples.

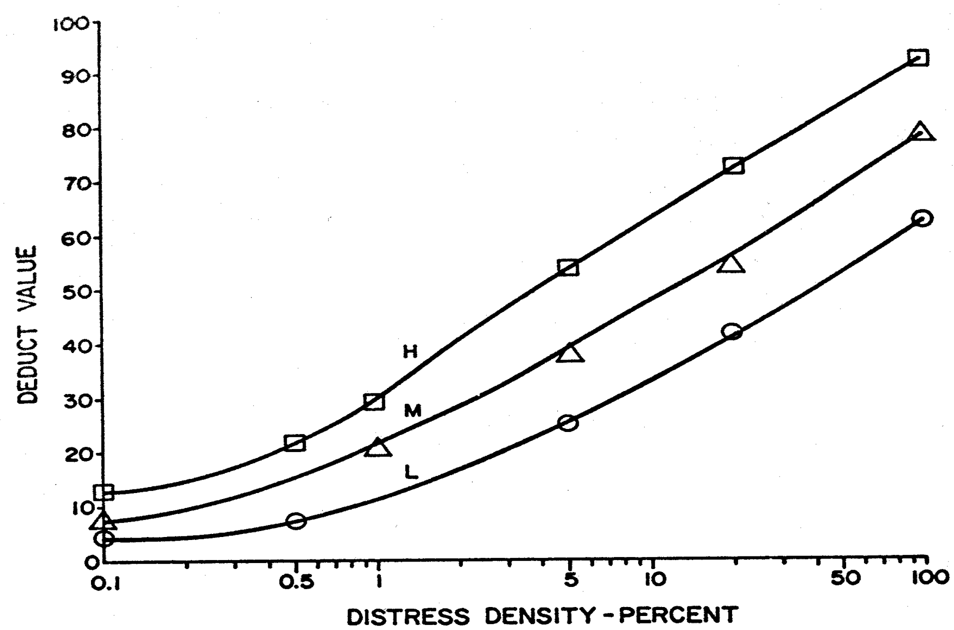

Figure 2-1. Example of a deduct curve for alligator cracking (Shahin and Kohn 1979).

In the last step, the total deduct-value is computed by adding the individual distress type deduct-values. On severely distressed pavements with multiple distress types, the total deduct-value can exceed 100. Thus, under the philosophy that a pavement with two type-severity distress combinations which each has a deduct-value of 35 is not in a state as bad as a pavement with a deduct-value of 70 for one type-severity combination, a series of curves were established for correcting the total deduct-value, as shown in Figure 2-2 (Haas et al. 1994). The corrected deduct-value is determined and subtracted from the maximum possible PCI. However, the above steps should be repeated for field-testing, revision, and improvement to ensure that the distress definitions accurately described field conditions and that the PCI agreed closely with the collective judgement of the experienced pavement engineers.

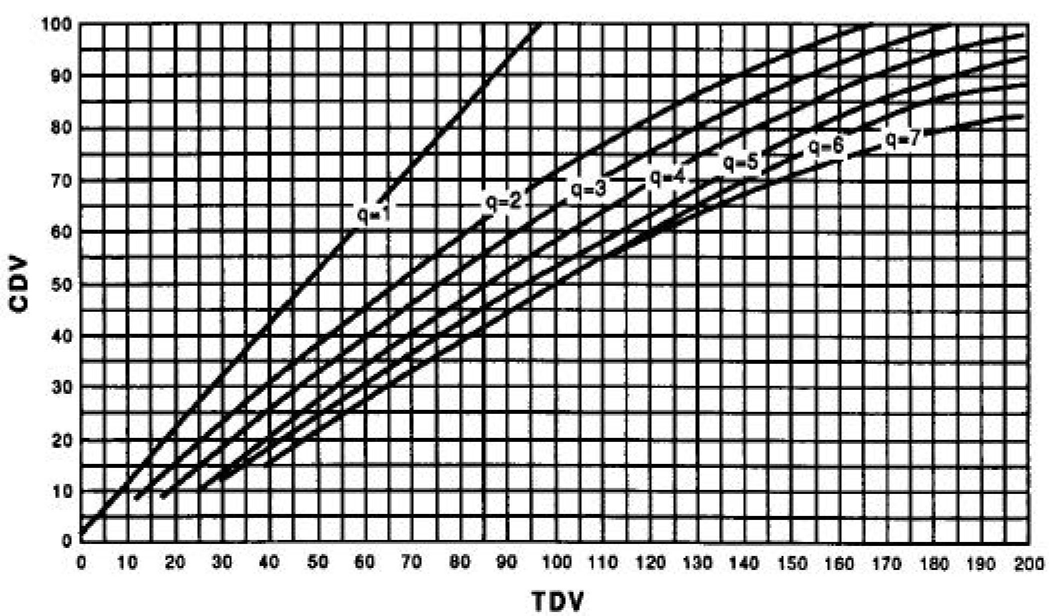

Figure 2-2 Corrected deduct-value curves (for asphalt pavements, Shahin 1979).

The PCI model can be mathematically expressed as:

$$PCI = 100 - \left[\sum_{i=1}^{p} \sum_{j=1}^{m_i} DV_{ij} \right] \cdot F\left(TDV, q\right) \qquad (2\text{-}1)$$

where,

100 = maximum value for *PCI*, on a 0~100 scale;

DV_{ij} = deduct-value for distress type i, and severity level j;

i = counter for the number of distress types;

j = counter for distress severity levels;

p = total number of distress types;

m_i = total number of distress severity levels for the i^{th} distress type;

$F(TDV, q)$ = an adjustment function for multiple distresses that vary with TDV, and q;

TDV = total deduct-value, which is given by

$$TDV = \sum_{i=1}^{p} \sum_{j=1}^{m_i} DV_{ij} \text{ ; and} \qquad (2\text{-}2)$$

q = total number of deducts with a deduct-value greater than 2, q£ p;

For practical applications of the PAVER method to determine PCI, there is a complete set of nomographs for both deduct-value for each type, severity, and density of distress, and the adjustment function. These graphs can be found in Shahin and Kohn (1979), and Shahin (1994). With the help of these curves, the determination of PCI for any distress sample is simply a step-by-step process as illustrated in Figure 2-3.

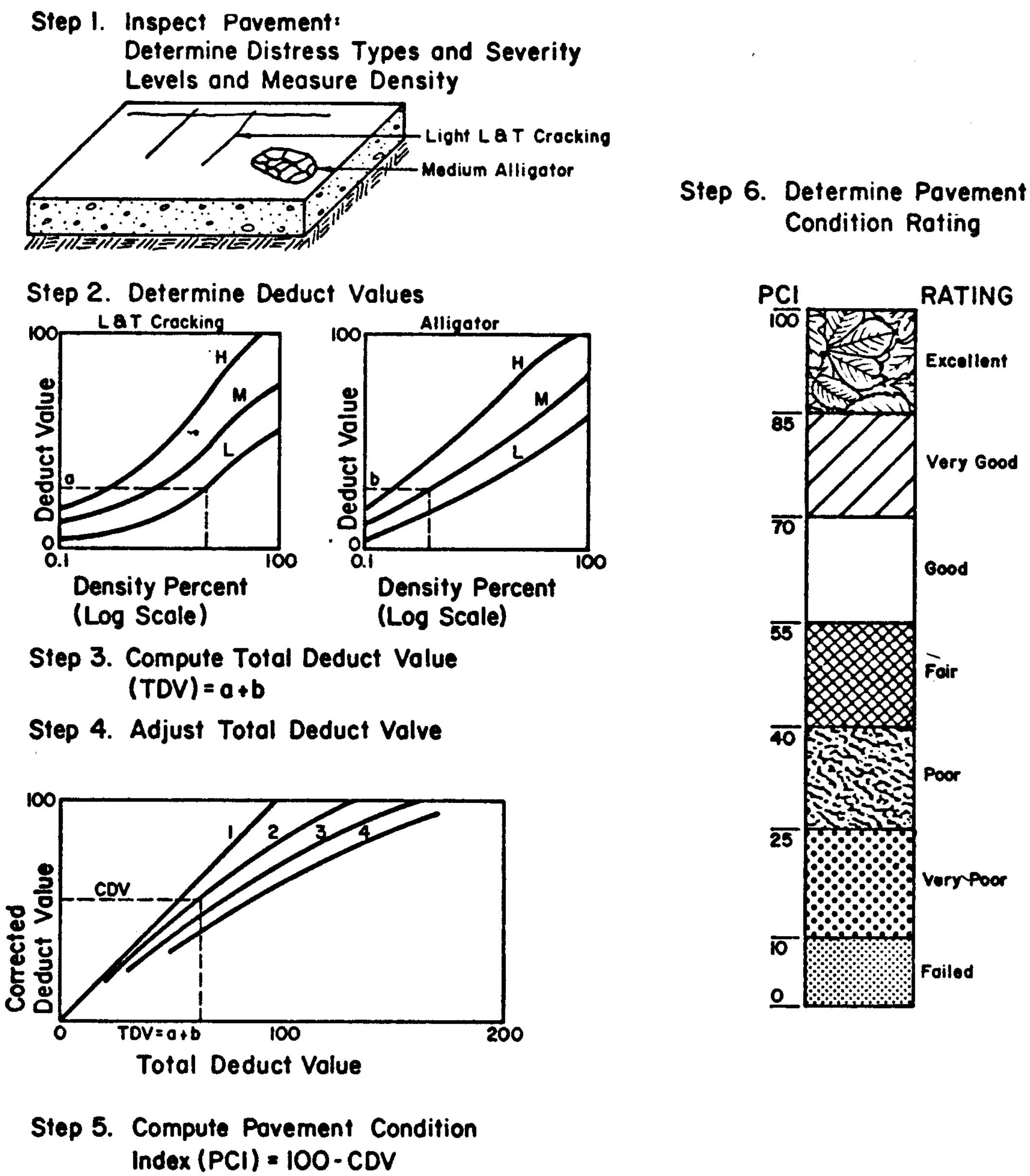

Figure 2-3. Working steps for PCI calculation (Shahin and Kohn 1979).

2.3 The Modified PAVER Method by MTC

The PCI procedure considers 19 types of distresses for asphalt-surfaced roads, streets, and parking lots. Some users have expressed interest in reducing the number of distresses used in the PCI procedure to expedite field inspection. The Metropolitan Transportation Commission (MTC) of Oakland, California, presented a modified PCI method in its PMS implementation. MTC consolidated the 19 distress types to only 7, leaving out some less frequent distress types. The major objectives for the consolidation were to expedite the pavement condition survey process and minimize the time required to train the staff, who will do the survey, while still preserving adequate amount of information to make reasonable maintenance rehabilitation decisions. An analysis of the effect of reducing the number of distresses on the PCI values was hence conducted (Shahin et al. 1995). The study compared the standard PCI method to the modified method used by MTC. It is found that there is a deviation from the standard PCI when consolidating the distress types. However, this difference is between 1 to about 7-points, depending on the database used, and types of distresses that exist in any specific site or region. The author cautioned that each agency would have to assess the benefit of reducing the number of distresses versus the deviation from the true PCI.

2.4 The Modified PAVER PCI Method by StanTech

Some PMS software developers chose to embed the deduct-value method for their PMS. The PAVER deduct-value method was modified by StanTech Consulting Ltd. (StanTech

1999) and implemented in their software package. Two major modifications to the original PAVER PCI method were made. The primary one is the way the multiple deduct-values is combined to determine the Corrected Deduct-Value (CDV). The other modification is that the individual deduct-value curves are expressed in a standardized log equation form. This modified version of PAVER procedure has been implemented in South Carolina, New Jersey, Tennessee, Alberta, and British Columbia (StanTech 1999).

In the modified method, PDI is represented on a 0~10 scale, which can be expressed as

$$PDI=10.0-CDV \tag{2-3}$$

where,

CDV = Corrected Deduct-Value, which is transformed from the *TDV* for each pavement segment, and is calculated as:

$$CDV = 10^{(0.0014-0.3958\times Log_{10}(NED)+0.9565\times Log_{10}(TDV))} \tag{2-4}$$

for asphalt pavements, and

$$TDV = \sum_{i=1}^{m}\sum_{j=1}^{n_i} DVij \tag{2-5}$$

$$NED = \sum_{i=1}^{m}\sum_{j=1}^{n_i} \frac{DV_{ij}}{DV_{\max}} \tag{2-6}$$

NED = Number of Equivalent Distress;

i = counter for distress types;

j = counter for distress severity levels, *j*=1, 2, and 3 representing Low, Medium and High severity levels, respectively;

m = maximum number of distress types considered;

n_i = maximum number of distress severity levels for distress type i;

DV_{ij} = the deduct-value for distress type i and severity level j, which is related to the percent distressed area PDA_{ij} according to Equation 2-7:

$$Log(DV_{ij}) = a_{ij} + b_{ij} \times Log(PDA_{ij}) \quad (2\text{-}7)$$

a_{ij} = regression coefficients;

b_{ij} = regression coefficients;

DV_{max} = the maximum deduct-value observed in a specific sample, which can be expressed as:

$$DV_{\max} = \underset{i,j}{Max}\ (DV_{ij}) \quad (2\text{-}8)$$

2.5 The Baladi's Method

Baladi (1991) proposed a procedure for formulating pavement condition index for individual distress. There are several steps in this process, which starts with the identification and determination of types of distress, severity levels for each type of distress, and the determination of a rating scale, such as 0 to 100. Based on these definitions and the rating scale, a panel of engineers is asked to determine the maximum tolerable density for each type-severity distress before any treatment will be scheduled. This density level is hence designated as the threshold deduct-value, or the so-called engineering criterion for that particular type-severity distress. Finally, deduct-values for other density levels for the same type-severity distress are obtained by linearly scaling up and down according to the designated engineering criterion. The individual condition index may be further combined using weighting factors assigned by the user to form a composite PDI. This process has been adopted by North Carolina and South Dakota, respectively (Chan et al. 1997, Jackson et al. 1996).

2.6 The China Method

In the development of several PMS in China, Sun and Yao (1991) adopted the deduct-value concept in formulating the distress indexes for asphalt pavements. According to the local experiences, they proposed a different procedure for PDI formulation based on a different set of distress definition and measuring method. The following is a description of the procedure.

(1) The Standardization of distress classification and measurement

Pavement distresses, in this method, are classified into four categories, namely cracking, deformation, surface defects and potholes. The first category may include four different types of cracking distress, namely longitudinal, transverse, block, and alligator cracking. Deformation category may include depression, rutting, shoving and corrugation 4 types of distresses. Distresses such as polishing, raveling, bleeding, and patching types belong to the surface defect category. This distress classification and definition system is tabulated in Table 2-1 with detailed explanations. The convention for distress measurement is also clearly defined. Longitudinal and transverse cracking distress are measured in linear meters. All other distresses are measured by the area of the outer

Table 2-1. The standardized distress classification system for the China method (Sun and Yao 1991).

Type of Distress	Description	Rating Standards
Longitudinal Cracks	Longitudinal cracks are cracks that are usually straight and parallel to the pavement centerline, situated at or near the middle of the lane. It can occur singly or as a series of almost parallel cracks or with some limited branching.	Low: Cracks are narrower than 3mm with low severity or no spalling. High: Cracks are wider than 3mm with high severity spalling.
Transverse Cracks	Transverse cracks are unconnected cracks running transversely (relatively perpendicular to pavement centerline) across the pavement.	Low: Cracks are narrower than 3mm with low severity or no spalling. High: Cracks are wider than 3mm with high severity spalling.
Block Cracks	Block cracks are interconnected cracks forming a series of blocks, approximately rectangular in shape. Block sizes are usually greater than 300mm and can exceed 3000 mm.	Low: Cracks are narrower than 3mm with low severity or no spalling. The block diameter is between 100-300cm; High: Cracks are wider than 3mm with high severity spalling and the block diameter is between 50-100cm.
Alligator Cracks	Alligator cracks are interconnected or interlaced cracks which forms a network of multi-sided blocks resembling the skin of an alligator. The block size can range from 100 to about 300 mm.	Low: Mainly longitudinal cracks, with some transverse cracks. The diameter of the blocks falls within 30-50cm. Cracks are not spalled. Medium: Cracks form a pattern of articulated pieces that may be slightly or moderately spalled. The diameter of the blacks falls within 10-30cm. High: The diameter of the blocks is less than 10cm. Cracks are severely spalled and loosened at edges. The pieces rock under traffic and pumping may exist.
Depression	Depressions are localized areas within a pavement with elevations lower than the surrounding area. They may not be confined to wheel paths only but may extend across several wheel paths.	Low: The depression is lower than 25mm. High: The depression is deeper than 25 mm.
Rutting	Rutting is longitudinal deformation or depression in the wheel paths that occur after repeated applications of axle loading. It may occur in one or both wheel paths of a lane. The length to width ratio would normally be greater than 4 to 1.	Low: Rutting depth is lower than 25 mm; High: Rutting depth is higher than 25 mm;
Corrugation and Shoving	Corrugations are regular longitudinal undulations, closely spaced alternate valleys and crests with wavelengths of less than 2m. Shoving is permanent, longitudinal displacement of a localized area of the pavement surface caused by traffic pushing against the pavement. Traverse shoving may arise with turning movements.	Low: The difference between the valley and the crest is less than 25 mm. The height of the shoving area is less than 25 mm. High: The difference between the valley and the crest is more than 25 mm. The height of the shoving area is more than 25 mm.
Polishing and Raveling	Polishing is the smoothening of the upper surface of the road stone. The coarse aggregates are exposed and become glossy and smooth in appearance. Raveling is the wearing away of the pavement surface caused by the loss of binder or the dislodging of aggregate particles or both.	Low: Polishing. High: Raveling.
Bleeding	Bleeding is identified by a film of bituminous material on the pavement surface that creates a shiny, glass-like, reflective surface that results in less friction..	No.
Patching	Patch is an area where the pavement has been removed and replaced with a new material.	Low: Patch is in good condition and has low severity distresses of any type. High: Patch has high severity distresses of any type.
Potholes	Pothole is a bowl-shaped cavity in the pavement surface after the loss of surface materials.	Low: Depth of the pothole is less than 25 mm; High: Depth of the pothole is more than 25 mm.

rectangle of the specific distress, with the long-side of the rectangle parallel with the center line of the pavement.

(2) The formulation of PDI

The idea for the PDI formulation in this approach is graphically shown in Figure 2-4. The calculating process is broken down into a step-by-step weighing process. In mathematical form, the PDI is computed as:

$$PDI = 100 - \left\{ \sum_{c=1}^{4} \left[\sum_{i=1}^{m_c} \left(\sum_{j=1}^{n_{ic}} DV_{ijc} \cdot w_{ijc} \right) \cdot w_{ic} \right] \cdot w_c \right\} \qquad (2\text{-}9)$$

where,

100 = the highest *PDI* value, or the ceiling of the *PDI* scale;

DV_{ijc} = deduct-value for the i^{th} type, j^{th} severity level, and c^{th} category;

w_{ijc} = weight specific for DV_{ijc}, and it is given by

$$w_{ijc} = z_1 \left(DV_{ijc} \Big/ \sum_{j=1}^{n_{ic}} DV_{ijc} \right) \qquad (2\text{-}10)$$

w_{ic} = weight for the composite deduct-value for the i^{th} type, c^{th} category of distress, after the combination of the different severity-levels for that type, and category of distress. w_{ic} is given by:

$$w_{ic} = z_2 \left(\sum_{j=1}^{n_{ic}} DV_{ijc} \cdot w_{ijc} \Big/ \sum_{i=1}^{m_c} \left(\sum_{j=1}^{n_{ic}} DV_{ijc} \cdot w_{ijc} \right) \right) \qquad (2\text{-}11)$$

w_c = weight for the composite deduct-value for the c^{th} category of distress, after the combination of m_c different types, and different severity levels for each type of distresses contained in that category. w_c is given by:

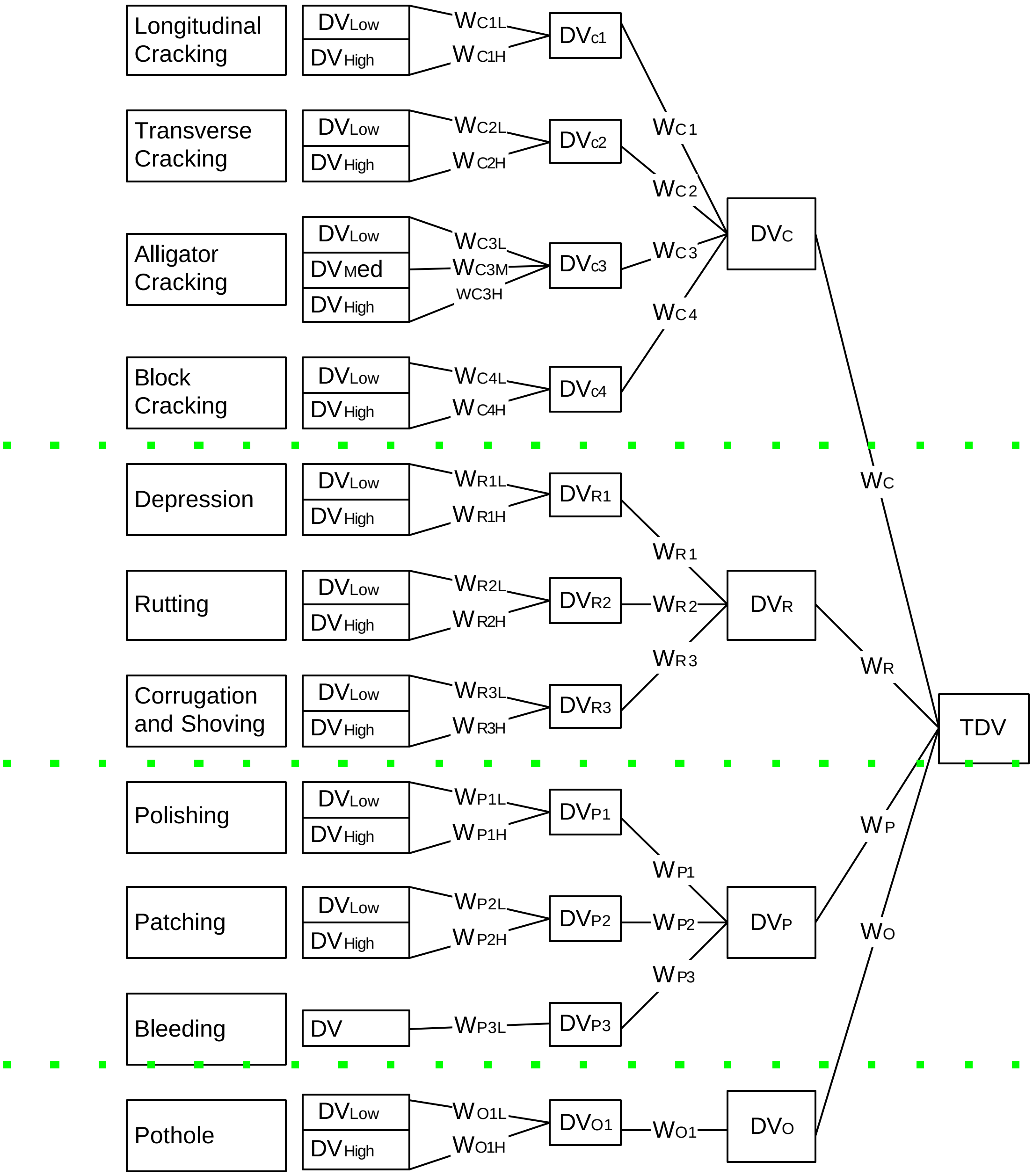

Figure 2-4. The flow-chart of PDI calculation in the China method (Sun and Yao 1991).

$$w_c = z_3\left\{\sum_{i=1}^{m_c}\left(\sum_{j=1}^{n_{ic}} DV_{ijc}\cdot w_{ijc}\right)\cdot w_{ic} \Bigg/ \sum_{c=1}^{4}\left[\sum_{i=1}^{m_c}\left(\sum_{j=1}^{n_{ic}} DV_{ijc}\cdot w_{ijc}\right)\cdot w_{ic}\right]\right\} \tag{2-12}$$

m_c = total number of distress types for category c;

n_{ic} = total number of severity levels for the i^{th} distress in the c^{th} category;

i = counter for distress types;

j = counter for distress severity levels, j=1, 2, or 3;

c = counter for distress categories, $1 \leq c \leq 4$;

(3) Determination of the weight function $z_1(\ )$, $z_2(\ )$, *and* $z_3(\ )$

Obviously, determination of these weights in Equation 2-9 is crucial for this procedure to be functional. Since pavements are rated based on the prevailing distress conditions, Sun and Yao (1991) contended that the weight for any single distress might be considered as a function of its proportion in the total distress that is present for a road section. As a matter of fact, if only one type of the distress is present, then the evaluation will be based solely on this type of distress, hence the weight for this distress will be 1.0. When there is no such distress, then this type of distress will not be considered in the evaluation process, i.e. the weight is zero. Because these weights are practically unutterable but contained in the user-rated PDI values, mathematical calculations are entailed to extract these weights. It is clear that the deduct-values and their corresponding weights are both unknown in Equation 2-9. An iterative method similar to that employed in PAVER is necessary to determine these weights. Several steps are involved in this process.

Step 1. Determine the weighting factors for different severity levels of a single distress type. Select several road sections with a single defect type, but different combinations of distress severity and density, and ask the engineers to give their ratings. The ratings are based on a 0 to 100 scale, and noted as Pavement Condition Rating (*PCR*). Assume the deduct-values for a specific distress type-severity first, and the weights for different severity levels can be determined by:

$$\sum_{j} \left| \sum_{i=1}^{2} \left(w_i \cdot DV_i \right) - \left(100 - \overline{PCR_j} \right) \right| = e \tag{2-13}$$

where,

i = the different severity levels for the single type of distress under study, i=1, 2;

j = different road sections with the same type of distress;

w_i = weight for severity level i corresponding to DV_i, given by

$$\left(DV_i \Big/ \sum_{i=1}^{2} DV_i \right) \times 100\% ; \tag{2-14}$$

PCR_j = average rating from all of the raters for road section j;

DV_i = the deduct-value for severity level i;

e = difference between *PDI* and *PCR*. If e is small enough, then the assumed DV_i and the derived w_i are acceptable. Otherwise, assume DV_i and compute w_i again, until e is satisfactorily small.

Setp 2. Repeat the process in Step 1 to obtain w_i for different DV-percentages for a single distress type within a specific distress category.

Step 3. Repeat Step 1 and Step 2 for all the other distress types to obtain single deduct-value for each type-severity of distress and the weights corresponding to their DV-percentages.

Step 4. Determine the weighting factors for the combination of different types of distresses. This step needs to use the product from the previous steps first to compute the composite deduct-value for each type of distress. Then Equation 2-14 is used for the iterative process to determine the weights for each different DV-percentage. Select road sections with different combinations of different types of distresses, ask the engineers to rate these sections and obtain the average PCR values. Use Equation 2-14 to calculate the corresponding deduct-values.

$$\sum_{l} \left| \sum_{k} (w_k \cdot \mathrm{DV_k}) - (100 - \overline{\mathrm{PCR_l}}) \right| = e \qquad (2\text{-}15)$$

where,

k = different types of distress contained in a road sample;

DV_k = composite deduct-value for distress type k by combining different severity levels in that type;

l = the different road sections with similar distress types, $l = 1, 2, \ldots, m$;

m = the total number of such road sections;

PCR_l = the average rating of the rating group for road section l.

In actual experiment, it is very difficult to obtain enough number of road sections to satisfy Equation 2-13, therefore, iterative method is inevitable, i.e., assume the deduct-value first, calculate weight value and check the value of e. If e is not small enough, then adjust deduct-values, re-calculate the weights until e is acceptable. Normally, 5% is an acceptable value for e. The obtained deduct-values are shown in Table 2-2.

When all the weight points are plotted against the DV-percentage, the researchers found that all the three functions, $z_1(\ ), z_2(\ )$, and $z_3(\ )$ can be represented using a single curve, called weight-curve as shown in Figure 2-5. A cubic polynomial fitting of the curve by this study is found to be: $w = 2.94x - 4.40x^2 + 2.45x^3$, ($r^2$=0.99) where, w is the corresponding weight for a specific deduct-value, and x is the corresponding DV-percentage. The researchers reported that the weight-curve had satisfactorily captured the rating behavior of pavement raters, and it is found to be reasonably stable across China. This weight-curve was hence used to simplify the PDI formulation process. An application reported that this weight-curve was also applicable for PDI formulation for concrete pavements (Zou et al. 1991).

2.7 Summary

Several existing deduct-value methods are reviewed in this Chapter. These include the original and modified PAVER PCI method, the Baladi's method, and the China method. As a summary, this section provides some comments on the advantages and disadvantages of these methods. The PAVER PCI method is a widely accepted and implemented method, and it has produced profound impacts on the formulation method of pavement distress index. It is valid in concept, comprehensive by nature, and simple to

Table 2-2. Deduct-values for different distresses in the China method (Sun and Yao 1991).

Distress Type-Severity Index and Description			Distress Density Index					
			1	2	3	4	5	6
		Density	0.1%	1%	5%	10%	40%	>40%
1	Longitudinal Cracking	Low	6	16	16	32	70	70
2		High	10	15	25	44	80	80
		Density	0.1%	0.5%	1%	3%	5%	>5%
3	Transverse Cracking	Low	1	6	8	18	25	25
4		High	4	9	12	25	38	38
		Density	0.1%	1%	5%	10%	50%	100%
5	Alligator Cracking	Low	8	12	18	30	50	60
6		Medium	10	14	22	35	55	70
7		High	12	17	23	45	70	90
8	Block Cracking	Low	5	8	16	25	32	40
9		High	8	12	20	35	62	68
10	Depression	Low	2	10	20	33	65	75
11		High	4	12	27	40	75	100
12	Rutting	Low	1	5	10	20	45	60
13		High	3	10	20	30	60	80
14	Corrugation/ Shoving	Low	3	6	12	25	47	70
15		High	5	12	22	35	63	90
16	Polishing/ Raveling	Low	1	3	6	12	18	20
17		High	2	6	20	40	55	60
18	Patching	Low	2	6	10	15	20	35
19		High	4	10	15	20	30	50
20	Bleeding	N/A	1	5	10	12	20	30
21	Pothole	Low	1	12	25	42	67	80
22		High	10	17	30	52	77	100

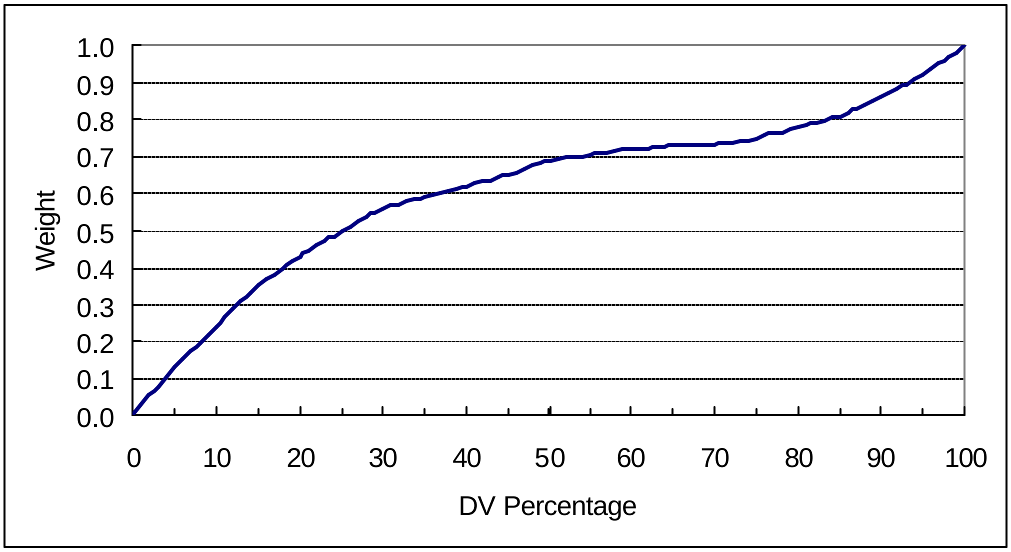

Figure 2-5. The weight-curve for the stepwise China method (Sun and Yao 1991).

use. However, some limitations of the PAVER method are also apparent. Firstly, this method is developed to be implemented throughout the U. S. Army installations, it is intended to be a default procedure, and therefore there is no calibration procedure for this method that is readily available. It originates from airport applications, and later on extends to applications for local roads and parking lots. As acknowledged by the authors, the PCI has not been validated for high-speed roads such as the interstate highways (Shahin and Kohn 1979). In addition, the construction of this method is iterative by nature, which involves the use of hypothetical samples and time-consuming calibration process afterwards. What is more important, all the resultant deduct-values are dependent on the distress definitions in PAVER, and are in fact not portable. Despite the various attempts to simplify or modify the PAVER method, the two modified PAVER Methods as introduced by MTC and StanTech, respectively has neither made it easier to be customized.

The Baladi's method is primarily intended for the formulation of individual distress indexes. It is conceptually simple and easy to implement. However, its shortcomings are also significant in several aspects: (1) It is hard to find enough field data covering the full range of densities for a particular distress, because pavement distresses are highly correlated (Hajek and Haas 1987). Based on the imagination of the panel engineers, direct rating of individual distress without field validation may be misleading. (2) It is questionable that the deduct-values for different densities may be reliably determined by linear extrapolation. Studies have shown that the relationship between deduct-values and densities is linear only in a log-log coordinate system (Jackson et al. 1996, StanTech 1999). (3) This type of deduct-values should be calibrated by actual performance curve (Jackson et al. 1996), which involves an iterative process between the engineering criteria and the performance curves. In addition, good quality performance data is also difficult to obtain. (4) The compatibility between different individual distress indexes entails careful calibration before they can form some meaningful composite indexes to enable the comparison of projects with different deterioration pattern.

The major disadvantage of the China method is its heuristic iterative method. For a typical road section, several types of distresses are common. Thus, which deduct-value should be adjusted is a big problem. The worst thing may happen is that the wrong item is adjusted, and a small enough ε is also reached. This iterative method lacks some reliable and systematic criteria. Consequently, the quality of the results may be compromised. Furthermore, the awkward distress categorization system will undoubtedly limit the applicability of this method. Unless an agency is willing to accept the distress definition dictated by this method, and also its much more computation entailed, practically, the agency is unlikely to adopt this method. However, this method is brilliant in several aspects. It incorporates rater's behavior into the PDI formulating process. In addition, this weight-curve is also found to be reasonably stable across China and applicable to other facilities such as concrete pavements. Obviously, if the weight-curve is reasonably stable, then the inter-reaction between deduct-values and their corresponding weights are severed. This would greatly simplify the formulation and customization process, so that the application of the deduct-value method may be facilitated.

Based on this review, it is clear that several steps are common to establish a PDI. First of all, a distress survey manual and procedure is developed, which determines exactly what type, severity level, and density of distresses to be collected, and how these distresses should be measured. The next step is to establish a rating scale and incorporate appropriate threshold values, i.e. at which the pavement is considered in need of repair. This rating scale can be based on values from 0 to 100, or any other ranges. The threshold value depends on the collective engineering judgement and criteria. The last step is to construct the relationships between subjective ratings and objective measurements of pavement distresses.

It is also clear that the conventional PDI formulation methods are faced with a dilemma. These methods entail time-consuming iterative processes, because the deduct-value for each defined distress and the combination schemes are both unknowns. On the other hand, the established PDI model is applicable only to the selected distress definition. Update of this distress definition may render the established model useless. As most agencies collect pavement distress information, and use PDI as an important criterion for their pavement maintenance decisions, each agency therefore needs a responsive PDI model of its own. A customizable and hence simple procedure for PDI formulation is thus highly desirable.

Chapter 3 The Proposed Procedure: Part I—Determination of the Weight-Curve

3.1 Introduction

This Chapter describes the first part of the proposed procedure. The main objective of this Chapter is to: (1) Introduce the proposed formulation, which formulates PDI as the maximum PDI value in a user-defined scale minus the Total Deduct Value (TDV), which is the sum of the product of each individual deduct-value and its corresponding weight; (2) Define the relationship between each individual deduct-value's DV-percentage and its corresponding weight as the weight-curve, and identify the existence of the weight-curve in both PAVER and China method; (3) Determine the appropriate form of the weight-curve, and verify its reasonable stability. Sample data generated according to the PAVER and China method are employed throughout this Chapter.

3.2 The Proposed Formulation

Based on the studies of PAVER and Sun and Yao (1991), a generic PDI formulation for a specific sample pavement segment is proposed as:

$$PDI = S_{PDI} - \sum_{i=1}^{M} \left(S_i \cdot DV_i \cdot w_i \right) \quad (3\text{-}1)$$

where,

S_{PDI} = maximum value of PDI in a user-defined scale of 0 to S_{PDI}. Different agencies may specify different values such as 5, 10, and 100 for S_{PDI}. S_{PDI}=100 is adopted in this dissertation unless otherwise specified;

S_i = $<b_1, b_2, \ldots, b_i, \ldots, b_M>$, which is a vector with binary elements, and $b_i \in \{0, 1\}$;

M = maximum number of type-severity-density states in the user's distress definition;

i = counter for the type-severity-density states, $1 \leq i \leq M$;

DV_i = deduct-value for the i^{th} type-severity-density distress;

w_i = weight specific to the DV-percentage of DV_i, which is given by an unknown function $f(\;)$:

$$w_i = f\left(\frac{S_i \cdot DV_i}{TDV}\right), \text{ and} \tag{3-2}$$

$$TDV = \sum_{i=1}^{M} \left(S_i \cdot DV_i\right) \tag{3-3}$$

There are several advantages associated with this formulation. First of all, it is much simpler as compared with Equation 2-9. It is thus much easier to use. This formulation is also able to accommodate any distress definitions, because it defined the weight for an individual deduct-value as a function of the quotient of the specific deduct-value over the total deduct-value of all the distresses in a specific sample. In addition, this formulation directly incorporates the human rating behavior into the PDI formulation process. The human behavior is defined as how pavement raters assign the contribution of each specific deduct-value towards the total deduct-value for a specific multi-distressed road segment. What is more, if the rating behavior of the pavement experts, i.e. the weight-curve, is assumed to be reasonably stable, Equation 3-1 will be a generically customizable formulation.

Based on the proposed formulation, PDI is now dependent on the deduct-values alone. Therefore, practitioners may calibrate the deduct-values for each distress according to their own distress definition, and obtain a totally responsive PDI. The implication of this calibration is that the time-consuming iterative process common to the establishment of both PAVER and China methods are thus eliminated. Apparently, this advantage depends on a stable rating behavior of pavement engineers.

The difficulty of the establishment of the proposed procedure lies in the identification of the unknown weight-curve, because mathematically this weight-curve may not be unique. It is very difficult to establish the weight-curve in Equation 3-1 from scratch using field samples, because the size and extent of data needed for this purpose is beyond the resources available. This may be one of the reasons why both PAVER and China methods have avoided the proposed formulation. To avoid reinventing the wheel, this study identifies the weight-curve by approaching the existing PAVER and China methods.

3.3 Overview of the Research Methodology

The approach of this research has three parts, in which the proposed procedure is established in the first two parts. In the first part, this study demonstrates the existence of the weight-curve, as defined by this study, in both PAVER and China method, and verifies its reasonable stability in both format and functional relationship. In other words, the objective of this step is to determine w_i given DV_i and PDI in the proposed formulation. In this process, sample data simulated according to both PAVER and China methods will be used.

In the second part, this study will demonstrate how individual deduct-value may be identified by making use of the reasonably stable and, hence, fixed weight-curve. The objective of this part is to determine DV_i, given w_i and PDI in the proposed formulation. The distress definition and PDI computation procedure of PAVER are used to generate the sample data.

To further elaborate the proposed procedure, the last part of this study will demonstrate how this procedure may be customized using real-world distress-survey data. This is a practical application of the proposed formulation. PDIs for real-world, as opposed to simulated, distress samples can be determined given both DV_i and w_i. Distress survey data from Minnesota will be used in this case study. The first part is detailed in this chapter, while the second and third parts will be presented in Chapters 4 and 5, respectively.

3.4 Sample Data Generation

3.4.1 Reducing the Sampling Space

A complete distress sample is composed of a series of distresses and a corresponding PDI rating. The type, severity, density, and the total number of the distresses in one sample are varied, but the type and severity are not repeated. Samples used to identify the weight-curve are randomly generated based on the PAVER method. There are altogether 19 types of distresses considered in the PAVER method for asphalt pavements. Except for the polished-aggregate distress, which has only one severity-level, all other distress-types have low, medium, and high three severity-levels. This amounts to 55 type-severity distresses. Each type-severity distress has a continuous deduct-value curve along the distress-density, which ranges from 0% to 100%.

Several steps are followed in the sample generating process. First of all, each type-severity-density distress in the PAVER method is coded with a Distress IDentification number (DID), so that each DID has a specific deduct-value. Because the density dimension for these distresses is continuous, it is digitized into 6 levels first for simplicity, i.e. 6 points are used to represent each continuous deduct-value curve. These points are chosen to best represent the curve as reported in Shahin and Kohn (1979). The chosen points are listed in Table 3-1. After the digitization, the sampling space encompasses 55x6=330 DIDs, with each DID having a specific deduct-value as illustrated in Table 3-2, called the PAVER DV-Table. It can be read from the DV-Table that different types of distresses have different deduct-values; and for the same type of distress, deduct-values increase with the increase of both distress density and severity level.

Table 3-1. Chosen digitization points for the deduct-value curves in the PAVER method.

Type-Severity Index and Description			Extent Index*					
			1	2	3	4	5	6
1	Alligator Cracking	Low	0.1%	1%	5%	10%	50%	100%
2		Medium	0.1%	1%	5%	10%	50%	100%
3		High	0.1%	1%	5%	10%	50%	100%
4	Block Cracking	Low	1%	1%	5%	10%	50%	100%
5		Medium	0.5%	1%	5%	10%	50%	100%
6		High	0.1%	1%	5%	10%	50%	100%
7	Corrugation	Low	0.1%	1%	5%	10%	50%	100%
8		Medium	0.1%	1%	5%	10%	50%	100%
9		High	0.1%	1%	5%	10%	50%	100%
10	Longitudinal/Transverse	Low	2%	5%	10%	20%	50%	100%
11	Cracking	Medium	0.5%	5%	10%	20%	50%	100%
12		High	0.3%	5%	10%	20%	50%	100%
13	Patching/Utility Cut	Low	0.3%	1%	5%	10%	20%	50%
14	Patching	Medium	0.1%	1%	5%	10%	20%	50%
15		High	0.1%	1%	5%	10%	20%	50%
16	Rutting	Low	0.1%	1%	5%	10%	50%	100%
17		Medium	0.1%	1%	5%	10%	50%	100%
18		High	0.1%	1%	5%	10%	50%	100%
19	Weathering and Raveling	Low	0.5%	1%	5%	10%	50%	100%
20		Medium	0.1%	1%	5%	10%	50%	100%
21		High	0.1%	1%	5%	10%	50%	100%
22	Bleeding	Low	1%	1%	5%	10%	50%	100%
23		Medium	0.1%	1%	5%	10%	50%	100%
24		High	0.1%	1%	5%	10%	50%	100%
25	Bumps and Sags	Low	0.35%	1%	5%	10%	20%	35%
26		Medium	0.35%	1%	5%	10%	20%	35%
27		High	0.35%	1%	5%	10%	20%	35%
28	Depression	Low	0.1%	1%	5%	10%	50%	100%
29		Medium	0.1%	1%	5%	10%	50%	100%
30		High	0.1%	1%	5%	10%	50%	100%
31	Edge Cracking	Low	0.35%	1%	5%	10%	20%	60%
32		Medium	0.35%	1%	5%	10%	20%	60%
33		High	0.35%	1%	5%	10%	20%	60%
34	Joint Reflection Cracking	Low	1.5%	5%	10%	20%	50%	100%
35		Medium	0.3%	5%	10%	20%	50%	100%
36		High	0.3%	5%	10%	20%	50%	100%
37	Lane Shoulder Dropoff	Low	1.5%	5%	10%	20%	30%	50%
38		Medium	1.5%	5%	10%	20%	30%	50%
39		High	1.5%	5%	10%	20%	30%	50%
40	Polished Aggregates	N/A	2.5%	5%	10%	20%	50%	100%
41	Potholes	Low	0.1%	1%	5%	10%	50%	100%
42		Medium	0.1%	1%	5%	10%	50%	100%
43		High	0.1%	1%	5%	10%	50%	100%
44	Railroad Crossing	Low	1%	3%	5%	10%	20%	50%
45		Medium	1%	3%	5%	10%	20%	50%
46		High	1%	3%	5%	10%	20%	50%
47	Slippage Cracking	Low	0.1%	1%	5%	10%	50%	100%
48		Medium	0.1%	1%	5%	10%	50%	100%
49		High	0.1%	1%	5%	10%	50%	100%
50	Shoving	Low	0.4%	1%	5%	10%	20%	50%
51		Medium	0.1%	1%	5%	10%	20%	50%
52		High	0.1%	1%	5%	10%	20%	50%
53	Swell	Low	1%	3%	5%	10%	20%	30%
54		Medium	1%	3%	5%	10%	20%	30%
55		High	1%	3%	5%	10%	20%	30%

*: Each extent index represents a specific percentage of distressed area for different types of distresses in a sample.

Table 3-2. Deduct-values for every distress in the PAVER method.

Type-Severity Index and Description			Extent Index*					
			1	2	3	4	5	6
1	Alligator Cracking	Low	5	11	26	33	53	62
2		Medium	8	22	39	47	68	78
3		High	12	30	54	62	82	91
4	Block Cracking	Low	0	0	5	9	20	28
5		Medium	0	3	11	17	34	43
6		High	0	8	20	30	59	71
7	Corrugation	Low	1	2	8	12	30	39
8		Medium	5	16	31	40	62	74
9		High	10	34	51	61	85	94
10	Longitudinal/Transverse Cracking	Low	0	4	8	12	20	29
11		Medium	0	11	18	27	37	44
12		High	0	23	34	50	73	87
13	Patching/Utility Cut Patching	Low	0	2	10	17	23	33
14		Medium	2	10	22	31	41	58
15		High	7	20	38	51	68	80
16	Rutting	Low	1	9	21	28	46	50
17		Medium	5	19	36	44	63	68
18		High	7	29	49	61	85	90
19	Weathering and Raveling	Low	0	1	3	5	12	16
20		Medium	4	9	13	19	35	43
21		High	6	16	30	41	69	78
22	Bleeding	Low	0	0	1	3	12	20
23		Medium	1	3	9	13	29	40
24		High	2	7	15	23	55	72
25	Bumps and Sags	Low	0	3	10	18	29	40
26		Medium	0	12	29	41	60	80
27		High	0	34	60	72	89	100
28	Depression	Low	5	5	10	18	41	49
29		Medium	9	9	19	30	57	60
30		High	11	18	30	44	69	74
31	Edge Cracking	Low	0	2	4	5	9	15
32		Medium	5	6	10	14	20	28
33		High	8	9	16	24	34	46
34	Joint Reflection Cracking	Low	0	4	7	10	18	27
35		Medium	0	10	17	26	38	42
36		High	0	20	31	49	69	72
37	Lane Shoulder Dropoff	Low	0	0	4	7	19	26
38		Medium	0	4	10	17	39	42
39		High	0	10	20	32	69	72
40	Polished Aggregates	N/A	0	1	4	7	12	20
41	Potholes	Low	2	20	44	55	84	100
42		Medium	7	31	68	87	100	100
43		High	20	52	88	100	100	100
44	Railroad Crossing	Low	2	4	7	12	17	20
45		Medium	7	18	27	39	46	50
46		High	20	38	50	68	77	80
47	Slippage Cracking	Low	0	4	19	27	46	53
48		Medium	2	11	32	44	63	70
49		High	4	19	51	67	86	91
50	Shoving	Low	0	4	14	20	28	36
51		Medium	3	10	25	35	49	64
52		High	8	19	38	52	66	80
53	Swell	Low	2	7	9	11	17	20
54		Medium	12	21	27	35	44	50
55		High	34	40	45	53	64	70

*: Each extent index represents a specific percentage of distressed area for different types of distresses in a sample.

According to the PAVER method, the sampling space may be further reduced by the fact that the maximum deduct number for a single sample is no more than seven. However, even after these two reductions, the possibilities of forming a sample are still extremely large. For example, there are C_1^{330}=330 possibilities for a single type-severity sample; While for a two type-severity sample, the possibilities will be the permutation of C_2^{330}=54285, and for a 7 type-severity sample, the possibilities will be the permutation of C_7^{330}=7.931345505e^{13}.

3.4.2 Generating the Random Samples

It is impractical for this study to explore such extremely large sample space entirely. Random process is therefore used to generate samples. Three pseudo random numbers are used in this process. The first number is used to generate the total number of distresses in one sample, which ranges from 1 to 7. The next one produces random numbers between 1 and 55, representing each distress type-severity. The third one generates random numbers between 1 and 6, representing the six digitized density levels for each type-severity distress. The combination of the last two random numbers corresponds to a unique deduct-value as listed in Table 3-2. For example, “53” and “6” combination will point to a deduct-value of “20”. This is a low-severity “swell” distress, with the highest density level, which constitutes one distress in a sample. The combination of the last two random numbers also corresponds to a unique DID. For the example above, the DID will be $((53-1)\times 6+6)$, which is “318”. A fixed random seed is used in order to make this process repeatable.

A C++ program is developed to generate these samples. The flow chart of this program is shown in Figure 3-1. Because not every sample generated randomly is viable, two constraints are used in the program to rule out some unpractical samples. The first constraint is that the TDV should not exceed 166, 180, and 200, for two-distress, three-distress, and four-or-more-distress samples, respectively. The rationale for these TDV caps are that the U. S. Army Corps Engineers had not observed those roads with a higher TDV in their study. These specific values are based on the corrected curves in PAVER (Shahin and Kohn 1979). The other constraint is that no same type-severity distress may exist in one sample. As the possibility of a totally repeated sample is very low, it is not enforced as a criterion in this study. For a single type-severity sample, the probability of such a repetition is 1/330=0.3%, and for a seven type-severity sample, the probability is $1/C_7^{330}$, which is practically zero.

3.4.3 Verifying the Randomness of the Generated Samples

As some constraints have been enforced during the sample generating process, it is necessary to check the randomness of the generated samples. This verification process may include two aspects. The first aspect is the verification of whether every one of the 330 DIDs has been sampled uniformly, so that each individual DID will have an equal opportunity in building samples. On the other hand, for a group of generated samples, the frequency of samples composed of different number of distresses are also checked for their uniformity. In other words, a 1-distress, 2-distress, or a 7-distress sample should enjoy an equal opportunity of being sampled.

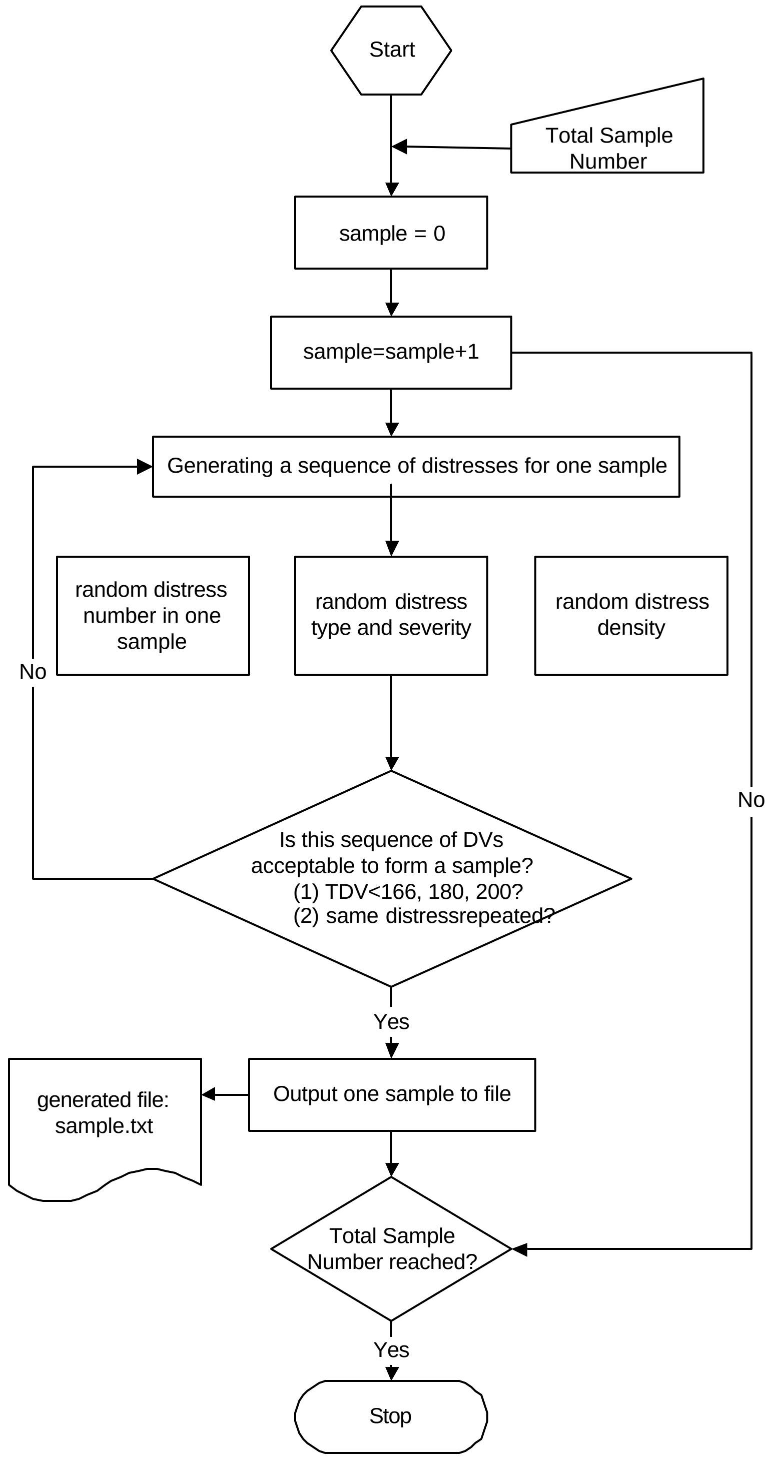

Figure 3-1. Flow chart of the program for random sample generating.

20,000 samples are generated using the PAVER DV-Table. Table 3-3 shows an example sheet of 20 such generated samples. These samples are separated sequentially into 10 groups, with 2,000 samples in each group. Each group is taken as the result from a separate sampling process. According to these 10 repeated sampling processes, the observed average frequency, and standard deviation for 1-distress, 2-distress, …, 7-distress samples, are listed in Table 3-4. The theoretical average frequency should be 2,000/7=285.71. Statistical t-tests for mean are conducted for each type of samples, and the results are also tabulated in Table 3-4. Clearly, these t-tests support that these different types of samples have been sampled uniformly at a 99% significance level. The plot in Figure 3-2 shows the variation of these average frequencies.

Table 3-3. An illustration of the generated DV-sequence data (20 samples).

Sample Number	DV1	DV2	DV3	DV4	DV5	DV6	DV7	PDI*
1	18	27	2	4	27	49	1	34.5
2	9							91
3	3	34	10	2				71.49
4	4	2	3	60	40	69		13.4
5	4	4	74	40	8	68	1	11.2
6	5	33	40	4	59	8	7	28.4
7	11	7	17					80.25
8	50	2	59	43	4	2		14.6
9	26	61	14	1	17	4		36
10	55	9						53.2
11	7	17	51	9	38	2	22	30
12	9	67	8	10	33			33.5
13	7	4						91.97
14	47	10	44					35.5
15	67	39						26.4
16	4							96
17	8	44	35					44.45
18	87	9						32.4
19	8	31	3	16	42			43
20	26	12	51	8	39	17	41	18.6

* PDI is calculated using the PAVER method.

Table 3-4. Sample randomness study: randomness of number of distress in one sample.

Number of Distress in One Sample	Average Frequency for 10-times Sampling	Standard Deviation	t-statistics
1	278.80	15.30	1.43*
2	289.40	14.67	0.79
3	291.00	7.76	2.15
4	288.40	10.29	0.83
5	281.70	17.49	0.73
6	288.50	19.72	0.45
7	282.20	13.99	0.79

Note: *is calculated using theoretical mean 2000/7=285.71, critical t-value =3.0 at 99% significance level.

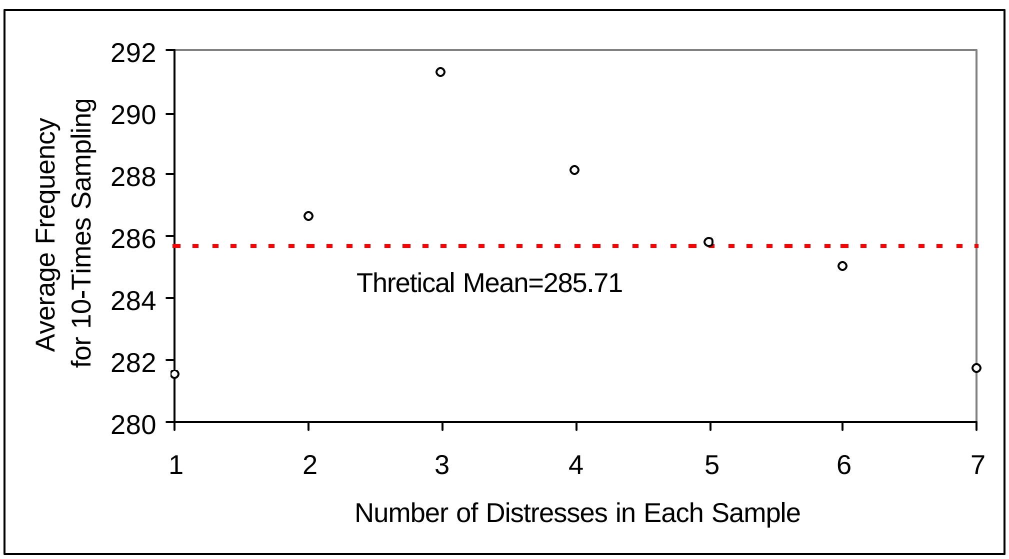

Figure 3-2. Sample randomness examination: average frequency for different types of samples.

For the ten groups of samples, the average frequency, or observed mean, and standard deviation for each DID are calculated and tabulated in Table 3-5. It is noticed that the frequencies for some DIDs are recorded as zero. This is due to the fact that there are 25 zero deduct-values among the 330 DIDs in the PAVER DV-Table as shown in Table 3-2. They have actually been excluded from the sampling process. Except for these zero frequencies, the rest frequencies also depict a wide range, from 9 to 35, which is shown in Figure 3-3. Because different types of samples are uniformly sampled, each type of sample has a probability of 1/7 of being sampled. Therefore, the average number of distresses in each individual sample should be:

$\left(\frac{1}{7}\times 1+\frac{1}{7}\times 2+\frac{1}{7}\times 3+\frac{1}{7}\times 4+\frac{1}{7}\times 5+\frac{1}{7}\times 6+\frac{1}{7}\times 7\right)=4$. The theoretical mean for each DID in the 2000 sample group should be $\left(\frac{2000\times 4}{330-25}\right)=26.23$. Statistic t-tests are conducted for each DID to verify whether significant difference exists between the theoretical and observed means. The results for these t-tests are also tabulated in Table 3-5. In order to save space, only an excerpt is shown. The results show that around 40% of these DIDs are not uniformly sampled, or the observed frequency is significantly different from the theoretical mean at a 95% significance level. The entire result is plotted in Figure 3-3 with the theoretical mean drawn in a solid line. According to our observation, DIDs with a very high deduct-value, say more than 60, or very low deduct-value, say less than 5 are prone to be less sampled. This can be ascribed to the confinement of the TDV caps, which renders DIDs with very high deduct-values easily discarded. Furthermore, as those survived samples with larger deduct-value is usually

Table 3-5. Sample randomness study: randomness of each DID.

DID Number	Average Frequency for 10-times Sampling	Standard Deviation	t-statistics
1	26.40	4.14	0.83
2	27.40	3.72	1.77
3	23.80	4.44	1.08
4	23.80	3.94	1.22
5	22.10	4.79	2.12
6	18.50	4.60	**4.49***
7	28.70	6.91	1.55
8	28.30	6.34	1.49
9	25.40	6.45	0.04
10	22.50	3.98	2.24
11	18.70	2.45	**8.53**
12	16.20	3.36	**8.58**
13	26.80	6.86	0.68
14	28.50	5.19	1.94
15	20.80	3.26	**4.38**
16	18.50	4.95	**4.35**
17	15.50	3.21	**9.68**
18	13.20	2.49	**15.42**
19	0.00	0.00	N/A**
20	27.60	4.53	1.60
21	30.60	4.95	**3.38**
22	29.60	5.15	2.63
23	25.60	3.72	0.24
24	25.20	4.02	0.09
	intentionally omitted to save space		
327	19.90	4.31	**3.98**
328	20.50	4.99	**3.05**
329	18.20	2.49	**9.05**
330	16.80	4.49	**6.00**

Notes: *t-value is greater than critical t-value=2.76 at 99% significance level. **zero deduct-value in PAVER, not sampled.

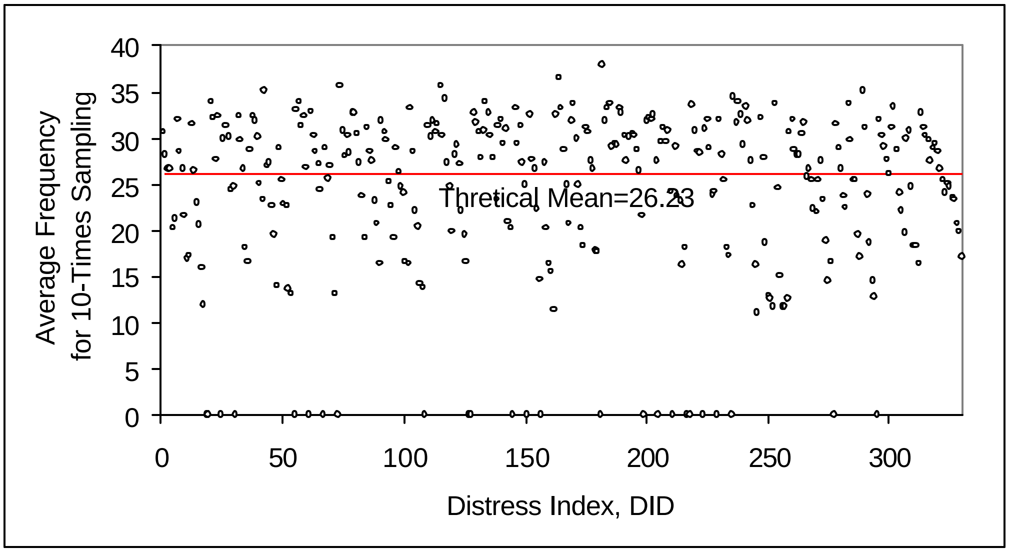

Figure 3-3. Sample randomness examination: average frequency for each DID.

accompanied by DIDs with smaller deduct-values, DIDs with a smaller deduct-value is hence easily underrepresented.

The generated samples may have reflected the actual pattern of pavement distress samples. As no agency will let its roads fail before scheduling some maintenance, a smaller content of DIDs with very high deduct-values is practically sound. However, data generated in this way does not reflect the bias common to a particular distress. Since pavement distresses are region-specific, the actual distress samples from a specific region may be biased, i.e. samples are dominated by some distresses more frequently occurred under the specific climate or load conditions. For example, in the State of Minnesota, thermo-cracking may be present in virtually every sample, and apparently this type of distress will be under-represented by the proposed sampling scheme. As it is hard to determine the extent to which a specific distress is biased for a specific region, it is extremely difficult to simulate these biases. The regional phenomenon of data is not simulated in this study.

3.5 Determination of the Shape of the Weight-Curve

3.5.1 The Formulation

Determination of the weight-curve is to determine the relationship between each DV-percentage and its corresponding weight. To be specific, it is to find a mapping function from DV-percentages to their weights as has been done differently in the China method. Based on the available PAVER method, the problem can be formulated as an optimization process in order to minimize the difference between the output from the proposed formulation and that from PAVER (S_{PDI} is set to 100). Mathematically speaking, this is to approach the PAVER method using the proposed formulation:

$$Min.\, e = \sum_{k=1}^{K}\left(\left(\sum_{i=1}^{M}(S_{ki}\cdot DV_{ki})\right)\cdot F(TDV_k, q) - \sum_{i=1}^{M}(S_{ki}\cdot DV_{ki}\cdot w_{ki})\right)^2 \quad (3\text{-}4)$$

where,

e = the total squared sum of the differences between the PDIs from the two methods;

S_{ki} = <b_{k1}, b_{k2}, …, b_{km}, …, b_{kM}>, which is a vector with binary elements, and $B_{km} \in \{0, 1\}$;

DV_{ki} = deduct-value for DID number i, in sample k;

$$TDV_k = \sum_{i=1}^{M}(S_{ki}\cdot DV_{ki}), \quad (3\text{-}5)$$

which is the sum of all the individual deduct-values contained in sample k;

$F(TDV_k, q)$ = the adjustment function in the PAVER method;

$$w_{ki} = f\left(\frac{S_{ki} \cdot DV_{ki}}{TDV_k}\right), \tag{3-6}$$

i.e. the corresponding weight for the DV-percentage of DV_{ki} is determined by an unknown function $f(\ )$. w_{ki} is the decision variable.

M = the maximum number of DIDs, which is 330 as defined in the PAVER method;

i = counter for the number of DIDs;

k = counter for sample numbers; and

K = total number of samples.

q = the same meaning as defined in Equation 2-1;

Apparently, without assuming the shape of the mapping function $f(\ )$, this least-square formulation is impossible to be solved directly. However, it is unwarranted to assume any shape of the weight-curve at this stage. Therefore, the problem is re-formulated in order to solve for some discreet points on the mapping function, and then obtain the mapping function by a curve-fitting process. If the mapping function is digitized into 101 corresponding points, and only integer DV-percentage values from 0% to 100% are considered, the problem will become the determination of the 101 corresponding values of v_h (0 =h=100) on the unknown function $f(\ )$. These v_h are determined when the summed squared error between the output from PAVER and the proposed method for K samples is minimized. Equation (3-4) may be reformulated as:

$$Min.e = \sum_{k=1}^{K}\left(\left(\sum_{i=1}^{M}(S_{ki} \cdot DV_{ki})\right) \cdot F(TDV_k, q) - \sum_{i=1}^{M}(S_{ki} \cdot DV_{ki} \cdot v_h)\right)^2 \tag{3-7}$$

Where,

$$v_h = f(h), \tag{3-8}$$

which is the decision variable, and

$$h = \text{int}\left(\frac{S_{ki} \cdot DV_{ki}}{TDV_k} \times 100\right) \tag{3-9}$$

where,

int( ) = integer operation.

3.5.2 Solution Techniques

Equation 3-7 is intentionally configured as an unconstrained non-linear programming problem. No constraint, even the range of each weight, which should logically be between 0 and 1, is enforced. The program is supposed to anneal by itself, so that the actual rating behavior may be captured. Non-linear programming techniques are the conventional choices in solving Equation 3-7. Since the function $f(\ )$ is unknown, the derivative of Equation 3-7 is non-existent. Therefore, only derivative-free techniques are feasible for this application. Among a host of derivative-free techniques, the direct search method as described by Hooke and Jeeves (1961) was selected and implemented for this study.

3.5.3 The Hooke-Jeeves Direct Search Method

Direct search is an important method for non-linear programming. It is conceptually simple. It works by changing one variable at a time while keeping all the others constant until the minimum is reached. For example, one method would set one of the variables, say x_1, constant and vary x_2 until a minimum was obtained. Then keeping the new value of x_2 constant, change x_1 until an optimum for the value of x_2 is achieved, and so on. The search directions for optimization is determined solely from successive evaluations of the objective function $y(x)$, where x is a vector. As compared with algorithms based on the evaluation of first and possibly second derivatives, direct search method requires much less problem preparation effort. Although the search method may execute slower than its counterparts making use of derivatives, it may cost less to implement and hence more satisfactory in the user's view of point (Himmelblau 1972).

Hooke and Jeeves (1961) proposed a logically simple strategy of search that made use of prior knowledge and at the same time rejected obsolete information concerning the nature of the topology of the objective function. This algorithm, as described by Himmelblau (1972) operates by two major phases, an exploratory search around the base point (the base point is the vector of initial guesses of the independent variables for the first iteration), and a pattern search in a direction selected for minimization. Before the exploratory search, all the elements of x and the initial incremental change Δx are initialized. To initiate an exploratory search, $y(x)$ is evaluated at the base point, and then each variable is changed in rotation, one at a time, by incremental amounts, until all the parameters have been so changed. To be specific, $x_1^{(0)}$ is changed by an amount $+\Delta x_1^{(0)}$, so that $x_1^{(1)} = x_1^{(0)} + \Delta x_1^{(0)}$. If $y(x)$ is reduced, $x_1^{(0)} + \Delta x_1^{(0)}$ is adopted as the new element in x. If the increment fails to improve the objective function, $x_1^{(0)}$ is changed by $-\Delta x_1^{(0)}$, and the value of $y(x)$ again checked as before. If the value of $y(x)$ is not improved by either

$x_1^{(0)}+\Delta x_1^{(0)}$ or $x_1^{(0)}-\Delta x_1^{(0)}$, $x_1^{(0)}$ is left unchanged. Then $x_2^{(0)}$ is changed by an amount $\Delta x_2^{(0)}$, and so on, until all the independent variables have been changed to complete one exploratory search. For each step or move in the independent variable, the value of the objective function is compared with the value at the previous point. If the objective function is improved for the given step, then the new value of the objective function replaces the old one in the testing. However, if a perturbation is a failure, then the old value of $y(x)$ is retained.

After making one (or more) exploratory searches in this fashion, a "pattern search" is made. Based on the successfully changed variables (i.e. those variable changes that decreased $y(x)$ a pattern search direction for minimization may be defined. A series of pattern searches is made along this vector as long as $y(x)$ is decreased by each pattern search. The magnitude of the step for the pattern search in each coordinate direction is roughly proportional to the number of successful steps previously encountered in each coordinate direction during the exploratory searches for several previous iterations. The change in step size, Δx, in the pattern search is taken as some multiple of the Δx used in the exploratory searches in order to accelerate the search. An exploratory search conducted after a pattern search is termed a type II exploratory search, and the success or failure of a pattern move is not established until after the type II exploratory search has been completed.

If $y(x)$ is not decreased after the type II exploratory search, the pattern search is said to fail, and a new type I exploratory search is made in order to define a new successful direction. If the type I exploratory search fails to give a new successful direction, Δx is reduced gradually, until either a new successful direction can be defined or each Δx_i becomes smaller than some preset tolerance. Failure to decrease $y(x)$ for a very small Δx indicates that a local optimum has been reached. Three basic tests must be satisfied for the sequence of searches to terminate. The first test occurs after each exploratory search and pattern search—the change in the objective function is compared with a prespecified small number. If the value of the objective did not vary by an amount more than the specified number from the previous base value of the objective function, the exploratory search or pattern search is considered a failure. In the absence of such a failure, a test is made to determine if the objective function was increased (a failure) or decreased (a successful search). This second test ensures that the value of the objective function is always being improved. The third test is conducted after an exploratory-search failure on the fractional change in Δx. The search can terminate if the change in each variable, $\Delta x_i^{(k)}$, is less than some prespecified number (Himmelblau 1972).

3.6 Preliminary Results and Analysis

A computer program was developed based on another by Johnson (1994) to implement the Hooke and Jeeves direct search algorithm. The user's guide for this program was documented in Appendix of this dissertation. A number of runs using the program were conducted. A series of randomly generated values between 0 and 1 were used as the initial guess of the 101 decision variables. The program would terminate when the minimum changes between the last two consecutive iterations were less than a threshold value of 0.1. Six sample sizes, namely 100, 300, 500, 1000, 2000, 20000 simulated according to the PAVER method were studied.

It is found that starting values sorted in an ascending fashion could speed up the converging process. Although no constraints have been applied, the final results satisfy the constraints reasonably well. It is rare that values less than 0, or above 1 would appear in the solution. When the determined 101 decision variables, or the mapped weights are charted against the corresponding DV-percentages, the results from different sample sizes depict quite similar trends. The results for the sample size of 100, 1000, and 20,000 are shown in Figure 3-4. It can be seen that the DV-percentage is not linearly mapped to the weight, because the curve these discreet points fit is not a straight line. However, DV-percentage and the mapped weight do display some positive proportional relationship. A larger DV-percentage will always correspond to a larger weight, and vice versa. It can also be observed from Figure 3-4 that sample size has very little effects on the shape depicted by these discreet points. These results support the existence of a weight-curve associated with the PAVER method. A sample size of 1000 may well determine the non-linear shape of the weight-curve. Larger sample size will not result in a significantly different shape of the weight-curve. Experiments with curve-fitting software show that these points can be represented by a series of polynomial, and better fit can be reached by increasing the degree of the polynomial.

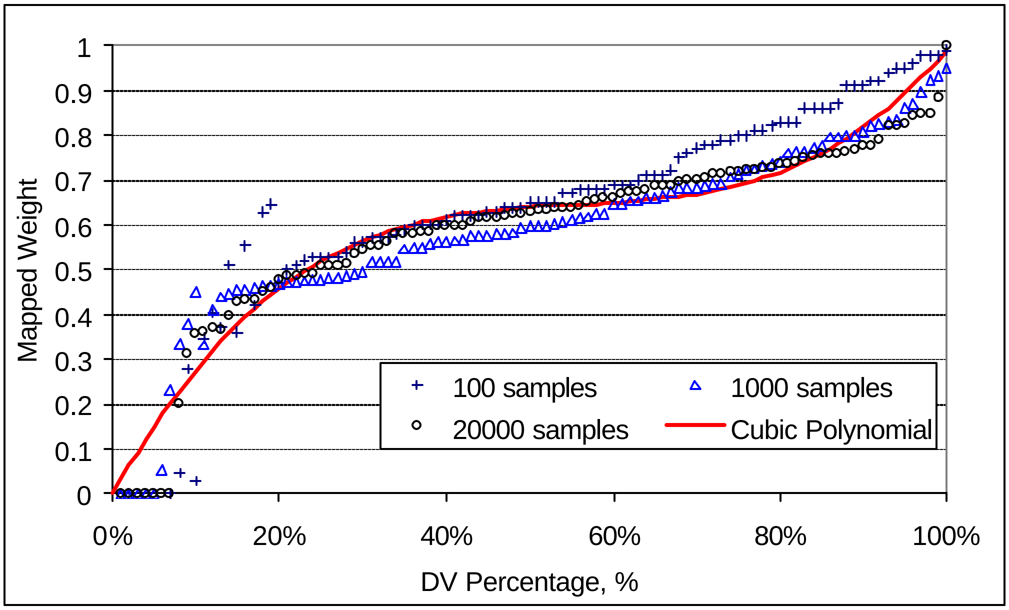

Figure 3-4. Weight-curve associated with the PAVER method.

In order to corroborate this finding, this research also identified the existence of the weight-curve in the stepwise China method (Sun and Yao 1991). A similar formulation to Equation 3-5 was initiated to use the proposed formulation to approach the China method as introduced in Chapter 2. The formulation is:

$$Min.e = \sum_{k=1}^{K}\left(\sum_{c=1}^{4} S_{kc}\cdot\left[\sum_{i=1}^{m_c} S_{kci}\cdot\left(\sum_{j=1}^{n_{ic}} S_{kcij}\cdot DV_{kcij}\cdot w_{kcij}\right)\cdot w_{kci}\right]\cdot w_{kc} - \sum_{p=1}^{N} S_{kp}\cdot DV_{kp}\cdot v_h\right)^2$$

(3-10)

where,

S_{kc} = <b_{k1}, …, b_{kr}, …, b_{k4}>, which is a vector with binary elements, and $B_{kr} \in \{0, 1\}$;

S_{kci} = <b_{k11}, …, b_{krs}, …, b_{k4m_c}>, which is a vector with binary elements, and $B_{krs} \in \{0, 1\}$;

S_{kcij} = <b_{k111}, …, b_{krst}, …, $b_{k4m_c n_{ic}}$>, which is a vector with binary elements, and $B_{krst} \in \{0, 1\}$;

S_{pk} = <b_{k1}, …, b_{ku}, …, b_{kN}>, which is a vector with binary elements, and $B_{ku} \in \{0, 1\}$;

N = maximum number of DIDs, N=22×6=132 as defined in Table 2-2;

p = counter for DIDs;

k and K are as defined in Equation 3-4;

all undefined variables are as that defined previously.

The term v_h in this formulation was also solved by the Hooke and Jeeves direct search technique (Hooke and Jeeves 1961). Sample data generated according to the DV-Table of the China method were used. Refer to Table 2-2. After plotting these weights against the corresponding DV-percentage, a very similar weight-curve to that shown in Figure 3-4 is obtained, refer to Figure 3-5. The weight-curve is a monotonously increasing function, which can be fitted closely by a polynomial. It was found that sample size has very little effect on the shape of the weight-curve, unless it is very small, say less than 100.

These two studies show that both the PAVER and China method can be approached by the proposed formulation, using a polynomial-shaped weight-curve. In fact, these two weight-curves are pretty similar despite that the PAVER weight-curve displays a flatter middle part. For any DV-percentage, the maximum difference of the mapped weight between these two weight-curves is 0.09, refer to the imposed PAVER weight-curve in

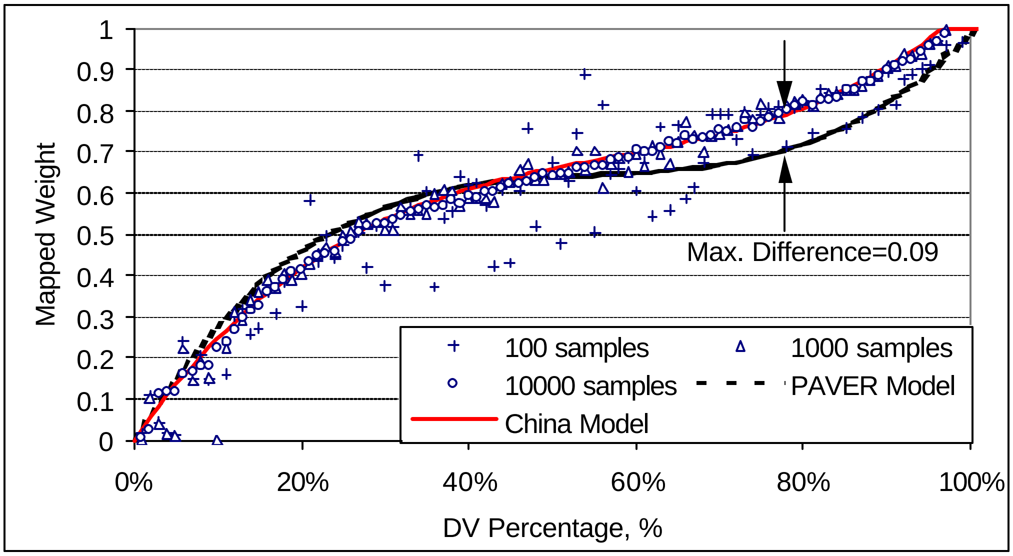

Figure 3-5. Weight-curve associated with the China method.

Figure 3-5. The weight-curve characterizes the way in which pavement raters convert DV-percentage into weight, or the contribution from a specific distress among a series of other distress for a road sample. Despite the fact that there is little similarity between the PAVER and China method in their distress definition, geographical location, and pavement raters, they both possess a similar weight-curve. This fact indicates that the rating behavior for the U. S. Army and China Engineers are similar: higher DV-percentage receives higher weight, and lower DV-percentage maps to lower weight. This reasonably stable behavior may be used as the anchorage for PDI formulation. This constitutes the foundation of the proposed procedure.

3.7 Determination of the Weight-Curve as a Polynomial

3.7.1 The Formulation and Solution

Based on the ascertained shape of the weight-curve, this study further obtained the continuous mapping relationship using the conventional Least Squared Estimation (LSE) technique. For Equation 3-1, if the weight-curve, the w_{ki} is assumed to be a L^{th} degree polynomial function of DV-percentage, h_{ki}, and let

$$h_{ki} = \frac{S_{ki} \cdot DV_{ki}}{TDV_k} \text{, then} \tag{3-11}$$

$$w_{ki} = f(h_{ki}) = \sum_{l=1}^{L} a_l \cdot h_{ki}^l \text{ ,} \tag{3-12}$$

where,

l = counter for the degree of the polynomial, and l=1, 2, …, L.

Therefore, the setup in Equation 3-4 becomes

$$Min.\, e = \sum_{k=1}^{K} \left(Z_k - \sum_{l=1}^{L} (a_l \cdot Y_{kl}) \right)^2 \tag{3-13}$$

Where,

$$Z_k = \sum_{i=1}^{M} S_{ki} \cdot DV_{ki} \cdot F(TDV_k, q) \text{, and} \tag{3-14}$$

$$Y_{kl} = \sum_{i=1}^{M} S_{ki} \cdot DV_{ki} \cdot h_{ki}^l \text{ ,} \tag{3-15}$$

a_l = coefficient for the L^{th} degree polynomial equation of the weight-curve.

The formulation in Equation (3-13) is a typical multi-linear regression formulation as shown in Equation (3-16).

$$\mathbf{Z_k} = \mathbf{aY^T} \tag{3-16}$$

where,

a = the matrix of the regression coefficients.

Given $\mathbf{Z_k}$, and $\mathbf{Y^T}$, **a** can be determined using the classical LSE technique. A multi-linear regression analysis program is developed to determine a_l (l=1, 2, …, L) in this study. The program has been successfully validated using a popular Statistics Software package called JMP (version 3.2.5) by SAS Institute Inc.

3.7.2 Why 3rd Polynomial?

In order to identify an appropriate degree of the polynomial for the weight-curve, a series of polynomial curves with different degrees are used to fit the sample data based on LSE. These include 1st, 2nd, 3rd, 4th, 5th, 6th, and 7th degree Polynomials. As suggested by Figure 3-4 and Figure 3-5, 1000 is chosen to be the sample size to identify the appropriate degree of polynomials to represent the weight-curve, because this size of sample has produced quite comparable trends to larger sample sizes. The regression coefficients and r^2 values for these different weight-curves are determined using the self-developed multi-linear regression program. The results are tabulated in Table 3-6, and the corresponding weight-curves are plotted and compared in Figure 3-6.

As Table 3-6 shows it that except the first and second-degree polynomials, all the other polynomials provide a very good fit to the samples (the r^2 value is no less than 0.97 for

Table 3-6. Regression results for different types of polynomials (1000 samples, PAVER method).

Power	a_0	a_1	a_2	a_3	a_4	a_5	a_6	a_7	r^2	F
1st	16.57	1.06	----	----	----	----	----	----	0.63	831.88
	zeroed	1.40	----	----	----	----	----	----	N/A	N/A
2nd	8.74	1.92	-1.26	----	----	----	----	----	0.91	3346.93
	zeroed	2.14	-1.34	----	----	----	----	----	N/A	N/A
3rd	5.13	3.09	-5.43	3.23	----	----	----	----	0.97	9284.54
	zeroed	**3.30**	**-5.77**	**3.46**	----	----	----	----	N/A	N/A
4th	4.85	3.51	-7.99	7.81	-2.45	----	----	----	0.98	7913.60
	zeroed	3.78	-8.82	8.95	-2.95	----	----	----	N/A	N/A
5th	4.71	4.61	-17.87	36.91	-36.98	14.24	----	----	0.98	7394.08
	zeroed	4.94	-19.30	39.82	-39.60	15.12	----	----	N/A	N/A
6th	4.44	3.04	1.48	-46.41	125.80	-133.00	50.04	----	0.98	6994.06
	zeroed	3.14	2.80	-55.11	145.66	-152.40	56.90	----	N/A	N/A
7th	4.47	2.32	12.86	-112.34	311.04	-404.15	248.50	-57.31	0.98	6151.15
	zeroed	2.60	11.46	-105.27	286.57	-358.58	207.79	-43.57	N/A	N/A

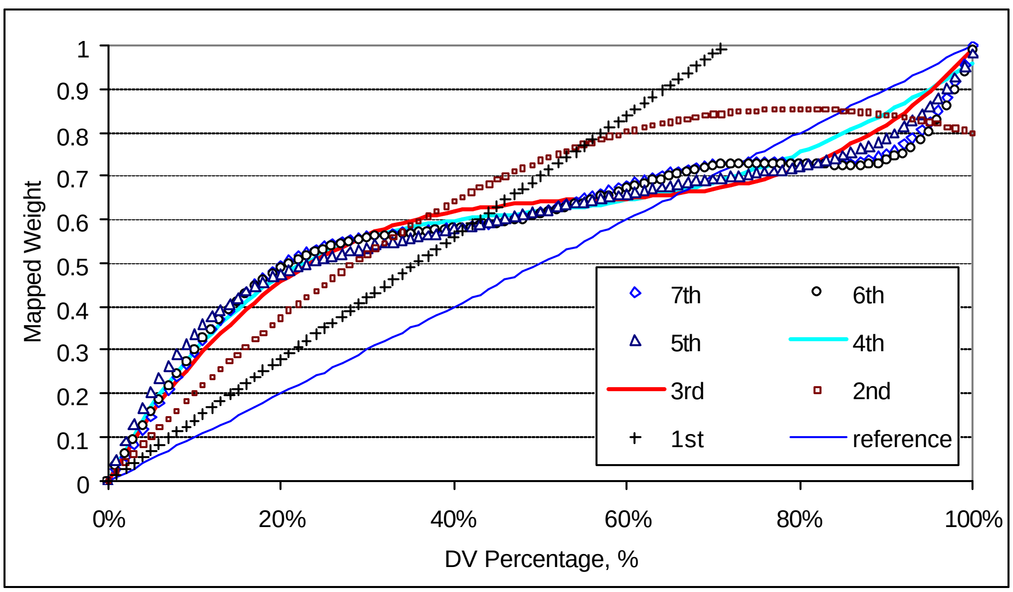

Figure 3-6. Selection of the 3^{rd} polynomial as the weight-curve for the PAVER method.

1000 samples). This indicates that the weight-curve is polynomial-shaped, other than a straight line or a parabola. As the weight-curve will logically pass the origin, the constant coefficient from the regression analysis are zeroed. For the 6^{th} and 7^{th} degree of polynomials, although they both have very high r^2 values, they are not selected. This is because these two polynomials display some additional curvatures, which causes difficulty in the practical interpretation of these curves. Their application also entails much more computation than a lower degree curve. The third-degree polynomial, though the simplest in format, gives quite comparable performance (r^2=0.97) to all the other higher degree polynomials. Therefore, the 3^{rd} polynomial is a better choice.

Logically, the weight-curves should also cross the (100%, 1.0) point, as shown in Figure 3-6. However, this constraint is not enforced during the regression analysis. This is because this enforcement during regression will result in the choice of some higher order weight-curves. Instead, the (100%, 1.0) point is enforced as an isolated boundary condition. In real applications, if only one distress exists, then the weight will be enforced to be 1.0, no matter what the output is from the weight-curve function. Indeed, every output from the weight-curve that is greater than 1.0 is also enforced to be equal to 1.0, because a weight that is greater than 1.0 is meaningless. This is true for several points in the China weight-curve as shown in Figure 3-5.

In order to investigate the stability of the cubic weight-curve with respect to sample sizes, a series of sample sizes are used to generate the cubic polynomial. These include 100, 300, 500, 1000, and 20000 samples. The regression results are tabulated in Table 3-7,

Table 3-7. The cubic weight-curves as determined using different sample sizes.

Sample Size	a_0	a_1	a_2	a_3	r^2	F
100	6.15	3.16	-5.79	3.48	0.97	811.83
	zeroed	3.43	-6.31	3.88	N/A	N/A
300	4.32	3.18	-5.70	3.42	0.98	3589.56
	zeroed	3.38	-6.09	3.72	N/A	N/A
500	4.59	3.17	-5.69	3.44	0.97	4484.05
	zeroed	3.36	-5.99	3.64	N/A	N/A
1000	5.13	3.09	-5.43	3.23	0.97	9284.54
	zeroed	3.30	-5.77	3.46	N/A	N/A
2000	4.29	3.17	-5.62	3.37	0.98	21070.82
	zeroed	3.34	-5.92	3.57	N/A	N/A
20000	4.62	3.16	-5.63	3.38	0.98	201623.47
	zeroed	3.35	-5.95	3.60	N/A	N/A

which shows very little difference in the coefficients. The two curves from 100, and 20,000 samples are plotted in Figure 3-7. The maximum difference between these two curves is just 0.025, which is practically insignificant. Therefore, the choice of 1000 as the sample size to generate the cubic polynomial is valid.

The stability of the cubic weight-curve with respect to the number of distress considered is also investigated. Samples generated using only seven types of distress as used in the MTC modified PAVER method are used to derive the cubic polynomial. Table 3-8 tabulates the regression coefficients for the obtained cubic polynomials. Sample sizes such as 100, 300, 500, 1000, and 2000 are employed. It can be seen that the coefficients from different sample sizes do not change significantly. The cubic weight-curve derived by 1000 samples is compared with its counterpart by using all 19 types of distress in Figure 3-8. The two weight-curves virtually overlap, and the maximum difference recorded is 0.0016, which is practically zero. This shows that the consolidation of the 19

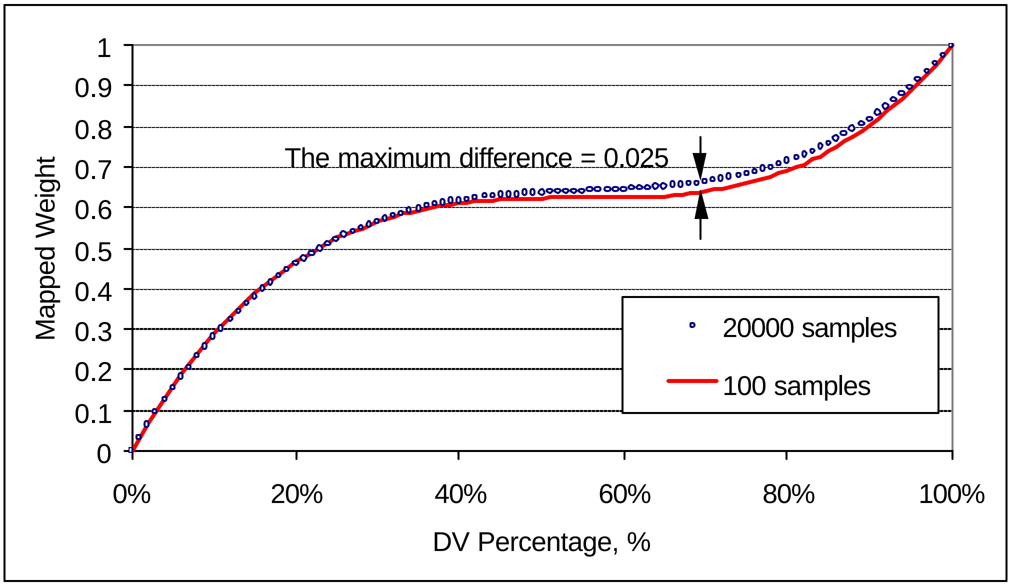

Figure 3-7. Influence of sample size on the shape of the cubic polynomial weight-curve.

Table 3-8. Cubic weight-curves determined using 7 types of distresses only in the modified PAVER method by MTC.

Sample Size	a_0	a_1	a_2	a_3	r^2	F
100	3.45	3.21	-5.69	3.43	0.98	1288.95
	zeroed	3.35	-5.93	3.59	N/A	N/A
300	6.25	3.05	-5.30	3.11	0.97	2413.53
	zeroed	3.30	-5.71	3.39	N/A	N/A
500	5.10	3.14	-5.59	3.36	0.98	4904.07
	zeroed	3.34	-5.90	3.57	N/A	N/A
1000	4.77	3.14	-5.56	3.32	0.98	10556.93
	zeroed	3.32	-5.84	3.51	N/A	N/A
2000	4.97	3.13	-5.54	3.31	0.98	20257.14
	zeroed	3.33	-5.84	3.51	N/A	N/A

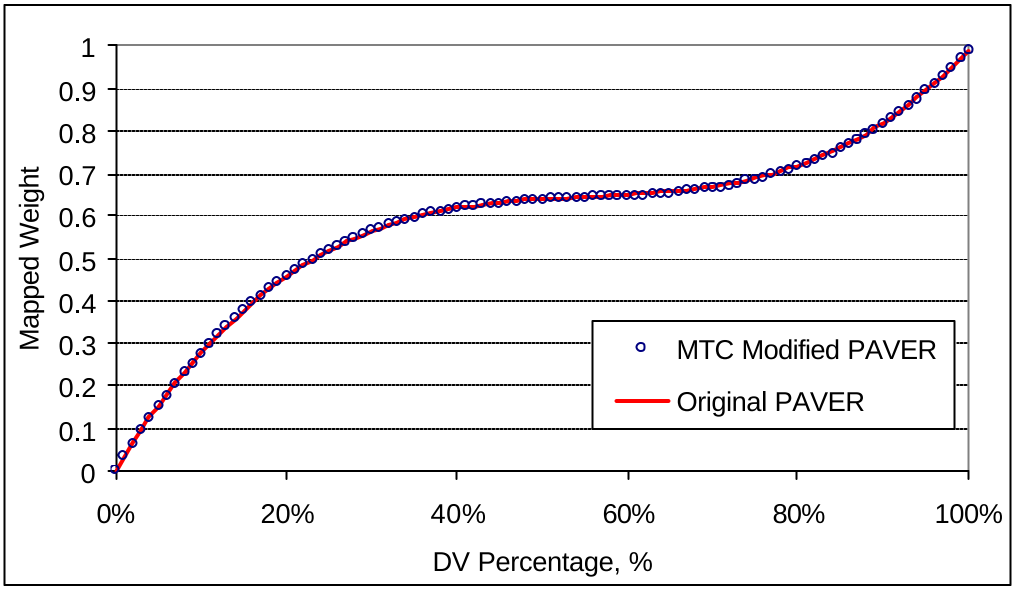

Figure 3-8. Difference between the cubic polynomial weight-curves obtained by considering different types of distresses.

distress types does not affect the shape of the cubic weight-curve associated with the PAVER method. It is believed that this conclusion holds for any subset of the 19 PAVER distresses, because PAVER method is valid for any subset of the 19 types of distress.

In order to further support that cubic polynomial is a better choice, weight-curves with different degrees of polynomials extracted from the China method are compared. 1000 is used as the standard sample size. The regression results are listed in Table 3-9 and shown in Figure 3-9. It is clear that the cubic polynomial almost overlaps with all the other weight-curves, except the 1st and 2nd degree weight-curves. As it is the simplest to use, the cubic is a better choice as the degree of the weight-curve. The influence of sample sizes for the cubic polynomials was also examined. The results as tabulated in Table 3-10

Table 3-9. Regression results for different degrees of polynomials for the China Method (1000 samples).

Power	a_0	a_1	a_2	a_3	a_4	a_5	a_6	a_7	r^2	F
1st	9.39	1.20	----	----	----	----	----	----	0.78	1817.68
	zeroed	1.40	----	----	----	----	----	----	N/A	N/A
2nd	3.42	1.93	-1.09	----	----	----	----	----	0.95	6023.77
	zeroed	2.02	-1.13	----	----	----	----	----	N/A	N/A
3rd	0.73	2.84	-4.35	2.56	----	----	----	----	0.98	11964.7
	zeroed	**2.87**	**-4.41**	**2.60**	----	----	----	----	N/A	N/A
4th	0.59	3.06	-5.69	4.95	-1.28	----	----	----	0.98	9760.68
	zeroed	3.09	-5.81	5.10	-1.34	----	----	----	N/A	N/A
5th	0.60	3.00	-5.15	3.33	0.65	-0.80	----	----	0.98	8128.46
	zeroed	3.04	-5.34	3.72	0.30	-0.68	----	----	N/A	N/A
6th	0.51	2.40	2.20	-28.06	61.63	-55.76	18.63	----	0.98	7033.09
	zeroed	2.40	2.47	-29.56	64.90	-58.87	19.72	----	N/A	N/A
7th	0.49	1.66	13.74	-94.53	247.57	-326.97	216.68	-57.11	0.98	6180.95
	zeroed	1.65	14.28	-97.63	255.33	-336.69	222.64	-58.53	N/A	N/A

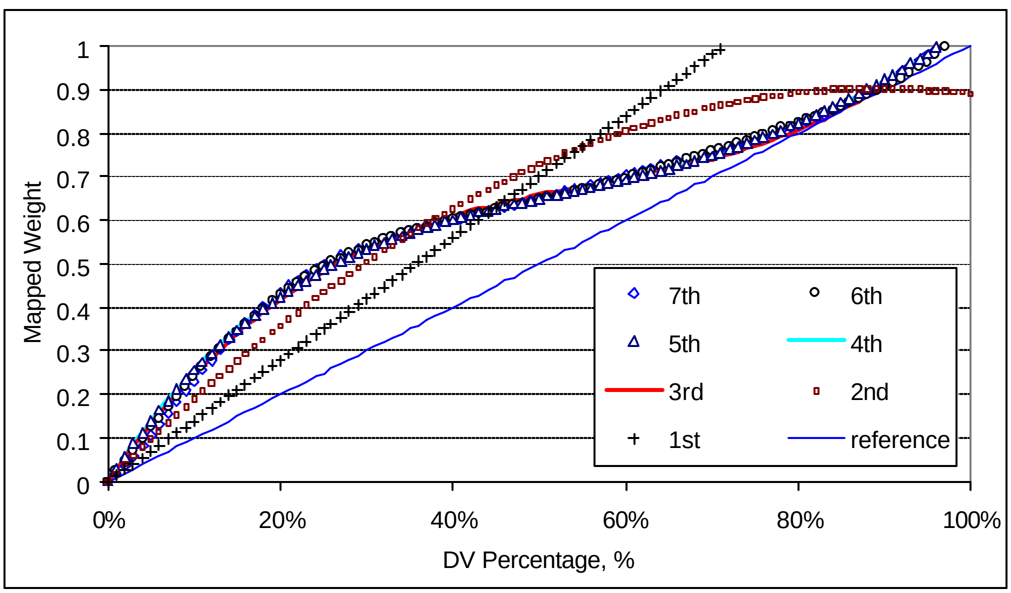

Figure 3-9. Comparison for weight-curves in different degrees of polynomials for the China method.

Table 3-10. Cubic weight-curves determined using samples from the China method.

Sample Size	a_0	a_1	a_2	a_3	r^2	F
100	0.983	2.85	-4.47	2.67	0.98	1220.10
	zeroed	2.89	-4.53	2.72	N/A	N/A
300	1.02	2.83	-4.36	2.58	0.98	4151.95
	zeroed	2.87	-4.44	2.63	N/A	N/A
500	0.63	2.84	-4.35	2.56	0.98	6715.57
	zeroed	2.87	-4.40	2.60	N/A	N/A
1000	0.73	2.84	-4.35	2.56	0.98	11964.70
	zeroed	2.87	-4.41	2.60	N/A	N/A
2000	0.84	2.83	-4.33	2.55	0.98	22624.23
	zeroed	2.87	-4.40	2.59	N/A	N/A
10000	0.85	2.82	-4.30	2.52	0.98	111071.16
	zeroed	2.86	-4.37	2.57	----	----

show that sample sizes have little effect on the obtained weight-curves, and 1000 samples are sufficient to determine a cubic weight-curve.

3.8 Stability of the Weight-Curve

It is true that the PAVER and China weight-curve in Figure 3-5 look similar in shape. It is the objective of this section to examine the quantitative difference between the two weight-curves, so that the stability of the weight-curve can be apprehended quantitatively. Take 101 points from the continuous cubic polynomial weight-curve corresponding to 0% to 100% of DV-percentage, and plot the difference between the two weight-curves with the DV-percentage in Figure 3-10. It can be seen that the difference between the two weight-curves is sigmoid. All the differences are within the range of

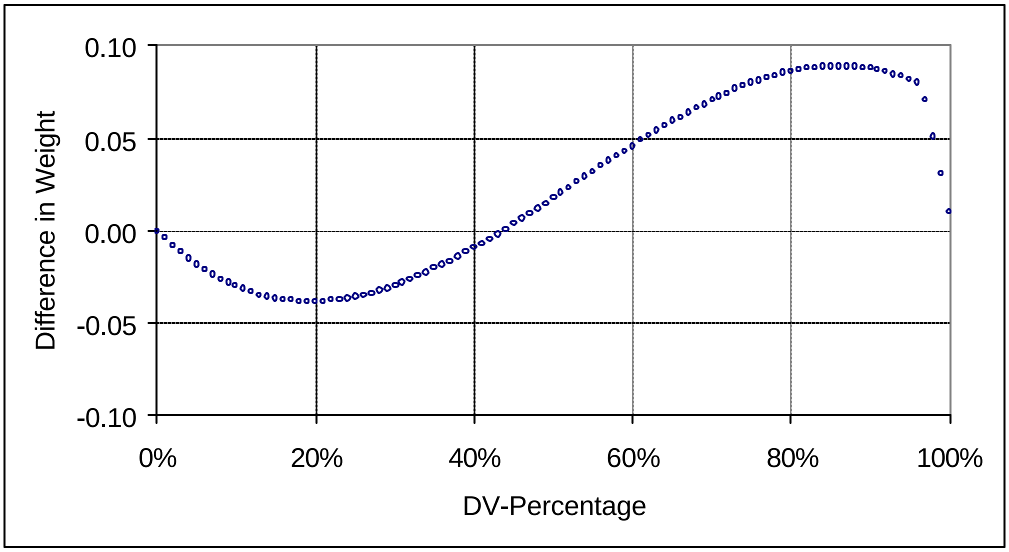

Figure 3-10. Difference between the two weight-curves.

-0.04 to +0.09. The two peak differences are reached at 20% and 80% DV-percentage, respectively.

The difference in weights may be transferred into the difference in total deduct-value, and hence PDI. For the extreme case, one deduct-value equals to 100, and it takes up to 80% of the total deduct-value in the sample, the variation in PDI caused by different weight-curves will be 9-points. The extreme case may happen actually in the rating according to a single distress. A 9-point difference is quite reasonable for the findings from two studies in different parts of the world. Indeed, this extreme case is rare. Most of the deduct-values for a single distress will be less than 100, and a single deduct-value seldom takes up to 80% of the total deduct-value. So most of the time, the variation in PDI will not go beyond 9-points.

These claims were verified using 1000 simulated data according to PAVER. Based on the same set of deduct-values in PAVER, the generated PDIs according to different weight-curves were plotted and compared in Figure 3-11. It is found that 95%, and 88% of the time, the difference between the two PDIs are less than 6-points, and 5-points, respectively. The range of the difference is –9 to +8-points. This result shows that the variation in the obtained PDI caused by interchanging the two weight-curves is acceptable.

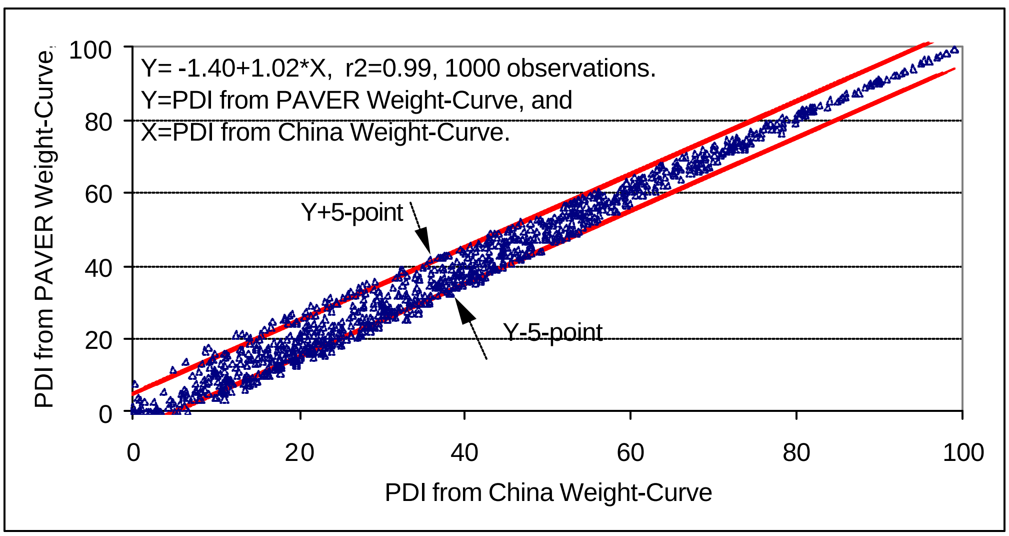

Figure 3-11. Impacts of interchanging the two weight-curves.

This finding also indicates that expressed in the weight-curve as defined in this study, the human rating behavior is pretty stable. As these two weight-curves were rooted in two independent studies, it could be inferred that the weight-curve from other similar studies should not be very much different from these two. Therefore, an agency may elect to use any of the two existing weight-curves as the default weight-curve in the formulation of its own PDI. This will not cause much lost in its own rating behavior, but will help eliminate the cumbersome iterative process of PDI formulation when starting from scratch.

It should be pointed out that adoption of a default weight-curve is different from the adoption of an entire default model, such as PAVER. The error introduced by adopting a default weight-curve may be roughly quantified, while the error by adopting an entire default model may be extremely difficult to discern and quantify. Not to mention the possible incompatibility of the default model with the specific situations of an agency. In addition, adopting a default weight-curve will not compromise the obtained PDI, because the error introduced is borne entirely by the deduct-values to be determined. If the weight-curve from the PAVER or China method is adopted, the error for an individual deduct-value will not go beyond 15-points in the worst case, as will be reported later in Chapter 4.

3.9 Conclusions

The first part of the proposed procedure is described in this Chapter. A generalized PDI formulation procedure is proposed using the weight-curve concept. It is concluded that the weight-curve as defined in this study is existent in both the PAVER and China methods. This weight-curve may be obtained by approaching the PAVER and China method using the proposed method. The unconstrained Hooke and Jeeves' direct search technique is proved to be simple, efficient, and effective in identifying the weight-curve. A cubic polynomial is found to be the simplest satisfactory shape of the weight-curve.

The weight-curve is shown to be reasonably stable, because the weight-curves associated with the PAVER and China methods are quite similar both graphically and quantitatively. The variation in PDI caused by interchanging the two weight-curves will not be more than 6-points on a 0 to 100 scale at 95% of the time. This finding has significant implications for the formulation of PDIs. A simple customization process may supersede the complicated formulation process. The two interacting parts in the proposed PDI formulation may be calibrated separately. Or more simply, PDI may be formulated by fixing the weight-curve and adjusting individual deduct-values only.

Chapter 4 The Proposed Procedure: Part II—Determination of the Individual Deduct-Values

4.1 Introduction

This Chapter describes the second part of the proposed procedure. The objective of this Chapter is twofold: (1) Introduce how to use the Broyden algorithm to extract the deduct-values based on a fixed weight-curve; and (2) Evaluate the performance of the proposed procedure in reproducing user-rated PDI. This Chapter is taken as an illustration of the proposed procedure, which is customized using user data simulated based on the PAVER method.

4.2 The Formulation

As the next integral step of the proposed procedure, deduct-values for individual DIDs have to be determined. By fixing the weight-curve, this problem may be formulated as an optimization process, i.e. deduct-values are determined when the total squared sum of the difference between the user-rated PDI and that produced by the proposed method for a series of samples is minimized. This can be expressed mathematically in the following form:

$$Min.\, e = \sum_{k=1}^{K}\left(PDI_k - \left(100 - \sum_{i=1}^{M}\left(S_{ki} \cdot DV_{ki} \cdot w_{ki}\right)\right)\right)^2 \tag{4-1}$$

St.

$$0 = DV_{ki} = 100, \qquad i=1, 2, \ldots, M \tag{4-2}$$

$$DV_{ki}=DV_{k(i+1)}, \qquad (j\text{-}1)\times 6+1 \le i \le (j\text{-}1)\times 6+6,\ j=1, 2, \ldots, 55; \tag{4-3}$$

$$DV_{ki}=DV_{k(i+6)}, \qquad (j\text{-}1)\times 3+1 < i \le (j\text{-}1)\times 3+3, \text{ for } j=1, 2, \ldots, 13; \text{ and}$$

$$(j\text{-}1)\times 3 < i \le (j\text{-}1)\times 3+2,\ j=15, 16, \ldots, 19; \tag{4-4}$$

By incorporating the weight-curve, Equation 4-1 may be rewritten as:

$$Min.\ \ e_{(DV_1, DV_2, \ldots, DV_M)} = \sum_{k=1}^{K}\left(PDI_k - \left(100 - \sum_{i}^{M}\sum_{l}^{L}\left(S_{ki}\cdot DV_{ki}\cdot a_l \cdot h_{ki}^{l}\right)\right)\right)^2 \tag{4-5}$$

where, ε is considered a function of all the defined DIDs. Equation 4-5 is constrained by not only the range for each deduct-value, but also the logical sequence for the deduct-values for a specific type of distress with different levels of severity and density. Equation 4-5 constitutes the other indispensable part of the proposed procedure. It is able to accommodate direct user distress survey data, and derive the deduct-values for each individual type-severity-density distress as defined by the user, based on a reasonably stable weight-curve when the objective function is minimized. Although Equation 4-5 may be used alternatively to determine a new weight-curve, it is not recommended, unless this update is justified by dedicated studies comparable to PAVER or Sun and Yao (1991).

4.3 Sample Data Preparation

Sample data simulated according to the PAVER method is used. The same algorithm for sample generating as described in Chapter 3 is adopted. Each typical sample is composed of a series of coded Distress IDentification number (DID) and a corresponding user-rated PDI. The number of DIDs in each sample is random. The user-rated PDI here is actually the PAVER_PCI, which is the rating of the U. S. Army Corps of Engineers. An excerpt of such DID sequence sample is shown in Table 4-1. Table 4-1 and Table 3-3 are inter-related by the PAVER DV-Table in Table 3-2. For example, the DID "148" at the upper-left corner of Table 4-1, its corresponding deduct-value is taken from the 25th, i.e. $((148-\mathrm{mod}(148,6))/6+1)$ row and 4th, i.e. $(\mathrm{mod}(148,6))$ column of Table 3-2, which is 18. mod(,) is an operation returning only the remainder of the division operation. For example, mod(148, 6) equals 4. The format of distress data has been designed based on the actual format of distress survey data from the State of Minnesota, North Carolina (North Carolina DOT 2000), and Washington (Kay et al. 1993, Jackson 1993). This will facilitate the possible implementation of the developed procedure.

Two independent sample groups with each having 5000, and 2000 samples, respectively have been prepared. The 5000 samples are used to identify a sufficient sample size for the Broyden algorithm to determine all those deduct-values, and the 2000 samples are used as a test set to investigate performance of the obtained deduct-values. Table 4-1 and Table 3-3 is just used to show the inter-relationship between the DV-sequence data and DID-sequence data. It does not mean that the same set of data is used for the extraction of both the weight-curve and also the individual deduct-values.

Table 4-1. Illustration of a DID-sequence sample (20 samples).

Sample Number	DID1	DID2	DID3	DID4	DID5	DID6	DID7	PDI*
1	148	267	139	224	280	305	91	34.5
2	194							91
3	134	197	206	74				71.49
4	289	79	111	174	326	179		13.4
5	115	224	48	326	57	102	37	11.2
6	164	78	138	289	35	57	314	28.4
7	316	201	76					80.25
8	324	313	35	30	115	259		14.6
9	208	106	297	37	76	237		36
10	244	116						53.2
11	238	317	88	135	309	259	8	30
12	169	292	57	230	4			33.5
13	247	289						91.97
14	10	75	286					35.5
15	292	268						26.4
16	237							96
17	7	243	322					44.45
18	72	185						32.4
19	193	82	146	114	228			43
20	222	131	291	32	9	207	167	18.6

* PDI is calculated using the PAVER method.

4.4 Solution Technique: The Broyden Algorithm

4.4.1 Why Broyden Algorithm?

Equation 4-5 is a complex constrained non-linear programming problem. The complexity of the problem lies first in its extremely large solution space. For the simulated user data, there are altogether 330 decision variables, with each variable having a possible solution of from 0 to 100. The problem may also be highly non-linear, depending on the degree of polynomial chosen for the weight-curve. For the simplest cubic weight-curve, the formulation is in the forth order of each decision variable. In addition, the large number of constraints that need to be enforced make the problem even more complicated. For example, every deduct-value should be within the range of 0 to 100. For the same type of distress, the deduct-value should logically increase when both the severity and density level increases. Based on this analysis, the technique chosen should have robust search capability to avoid the local optima that occur frequently for a non-linear programming problem. It should also be able to handle the large number of constraints effectively.

There are many conventional methods that may be employed to solve Equation 4-5, such as the direct search, or derivative-based algorithms. As a general rule, gradient and second-derivative methods converge faster than direct search methods (Himmelblau 1972). The setup in Equation 4-5 is definitely differentiable. It is sensible to employ faster derivative-based method. Termed as a quasi-Newton method, the Broyden method is by nature second derivative based. Therefore, it enjoys the robustness and efficiency of the second derivative method. However, it makes use only of the first derivative information, which saves the trouble of computing the second derivative and inverting the Hessian matrix. In addition, the performance of the unconstrained Broyden algorithm was identified to be superior, in terms of robustness, number of functional evaluations, and effectiveness, or computer time to termination (to within the desired degree of precision). Broyden algorithm was also found to perform better for more difficult problems than some best-known algorithms such as the Davidon-Fletcher-Powell (DFP) algorithm (Himmelblau 1972). Therefore, the Broyden algorithm is adopted in this study.

4.4.2 Description of the Broyden Algorithm

A general nonlinear programming problem without constraints may be formulated as

Min. $f(x)$, $x \in E^n$ (4-6)

where,

$f(x)$ = the objective function. The objective of the minimization process is to seek a stationary point of $f(x)$, that is the first derivative $\nabla f(x^*) = 0$, so that $f(x)$ is minimized.

What conventional non-linear programming methods have to determine is to specify the effective search direction and walking step toward the optimal point x^*. Specifically, this is to determine how to transit from a point $x^{(k)}$ at the k^th^ stage of the search to another point $x^{(k+1)}$, that is:

$$x^{(k+1)} = x^{(k)} + \Delta x^{(k)} = x^{(k)} + l^{(k)}\hat{s}^{(k)} = x^{(k)} + l^{*(k)}s^{(k)} \tag{4-7}$$

where,

$\Delta x^{(k)}$ = the walking step, which is a vector from $x^{(k)}$ to $x^{(k+1)}$;

$\hat{s}^{(k)}$ = a unit vector in direction $\Delta x^{(k)}$;

$s^{(k)}$ = any vector in direction $\Delta x^{(k)}$;

$l^{(k)}$, $l^{*(k)}$ = scalars such that

$$\Delta x^{(k)} = l^{(k)}\hat{s}^{(k)} = l^{*(k)}s^{(k)} \tag{4-8}$$

Depending on how the search direction and step length are determined, there are a variety of algorithms. The best-known Newton method makes use of second-derivative information, and specify both the search direction and step length by

$$x^{(k+1)} = x^{(k)} - \left[\nabla^2 f\left[x^{(k)}\right]\right]^{-1} \nabla f\left[x^{(k)}\right] \quad \text{, or} \tag{4-9}$$

$$x^{(k+1)} = x^{(k)} - l^{(k)} \frac{\left[\nabla^2 f\left[x^{(k)}\right]\right]^{-1} \nabla f\left[x^{(k)}\right]}{\left\| \left[\nabla^2 f\left[x^{(k)}\right]\right]^{-1} \nabla f\left[x^{(k)}\right] \right\|}, \text{ or} \tag{4-10}$$

$$x^{(k+1)} = x^{(k)} - l^{*(k)} \; H^{-1}\left[x^{(k)}\right] \nabla f\left[x^{(k)}\right] \tag{4-11}$$

where, H is the Hessian matrix of the objective function, defined as:

$$H\left[x^{(k)}\right] = \nabla^2 f\left[x^{(k)}\right] = \begin{bmatrix} \frac{\partial^2 f\left[x^{(k)}\right]}{\partial x_1^2} & \cdots & \frac{\partial^2 f\left[x^{(k)}\right]}{\partial x_1 \partial x_n} \\ \cdots & \cdots & \cdots \\ \frac{\partial^2 f\left[x^{(k)}\right]}{\partial x_n \partial x_1} & \cdots & \frac{\partial^2 f\left[x^{(k)}\right]}{\partial x_n^2} \end{bmatrix} \tag{4-12}$$

The essence of the Broyden method is to approximate the Hessian matrix or its inverse using only first-order derivatives. This saves the trouble of the computation of the second partial derivatives of the objective function, and also the inversion of the Hessian matrix. The algorithm computes a new x vector from the one on the preceding stage by an equation analogous to Equation 4-7:

$$x^{(k+1)} = x^{(k)} + l^{(k)} \, \hat{s}^{(k)} = x^{(k)} - l^{*(k)} \, h\left[x^{(k)}\right] \nabla f\left[x^{(k)}\right] \tag{4-13}$$

where, $h\left[x^{(k)}\right]$ is called the direction matrix and represents an approximation to the inverse of the Hessian matrix.

Let $h\left[x^{(k)}\right] \equiv h^{(k)}$, (4-14)

$h^{(k+1)} = h^{(k)} + \Delta h^{(k)}$, and (4-15)

let $\Delta h^{(k)}$ be a symmetric matrix with a rank of 1, Broyden (1967, cited in Himmelblau 1972) determined that

$$\Delta h^{(k)} = \frac{\left[\left(\Delta x^{(k)}\right) - h^{(k)}\left(\Delta g^{(k)}\right)\right]\left[\left(\Delta x^{(k)}\right) - h^{(k)}\left(\Delta g^{(k)}\right)\right]^T}{\left[\left(\Delta x^{(k)}\right) - h^{(k)}\left(\Delta g^{(k)}\right)\right]^T\left(\Delta g^{(k)}\right)} \tag{4-16}$$

where,

$$\left(\Delta x^{(k)}\right) = x^{(k+1)} - x^{(k)} \tag{4-17}$$

$$\left(\Delta g^{(k)}\right) = \nabla f\left[x^{(k+1)}\right] - \nabla f\left[x^{(k)}\right] \tag{4-18}$$

Equation 4-16 can be used as the recursive relations to calculate $h^{(k)}$ or to calculate $\hat{s}^{(k)}$ in Equation 4-13. In the simplest algorithm the minimization starts by choosing $x^{(0)}$ and $h^{(0)} > 0$, and then applying Equation 4-13, Equation 4-15, and Equation 4-16 in sequence until, say $\| \nabla f\left[x^{k}\right] \| < e$, where ε is a prespecified precision.

4.4.3 The First Derivative

Although the Broyden method does not require the information on second derivatives, it does entail the derivation of the first derivatives. For the objective function shown in Equation 4-5, the analytical first derivative can be derived as

$$\frac{\partial e}{\partial DV_t} = 2 \cdot \sum_{k=1}^{K} \left\{ \begin{aligned} &\left(PDI_k - \left(100 - \sum_{i}^{M} \sum_{l}^{L} \left(S_{ki} \cdot DV_{ki} \cdot a_l \cdot h_{ki}^{l} \right) \right) \right) \cdot \\ &\qquad \sum_{i}^{M} \sum_{l}^{L} a_l \cdot \left[(l+1) \cdot h_{ki}^{l} \cdot f_1(t) - l \cdot h_{ki}^{(l+1)} \cdot f_2(t) \right] \end{aligned} \right\} \tag{4-19}$$

where,

DV_t = the deduct-value for DID number t;

t = 1, 2, …, 330 for the current problem;

$$f_1(t) = \frac{\partial}{\partial DV_t}\left(S_{ki} \cdot DV_{ki}\right) = \begin{cases} 1, & if\ i = t,\ and\ S_{kt} = 1; \\ 0, & otherwise. \end{cases} \tag{4-20}$$

$$f_2(t)=\sum_{i=1}^{M}\left[\frac{\partial}{\partial DV_t}\left(S_{ki}\cdot DV_{ki}\right)\right]=\begin{cases}1, & if\ S_{kt}=1;\\ 0, & otherwise.\end{cases} \tag{4-21}$$

All undefined parameters are as defined previously.

Apparently, the derivative for each DV_t ($0\le t\le 330$, with each t corresponding to a DID) is obtained by summing up all the components contained in the K samples. The computer codes for the Broyden's algorithm as implemented by Himmelblau (1972) is referred to, but rewritten in order to implement in the Visual Basic® 5.0 environment.

4.4.4 Constraints Handling

As shown in Equation 4-2, Equation 4-3, and Equation 4-4, there are three types of constraints for the formulation in Equation 4-1. Firstly, each deduct-value is bound by the range as defined by the PDI scale. In the simulated data, the range is 0~100. A deduct-value outside this range is not defined and hence meaningless. The second type of constraint is called the sequence constraint, that is, for the same type of distress, higher density and severity levels should have higher deduct-values. In addition, some type-severity-density states may have specific values. As mentioned in Chapter 3, there are 25 deduct-values are zeroed in the sampling process, therefore, the deduct-values for these DIDs must be enforced to be zero.

These three types of constraints may lead to numerous constraints. In the simulated data, there are 330 decision variables. These include 19 types of distress, with each type having 3 severity levels, and 6 density levels, excluding the polished aggregate which has only one severity level and 6 density levels. Each type of these distresses may need 12 constraints to enforce the severity sequence, and 15 for density sequence. The polished aggregate may need 5 to enforce the density sequence. The number of such sequence constraints is 491. What is more, the logical range of these 330 variables may entail 660 constraints. If the 25 specific values are also considered, the total constraint number may be well beyond 1000.

Two methods have been explored in this study to handle these constraints. These include the heuristic, and the penalty method. In the heuristic method, the Broyden algorithm is used to solve the unconstrained problem, and all the constraints are dealt with heuristically. The basic operation is to feed the algorithm with constraint-compliant starting points. Solutions from a previous iteration or a complete run are adjusted to comply with all the constraints before they are used as the starting points of the next iteration or next run. This process iterates until the objective function stops to improve significantly. The final solution is sorted based on distress density and severity, respectively to satisfy all the sequence constraints. The possible negative values are replaced with zero, and the values greater than S_{PDI} are replaced with S_{PDI} to satisfy the range constraints. Clearly, this is essentially an application of the unconstrained Broyden algorithm.

The penalty method assesses penalty (add non-negative value to the existing objective function value) when any deduct-value violates the constraints. The penalty will be directly added to the original setup in Equation 4-5, to convert the original constrained problem into an unconstrained one. The final solution will hence satisfy both the original objective function and the penalty function. For a specific deduct-value for DID number *i*, the penalty may come from 6 sources: (1) density-related raw-penalty, assessed when *i* is a higher density DID but is associated with a lower deduct-value, called RP_1; (2) density-related raw-penalty, assessed when *i* is a lower density DID but is associated with a higher deduct-value, called RP_2; (3) severity-related raw-penalty, assessed when *i* is a higher severity DID but is associated with lower deduct-values, called RP_3 ; (4) severity-related raw-penalty, assessed when *i* is a lower severity DID but is associated with a higher deduct-value, called RP_4 ; (5) range-related raw-penalty, assessed when the deduct-value is above S_{PDI}, called RP_5 , and (6) range-related raw-penalty, assessed when the deduct-value is less than zero, called RP_6.

The amount of penalty is designed to be related to the amount of the violation. For the violation of range constraints, the raw-penalty is calculated as the squared amount that is beyond zero or S_{PDI}. On the other hand, if the sequence constraints are violated, the raw-penalty is calculated as the squared difference between a specific deduct-value and its immediate neighbor in the defined DV-Table. The total penalty is the summation of all the 6 raw-penalty components for all the samples in consideration, with each component being adjusted by a constant penalty multiplier. The total penalty function may be written as:

$$Pen = \sum_{k=1}^{K} \sum_{i=1}^{M} S_{ki} \cdot \left[m_1 \cdot RP_1 + m_2 \cdot RP_2 + m_3 \cdot RP_3 + m_4 \cdot RP_4 + m_5 \cdot RP_5 + m_6 \cdot RP_6 \right] \qquad \text{(4-22)}$$

where,

Pen = total penalty for the violations of constraints;

$m_1, m_2, m_3, m_4, m_5, m_6$ = constant multiplier for RP_1, RP_2, RP_3, RP_4, RP_5, RP_6, respectively;

$$RP_1 = \begin{cases} \left[DV_{ki} - DV_{k(i-1)}\right]^2, & if\ DV_{ki} < DV_{k(i-1)},\ (j-1)\times 6+1 < i \le (j-1)\times 6+6,\ j=1,2,\ldots,55, \\ 0, & otherwise. \end{cases} \tag{4-23}$$

$$RP_2 = \begin{cases} \left[DV_{ki} - DV_{k(i+1)}\right]^2, & if\ DV_{ki} > DV_{k(i+1)},\ (j-1)\times 6+1 < i \le (j-1)\times 6+6,\ j=1,2,\ldots,55, \\ 0, & otherwise. \end{cases} \tag{4-24}$$

$$RP_3 = \begin{cases} \left[DV_{ki} - DV_{k(i-6)}\right]^2, & if\ DV_{ki} < DV_{k(i-6)},\ (j-1)\times 3+1 < i \le (j-1)\times 3+3,\ j=1,2,\ldots,13, \\ \left[DV_{ki} - DV_{k(i-6)}\right]^2, & if\ DV_{ki} < DV_{k(i-6)},\ (j-1)\times 3-1 < i \le (j-1)\times 3+2,\ j=15,16,\ldots,19, \\ 0, & otherwise. \end{cases} \tag{4-25}$$

$$RP_4 = \begin{cases} \left[DV_{ki} - DV_{k(i+6)}\right]^2, & if\ DV_{ki} > DV_{k(i+6)},\ (j-1)\times 3+1 < i \le (j-1)\times 3+3,\ j=1,2,\ldots,13, \\ \left[DV_{ki} - DV_{k(i+6)}\right]^2, & if\ DV_{ki} > DV_{k(i+6)},\ (j-1)\times 3-1 < i \le (j-1)\times 3+2,\ j=15,16,\ldots,19, \\ 0, & otherwise. \end{cases} \tag{4-26}$$

$$RP_5 = \begin{cases} \left[DV_{ki} - S_{PDI}\right]^2, & if\ DV_{ki} > S_{PDI},\ i=1,2,\ldots,M, \\ 0, & otherwise. \end{cases} \tag{4-27}$$

$$RP_6 = \begin{cases} \left[DV_{ki} - 0\right]^2, & if\ DV_{ki} < 0,\ i=1,2,\ldots,\mathrm{M}, \\ 0, & otherwise. \end{cases} \tag{4-28}$$

The first derivative of the penalty function may be derived as:

$$\frac{\partial Pen}{\partial DV_t} = \sum_{k=1}^{K}\sum_{i=1}^{M} S_{ki}\cdot\left[m_1\cdot\frac{\partial RP_1}{\partial DV_t} + m_2\frac{\partial RP_2}{\partial DV_t} + m_3\cdot\frac{\partial RP_3}{\partial DV_t} + m_4\frac{\partial RP_4}{\partial DV_t} + m_5\cdot\frac{\partial RP_5}{\partial DV_t} + m_6\frac{\partial RP_6}{\partial DV_t}\right] \tag{4-29}$$

$$\frac{\partial RP_1}{\partial DV_t} = \begin{cases} 2\left[DV_{ki} - DV_{k(i-1)}\right]\cdot x_1(t) \\ 0 \end{cases} \tag{4-30}$$

$$\frac{\partial RP_2}{\partial DV_t} = \begin{cases} 2\left[DV_{ki} - DV_{k(i+1)}\right] \cdot x_1(t) \\ 0 \end{cases} \tag{4-31}$$

$$\frac{\partial RP_3}{\partial DV_t} = \begin{cases} 2\left[DV_{ki} - DV_{k(i-6)}\right] \cdot x_2(t) \\ 0 \end{cases} \tag{4-32}$$

$$\frac{\partial RP_4}{\partial DV_t} = \begin{cases} 2\left[DV_{ki} - DV_{k(i+6)}\right] \cdot x_2(t) \\ 0 \end{cases} \tag{4-33}$$

$$\frac{\partial RP_5}{\partial DV_t} = \begin{cases} 2\left[DV_{ki} - S_{PDI}\right] \cdot x_3(t) \\ 0 \end{cases} \tag{4-34}$$

$$\frac{\partial RP_6}{\partial DV_t} = \begin{cases} 2\left[DV_{ki} - 0\right] \cdot x_3(t) \\ 0 \end{cases} \tag{4-35}$$

$$x_1(t) = \begin{cases} 1, & i = t, \\ -1, & i - 1 = t, or\ i + 1 = t, \\ 0, & otherwise. \end{cases} \tag{4-36}$$

$$x_2(t) = \begin{cases} 1, & i = t, \\ -1, & i - 6 = t\ \ or\ i + 6 = t, \\ 0, & otherwise. \end{cases} \tag{4-37}$$

$$x_3(t) = \begin{cases} 1, & i = t, \\ 0, & otherwise. \end{cases} \tag{4-38}$$

4.5 Running of the Broyden Algorithm

There are many factors that affect the performance of the Broyden algorithm. These may include the constraint-handling methods, starting points, sample sizes, and the stopping criteria. These influencing factors should be carefully examined in order to ensure that the algorithm is run correctly, and a reliable result is obtained.

4.5.1 Start and Termination of the Broyden Algorithm

The Broyden algorithm entails an initial point to get started. Due to the non-linear nature of the problem, different starting points may influence the final solution, because there are many local optima in the solution space. Therefore, it is always sensible to run the problem using different starting points and take the best (with the smallest objective function value) as the final solution. Random starting points are the most appropriate choice for practical applications. The PDI scale, 0 to S_{PDI} may be a good range for randomizing the starting points. Because PAVER is an established procedure, its deduct-values may also be used as the starting points to obtain the customized deduct-values.

A single stopping criterion is used for terminating the Bryoden algorithm. It is the decrease of the objective function value between the last two consecutive iterations. Obviously, the terminating threshold will not exert any significant impact on the solution if it is sufficiently small. Lowering this threshold beyond a sufficiently small value may just unnecessarily increase the calculation load without improving much the quality of the solution. In this study, the initial threshold is chosen as 1% of the S_{PDI}. This value may be adjusted according to the converging curve and the terminal objective function value. A leveled-off converging curve after termination indicates that the current threshold is reasonable, because there is not much potential of further decrease of the objective function value. In contrast, if the program terminates when the converging curve is still in its steep decreasing process, the threshold should be adjusted lower. In addition, as a squared sum of the individual errors, the objective function value by itself signifies the average difference between the user-rated PDI and that produced by the current DV-Table. Therefore, a very big difference may well necessitate a decrease of the threshold, and vice versus.

4.5.2 Selection of the Constraint-Handling Method

Constraint-handling method is an integral part of a constrained non-linear programming problem. It plays a key role in ensuring the efficiency and quality of the final solution. In order to select the better constraint-handling method, the two constraint-handling methods described previously are compared. The comparison is conducted based on the following two criteria: (1) algorithm efficiency, which is embodied by the converging process; and (2) quality of the results, which is characterized by the constraint-compliance, and the terminal objective function value. The better algorithm will display faster converging process, and produce solutions with smaller objective function value.

4.5.3 Identification of a Sufficient Sample Size

Not all sample sizes are able to provide sufficient information for the determination of the deduct-values defined by the user. A sufficient sample size needs to be identified according to the required accuracy level. The accuracy level is characterized by the repeatability of the solution from different sample sizes. Such a sample size may be identified in the following manner. First of all, set an allowable error between the results from different sample sizes, such as 5-point on a 0~100 PDI scale, for the majority, say 95% of the decision variables. Second, start the Broyden algorithm with a small sample size, say 500 samples, and record the results. Third, add some more samples and pool them with the existing samples, run again, and compare the current results with the previous one from the fewer samples. Forth, check the distribution of the variation between the two solutions, and if the error is less than the allowable error, the smaller sample size will be the sufficient sample size. Last, keep on adding samples, and checking the results, until the sufficient sample size is identified.

4.6 Evaluation of the Performance of the Proposed Procedure

If the simulated data used in this Chapter is assumed to be real user data, the extraction of the deduct-values may be considered the customization process of the proposed procedure using the user data. The obtained deduct-values constitute the customized user DV-Table. Although the distress definition in the PAVER method is inherited in the simulated data, in reality, the user may elect to use any distress definitions.

Besides the extraction of the deduct-values according to the user distress definition and the fixed weight-curve, the proposed procedure is supposed to reproduce the user-rated PDI reliably. Together with the fixed weight-curve and the computed deduct-values, the proposed procedure should reproduce the user-rated PDI using data other than that used in deriving the deduct-values. This criterion is important because it verifies the practical applicability of the proposed procedure. Of course, the computed PDI will not be exactly the same as the user-rated PDI. Statistical analyses have to be conducted on the corresponding error between the two PDIs to gauge the quality of the reproduction. Such measures as maximum positive and negative error, mean, and standard deviation may be used to gauge the range and variation of the error. In addition, statistical t-test for mean and F-test for variance may also be used to verify whether the computed and user-rated PDI possess similar mean and variance. 2000 simulated samples will be used in this process.

As a spin-off, the interchangeability of the PAVER and the China weight-curve may be investigated by taking advantage of the above evaluation process. This may be done by replacing the PAVER weight-curve with the China weight-curve in calculating the computed PDI, and comparing the obtained PDI with the user-rated PDI. If the China weight-curve produces acceptable agreement with the user-ratings, this may indicate that the two weight-curves are interchangeable. This investigation helps justify the adoption of human rating behavior as the anchorage for simplifying the complicated PDI formulating process. The same set of statistical measures mentioned above are employed to gauge the quality of the reproduction based on the China weight-curve.

4.7 Results

4.7.1 Selection of the Constraint-Handling Method

The two constraint-handling methods are compared in this section with an aim to identifying the better method. The converging processes are compared first to show which method is more efficient. Two parallel runs, each adopting a different constraint-handling method, are conducted based on the same random starting points from 1 to 100, the same 2000 samples, and the same threshold of 0.1. The converging processes for these two parallel runs are shown in Figure 4-1.

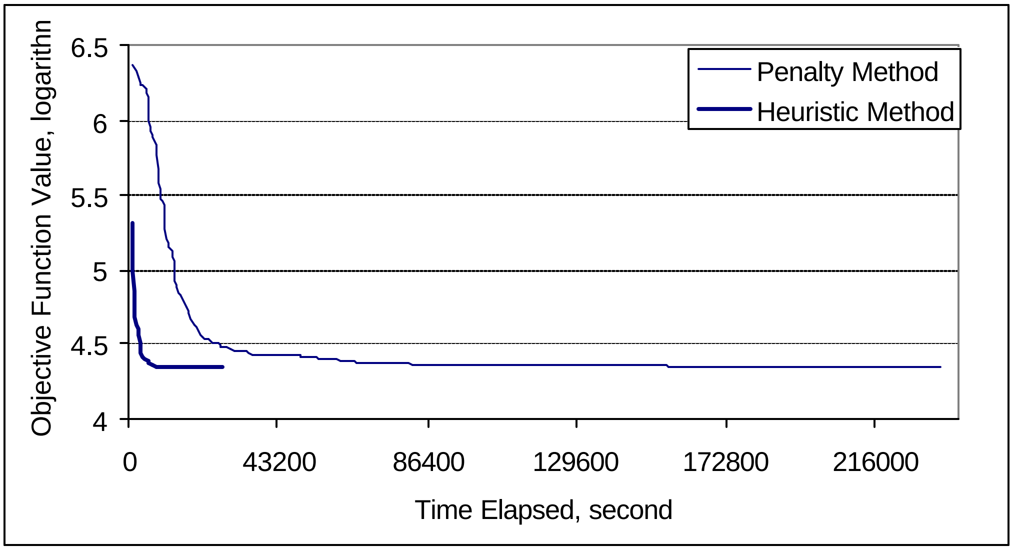

Figure 4-1. Comparison of the converging process of the heuristic and penalty method.

Obviously, the heuristic method is more efficient. The objective function value dropped very much sharper than that of the penalty method. Within five hours, the program reached the terminating threshold of 0.1. On the other hand, the penalty method took 7 times as much time to reach the same threshold level, only with the terminal objective function value still 3% ((22,695-21,983)/21,983×100%), higher than that of its counterpart. In order for the penalty method to reach the same terminal objective function value, it may take another 84 hours, because its converging rate is extremely slow: every 100 drop in the objective function value takes up to 12 hours.

All the multipliers for the individual penalty functions are chosen to be equal, and the constant of 100 is used. The multiplier, the threshold, and the desired accuracy level of the deduct-values should match internally. For example, for the desired accuracy level of 0.1 for the deduct-values, if the threshold is chosen to be 0.1, then the multipliers should not be less than 10. Otherwise even if there is a violation by 0.1 in the deduct-values, the objective function will be unable to detect it. Similarly, if the threshold is increased to 1.0, then the multipliers should also be increased to no less than 100. Multipliers satisfying this internal logic are found to perform similarly.

In addition to the comparison of the converging process, the solutions from the two methods are also compared. Table 4-2 is a typical derived user DV-Table produced by the Broyden algorithm. Besides its faster converging process, the heuristic constraint-handling method is also found to produce deduct-values of quite comparable quality to that by its penalty counterpart. The deduct-values obtained from the heuristic method are deducted from the corresponding deduct-values determined using the penalty method. The error distribution is shown in Figure 4-2. The majority (96%) of the differences is within ±2-points. The maximum positive difference is less than 6-points, and the minimum negative difference is less than 8-points. The mean of these errors is 0.08, with a standard deviation of 0.92.

It should be noted that the two constraint-handling methods are different by nature. The penalty method penalizes the Broyden algorithm if it searches outside the feasible zone, and eventually converges to a theoretically guaranteed constraint-compliant solution. On the contrary, the heuristic method does not constrain the operation of the Broyden algorithm at all. It just supplies the algorithm with constraint-compliant starting points, and there is no theoretical guarantee that the solution will be constraint-compliant. However, this method is observed to be both efficient, and effective for this particular

Table 4-2. A typical solution of the Heuristic Broyden Algorithm (2000 samples).

Type-Severity Index and Description			Extent Index					
			1	2	3	4	5	6
1	Alligator Cracking	Low	5	11	30	37	53	62
2		Medium	8	25	42	50	68	79
3		High	17	34	54	64	77	92
4	Block Cracking	Low	0	0	5	10	23	30
5		Medium	0	5	15	20	37	44
6		High	0	8	22	34	60	74
7	Corrugation	Low	0	8	9	14	34	44
8		Medium	6	20	35	42	65	75
9		High	10	38	54	62	78	94
10	Longitudinal/Transverse Cracking	Low	0	5	8	13	35	32
11		Medium	0	14	20	30	40	46
12		High	0	27	38	52	70	84
13	Patching/Utility Cut Patching	Low	0	0	14	20	27	36
14		Medium	0	6	26	34	44	59
15		High	5	25	41	55	69	81
16	Rutting	Low	0	11	24	30	45	51
17		Medium	6	22	42	45	63	65
18		High	8	34	52	62	80	88
19	Weathering and Raveling	Low	0	1	3	4	14	16
20		Medium	4	8	15	21	37	45
21		High	4	19	34	41	70	77
22	Bleeding	Low	0	0	1	4	13	24
23		Medium	0	5	10	13	31	40
24		High	0	7	18	27	55	71
25	Bumps and Sags	Low	0	4	10	20	33	43
26		Medium	0	16	30	44	61	81
27		High	0	37	59	74	85	100
28	Depression	Low	4	6	10	20	43	50
29		Medium	8	9	22	36	60	61
30		High	12	20	33	46	70	75
31	Edge Cracking	Low	0	0	6	7	7	17
32		Medium	5	5	9	15	24	31
33		High	8	8	21	28	36	50
34	Joint Reflection Cracking	Low	0	5	6	9	23	31
35		Medium	0	10	19	31	41	43
36		High	0	25	34	51	71	75
37	Lane Shoulder Dropoff	Low	0	0	5	7	22	33
38		Medium	0	4	12	21	43	44
39		High	0	11	24	35	70	72
40	Polished Aggregates	N/A	0	0	4	7	16	22
41	Potholes	Low	7	24	46	54	84	97
42		Medium	7	36	71	87	99	100
43		High	24	55	85	94	99	100
44	Railroad Crossing	Low	0	5	9	12	19	24
45		Medium	6	18	31	40	47	54
46		High	24	42	51	66	77	80
47	Slippage Cracking	Low	0	4	24	30	49	55
48		Medium	0	12	35	45	65	70
49		High	4	23	53	65	86	90
50	Shoving	Low	0	6	18	24	31	41
51		Medium	4	10	30	38	50	64
52		High	8	22	39	52	68	78
53	Swell	Low	0	6	8	8	20	23
54		Medium	12	27	31	37	46	52
55		High	36	43	47	52	63	68

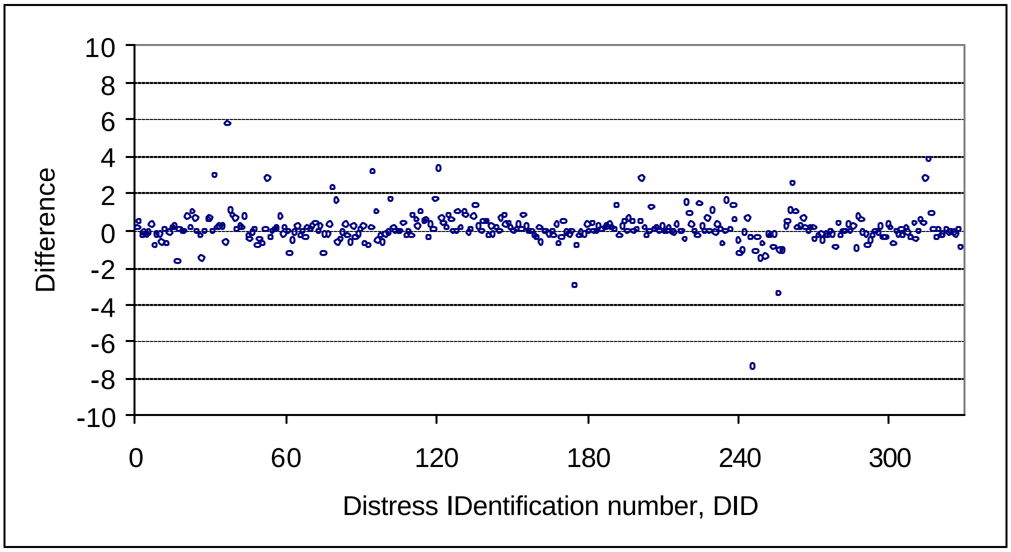

Figure 4-2. Analysis of the errors of corresponding deduct-values obtained by the heuristic and penalty method.

optimization setup, the heuristic method is hence selected for handling the constraints in this research. All the following discussions will be based on the heuristic method.

4.7.2 Influence of the Starting Points, and Sample Size on the Converging Process

The influence of the starting points, and sample sizes on the converging process of the heuristic Broyden algorithm are examined in this section. Four different starting points, namely the PAVER start, all-zero start, random start I (randomized from 1 to 100), and random start II (randomized from 10 to 15), and two sample sizes, namely 2000, and 5000 samples are employed and compared. The converging processes for the 2000, and 5000 samples with different starting points are shown in Figure 4-3, and Figure 4-4, respectively.

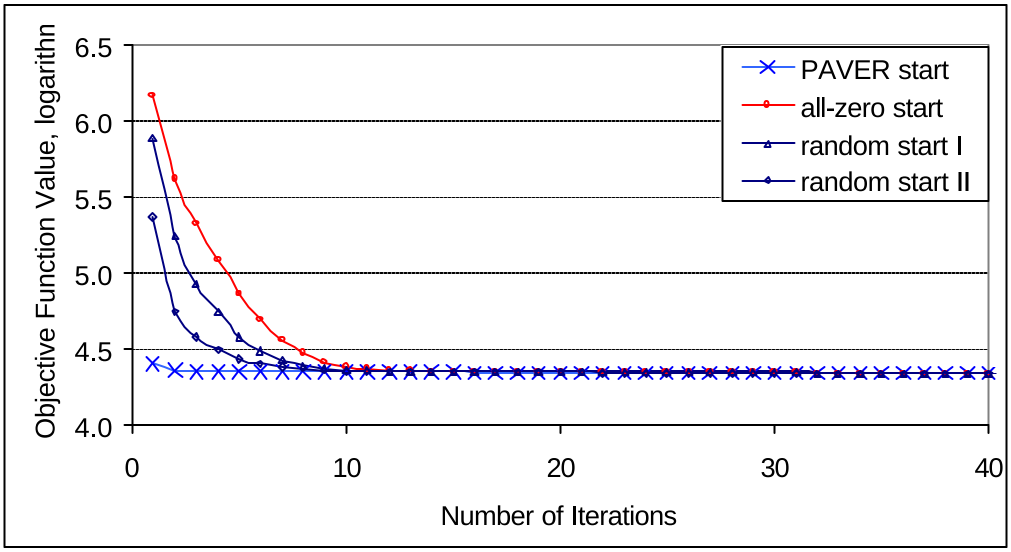

Figure 4-3. Comparison of the converging process for different starting points (2000 samples).

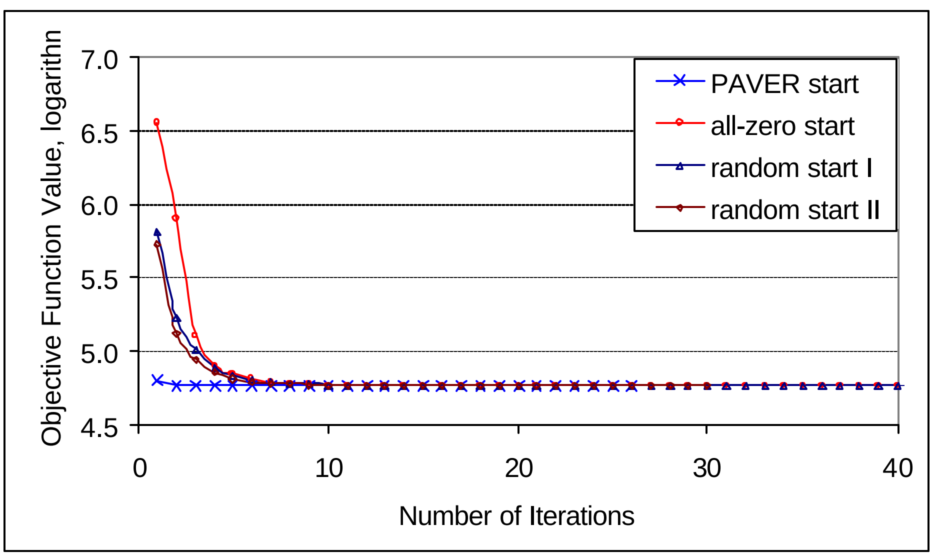

Figure 4-4. Comparison of the converging process of different starting points (5000 samples).

As it can be seen from Figure 4-3, that a better starting point will shorten the converging process. If the Broyden algorithm is started from the PAVER DV-Table, the initial objective function value is very low, and only several iterations will be enough for the algorithm to reach the neighborhood of the terminal objective function value. While the initial objective function value will be much higher if the algorithm is started from random starting points. For a random start run that all values are initialized between 1 and 100 (random start I), or 10 to 15 (random start II), or all-zero, at least 10 iterations will be needed for the algorithm to converge. In addition, as it is shown by these curves, starting points dictate the unique path of the converging process. Nonetheless, there is only marginal difference between the terminal objective function values from different random starts. The difference is observed to be on the order of 0.1%. This result is practically significant, because random starting points may be the most appropriate choice in real applications, and the Broyden algorithm is robust with respect to different starting points.

Larger sample size may not necessarily entail more iterations before convergence as shown by the comparison of Figure 4-3 and Figure 4-4. 40 iterations are enough for the derivation of the deduct-values using 2000 samples. The same number of iterations may be also enough for 5000 samples, although each such iteration will take longer time to complete. This shows that the Broyden method is very efficient in terms of the number of iterations needed. Since the initial parts of converging curves are much steeper for the 5000-sample case, this indicates that the Broyden method works better with larger sample sizes.

4.7.3 Identification of a Sufficient Sample Size

For the simulated data, five sample sizes are studied to find the sufficient sample size. These include 500, 1000, 1500, 2000, and 5000 samples, with each larger sample size encompassing all the samples contained in a smaller sample size. For example, the 1000 sample size is composed of the 500 samples in the 500 sample size and an additional 500 samples. The 1500 samples are the aggregation of the 1000 samples with another 500 samples, and so on.

The identification study started from a random initial DV-Table with the smallest sample size, 500 samples. With a terminating threshold of 0.1, the heuristic Broyden algorithm was run and a DV-Table similar to that as tabulated in Table 4-2 was obtained. The Broyden algorithm was then run with increasingly bigger sample sizes, such as 1000, 1500, 2000, and finally 5000. The DV-Table associated with each sample size was also recorded. The errors between the corresponding deduct-values for every two immediate neighboring sample size were hence obtained. Two typical error series between the 500 and 1000 samples, and the 2000 and 5000 samples were shown in Figure 4-5. The results of the statistical analyses for all the error series were tabulated in Table 4-3.

As it can be seen from Figure 4-5 that the solution from 500 samples are very much different from that from 1000 samples. The error range spans from –17 to +19, with a standard deviation of 5.64. There are also 10% of the error is larger than 10-points. This wide range variation of the result shows that the solution from 500 samples is not reliable. Once more information is given, the solution changes a lot. In contrast, the

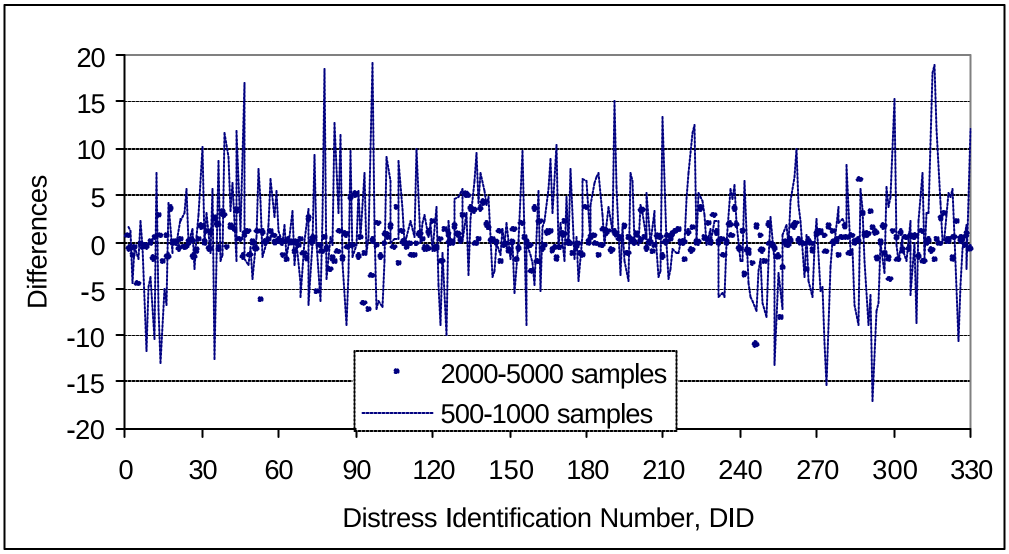

Figure 4-5. Plot of errors for individual DIDs between different sample sizes.

Table 4-3. Analysis of errors for individual DIDs between different sample sizes.

Measures	Source of the Error Series			
	500~1000 samples	1000~1500 samples	1500~2000 samples	2000~5000 samples
Mean	0.91	0.16	-0.05	-0.05
Variance	5.64	2.60	1.93	1.87
Error Range, Min./Max.	-17/19	-10/11	-8/11	-7/11
Error % >5-points	31	8	4	4
Error % >10-points	10	1	0	0

solution from 2000 samples is found to be very approximate to that produced by 5000 samples. There are 96% of the error that is less than 5-points, with a standard deviation of 1.87. The two solutions almost share the same mean: the mean difference is 0.05. This indicates that the results from 2000 samples were stable. There is very little marginal benefit to add additional samples to the existing sample set, because the solution will not improve much. 2000 is identified as the sufficient sample size.

As Table 4-3 shows, the errors in terms of mean, standard deviation, and range, are shrinking with the increase of sample sizes. This trend agrees very well with the fact that the more sample you use, the more reliable the results will be, if the samples are of the same quality (randomly generated). As shown in Figure 4-6, the shrinking trend of the standard deviation with respect to sample sizes may also help identify that 2000 is a sufficient sample size. Because the curve leveled off beyond the 2000 sample size, additional samples may not improve the variation of the errors significantly. It is the practitioners' responsibility to choose whether or not to add more samples to gain a marginal improvement in the stability of the solution. Based on this result, a sample size of 2000 was used to obtain the deduct-values for the following performance evaluation analysis.

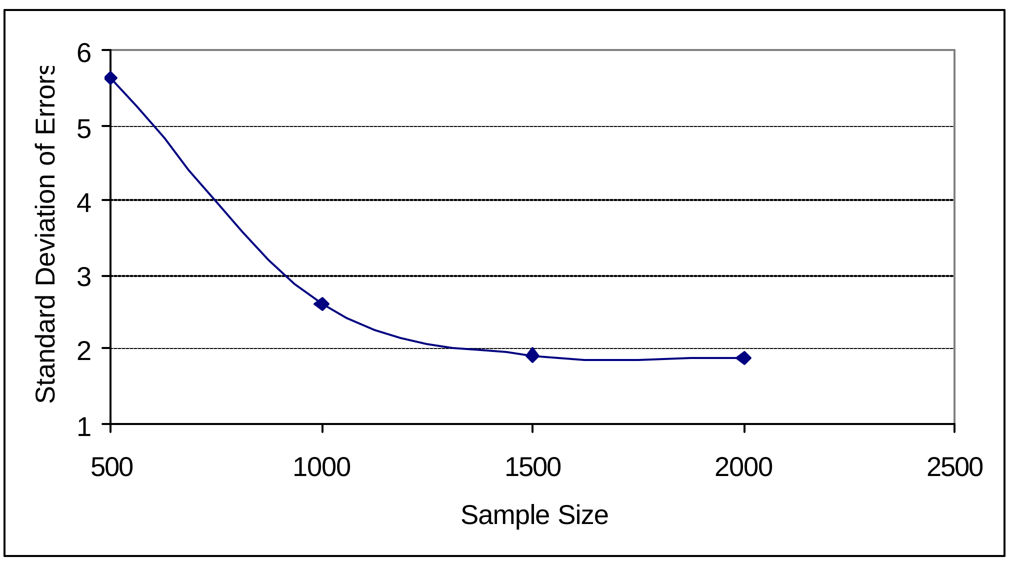

Figure 4-6. Determination of a sufficient sample size according to error variation.

4.7.4 Performance of the Proposed Procedure

Another 2000 samples are generated for the evaluation of the performance of the proposed procedure. The computed PDI is calculated based on the obtained DV-Table, as shown in Table 4-2, and the fixed PAVER weight-curve. The corresponding computed and user-rated PDIs for the 2000 samples are plotted and compared in Figure 4-7. The detailed statistics of the comparison is tabulated in Table 4-4.

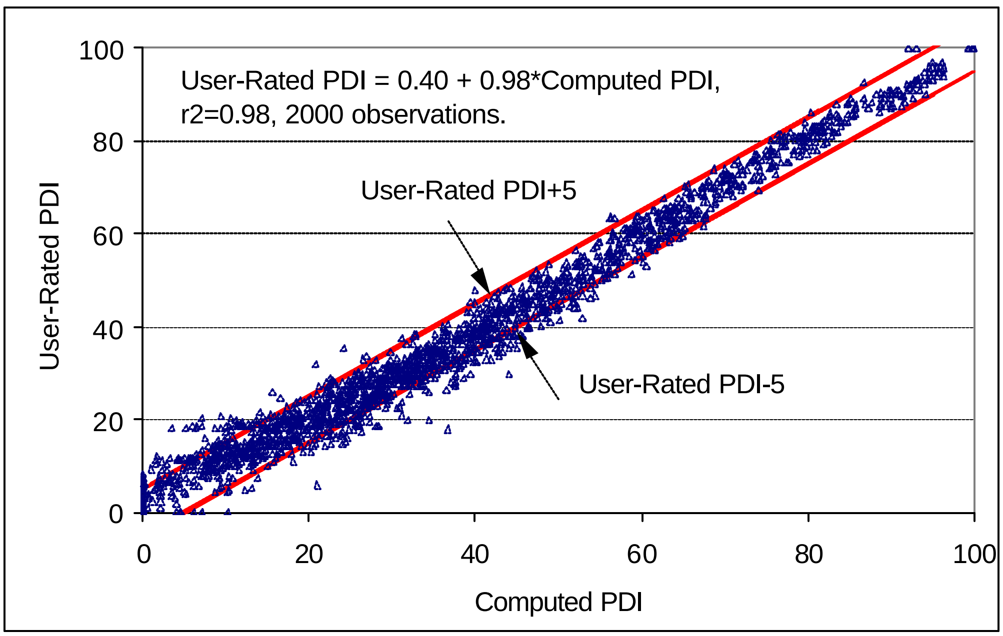

Figure 4-7. Performance of the customized deduct-values (PAVER weight-curve, 2000 samples).

The computed PDI agrees very well with the user-rated PDI for the 2000 testing samples. It can be seen that the majority of the corresponding points fall within the two parallel lines of "User-Rated PDI±5-points". For the differences, these two methods recorded a range of "-15" to "+19", and about 13% of the differences are larger than 5-points. However, only 2% of these differences are more than 10-points, with no difference

Table 4-4. Detailed statistics of the comparison between the derived PDI and user-rated PDI for the simulated data.

Items	PAVER Weight-Curve	China Weight-Curve
Mean	0.28	-1.80
Standard Deviation	3.61	4.06
Range, Min./Max.	-15/19	-24/12
Error >5-points, %	13	19
Error >10-points, %	2	3
Error >15-points, %	0	1
F-Value	1.01	1.00
t-Value	0.34	2.24
Sample size	2000	2000

t-test and F-test critical values: 1.96 and 1.11 is used for t_c and F_c at a 95% significance level, respectively; 2.58 and 1.17 is used at a 99% significance level, respectively.

beyond 15-points. This result indicates that customized DV-Table may reproduce the User-Rated PDI with an error of 10-points at 98% of the time. Statistical tests show that the computed PDI and User-Rated PDI also have similar means and variances at a 95% significance level. In addition, they are closely correlated by a regression relationship with a slope of 0.98.

Nonetheless, Figure 4-7 also indicates that there exist some discrepancies between the computed and user-rated PDIs, especially when the pavement conditions are bad, say PDI less than 15-points. This may be explained by the “incompatible” nature between the proposed and the PAVER method, because the User-Rated PDI is actually the PAVER PCI in the simulated data.

One simple example will help understand this incompatibility. Say a sample road section has two distresses, with deducts of 100 and 5-points, respectively. According to their TDV of (100+5)=105 and the total deduct number q=2, the PAVER-PCI can be determined as 25 using Figure 2-2 and Figure 2-3. However, for the proposed method, the PDI for this sample, as calculated by Equation 3-1 is only 9.25, i.e.

$$100 - \left[100 \times f\left(\frac{100}{100+5} \times 100\% \right) + 5 \times f\left(\frac{5}{100+5} \times 100\% \right) \right]$$

$$= 100 - [100 \times 0.90 + 5 \times 0.15] = 9.25 \tag{4-39}$$

which is more reasonable practically. According to our observation, this is one of the leading causes for the discrepancies between the two methods.

This difference can be ascribed to the different modeling concepts of the two models. The PAVER model contends that a pavement with two type-severity combinations with each having a deduct-value of 35 is not in as bad a state as a pavement with a deduct-value of 70 for a single type-severity distress (Haas et al. 1994). The final rating is adjusted based only on the total deduct-value and total number of deducts, without considering the composition of the distresses. On the other hand, the proposed model argues that raters base their ratings on the predominant distress. In the example illustrated, the dominating deduct, 100 dictates the final rating, although every distresses in the sample are considered. Fortunately, such discrepancies occur more often for very bad road, say PDI less than 15, and anyway such roads need to be repaired.

4.7.5 The Interchangeability of the Two Weight-Curves

For the 2000 testing samples, the computed PDI is calculated based on the obtained DV-Table, as shown in Table 4-2, and the China weight-curve (Table 3-9). The corresponding computed and user-rated PDIs are plotted and compared in Figure 4-8. The detailed statistics of the comparison is tabulated in Table 4-4.

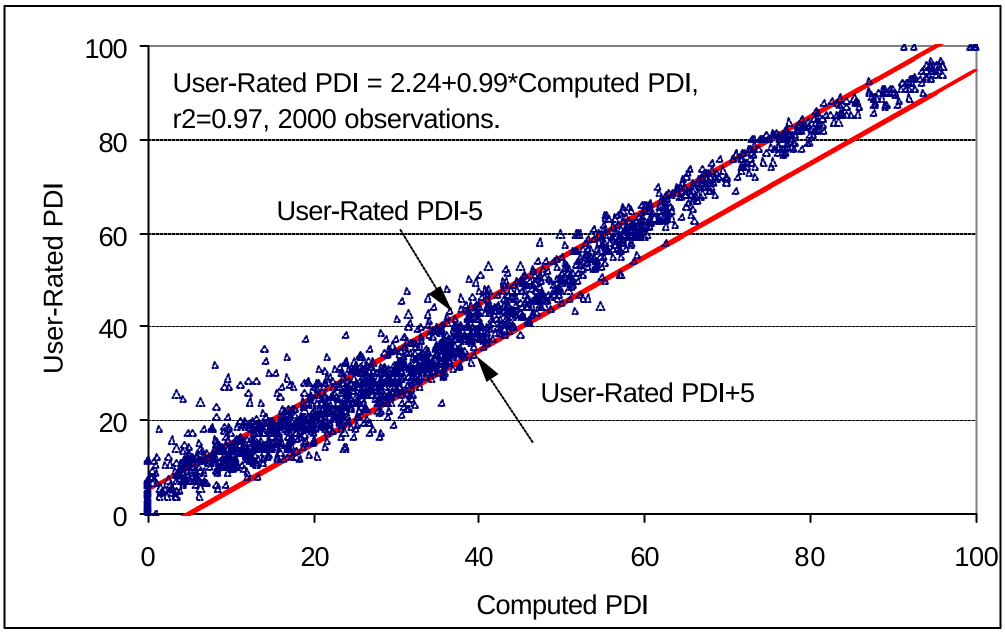

Figure 4-8. Performance of the customized deduct-values (China weight-curve, 2000 samples).

It is apparent that the agreement has deteriorated when adopting the China weight-curve. For the differences, these two methods recorded a wider range of “-24” to “+12”, and the differences more than 5-points have increased by 50%. Nonetheless, only 3% of these differences are recorded as more than 10-points, with 1% over 15-points. This result indicates that even with the China weight-curve, the customized DV-Table may reproduce the User-Rated PDI with an error of 10-points at 97% of the time. Statistical tests show that the Computed PDI and the User-Rated PDI have similar means and variances at a 99% significance level. In addition, the regression analysis produces a slope of 0.99 with r^2 =0.97, which indicates very good agreement between these two PDIs. Since the two weight-curves originated from two independent studies in different parts of the world, the interchangeability greatly supports that the rating behavior of pavement engineers are reasonably stable, and therefore can be used as the anchorage for the simplification of the PDI formulation process.

4.7.6 Impacts of the Default Weight-Curve

The proposed model is formulated based on a default weight-curve, and the error introduced is absorbed entirely by the deduct-values to be determined, because the PDI is not supposed to be compromised. It is the purpose of this section to examine how much these deduct-values will deviate from that tabulated in the original PAVER DV-Table.

Based on the 2000 training samples, the Broyden algorithm was run to derive the DV-Tables using the PAVER, and China weight-curve respectively. These two DV-Tables, together with the original PAVER DV-Table are numbered as DV-Table I, II, and III, respectively. The differences between the corresponding deduct-values in DV-Table I~III, II~III, and I~II, are computed and analyzed. The statistical results are tabulated in Table 4-5.

As Table 4-5 shows, the deduct-values obtained using the two default weight-curves are both different from the PAVER deduct-values, which are used to generate the training

Table 4-5. Analysis of the deviations of the deduct-values.

Items	DV-Table I~III	DV-Table II~III	DV-Table I~II*
Mean	0.13	-0.51	0.64
Standard Deviation	2.71	3.92	1.93
Range, Min./Max.	-6/12	-10/15	-6/5
Error >5-points, %	5	14	2
Error >10-points, %	0	2	0
Error >15-points, %	0	0	0
F-Value	1.13	1.16	0.97
t-Value	0.09	0.36	0.46
Sample size	330	330	330
t-test and F-test critical values: 1.96 and 1.20 is used for t_c and F_c at a 95% significance level, respectively.			

*DV-Table I is from PAVER Weight-Curve, DV-Table II is from China Weight-Curve, and DV-Table III is the original PAVER DV-Table, Table 3-2.

samples. When the PAVER weight-curve is used, 5% of the DIDs records a difference of more than 5-points. This reflects that the combining schemes employed by the proposed and the PAVER method are not compatible. Although the physical meaning of the deduct-value for a specific distress in the two methods is both defined as the "deduct" when a pavement is rated based on this specific distress alone, the deduct-value is not the same.

If the China weight-curve is used in determining these deduct-values, the maximum discrepancy may be as high as 15-points. However, the differences are less than 10-points at 98% of the time. Therefore, adoption of either of the two default weight-curves, the deduct-values obtained do not deviate very much from those listed in the original PAVER DV-Table.

It can also be seen from Table 4-5 that the deduct-values in DV-Table I~II agree very well between themselves. The maximum difference is only 6-points, and 98% of the DIDs recorded a difference of less than 5-points. These deduct-values also have a similar mean and variance at a 95% significance level as suggested by the statistical t-test and F-test. This result suggests that the two weight-curves are actually interchangeable in determining deduct-values.

4.8 Conclusions

The second part of the proposed procedure for PDI formulation is described in this Chapter. The individual deduct-values are successfully obtained using the Broyden algorithm. As an example application of the proposed procedure, the whole process also illustrated how the proposed procedure may be used to establish the user DV-Table through customization.

As an optimization technique, the Broyden algorithm is subject to the influence of many factors, such as the constraint-handling method, sample size, starting points, and termination criteria. It is concluded that the unconstrained Broyden algorithm with the proposed heuristic constraint-handling method is both efficient and effective. Of course, the practitioners may also elect to employ the penalty method for their applications. However, it should be realized that it is the responsibility of the practitioners to find the best sample size and terminating threshold for their particular applications. The parameters identified in this study were just for illustration purpose. It is important that the practitioners apprehend the manner in which the Broyden algorithm should be implemented, rather than what parameters others had used.

Chapter 5 Case Studies

5.1 Introduction

In Chapters 3 and 4, the proposed procedure has been completely formulated. It has also been verified using samples simulated by the PAVER method. In order to show its applicability for practical data, actual data from the State of Minnesota was used for validation purposes. The primary objective of this case study is to show how the proposed procedure can be customized according to the user's distress definition and distress data. Steps for application of the proposed procedure include: (1) Define the distresses according to the user's needs and preferences; (2) Collect the distress data and user-rated PDI for a series of sample road segments; (3) Determine the deduct-values for each defined type-severity-density distress using the Broyden algorithm according to a training set of the distress samples; and (4) Validate whether the determined deduct-value can reproduce user-rated PDI when similar pavement conditions occur according to a testing set of distress samples.

5.2 Case Study for Asphalt Pavements

5.2.1 Definition of the Distresses

There are 11 type-severity distresses that are collected for asphalt pavements in the Minnesota Department of Transportation (MnDOT). The density for each type-severity of distress ranges from 0% to 100%. These distresses include high, medium, and low severity Transverse Cracking, high, medium, and low severity Longitudinal Cracking, Multiple Cracking, Alligator Cracking, Rutting (depth>0.5-inch), Weathering and Raveling, and Patching. Because the "Weathering and Raveling" distress is seldom used in the MnDOT data collection, only 10 type-severity distresses are considered in this study. PDI in Minnesota is called Surface Rating (SR), which is represented on a scale of 0 to 4. A sample excerpt of the original distress data is illustrated in Table 5-1. In order to simplify the derivation process, the density of each type-severity distress is digitized into 6 levels, with each level representing a density range of 0~5%, 5.1~10%, 10.1~20%, 20.1~30%, 30.1~50%, and 50.1~100%, respectively. After the digitization, every type-severity-density distress will be given a unique DID number. The 10 type-severity distresses will produce 60 DIDs in total, with each distress having 6 density levels. Table 5-2 shows an excerpt sheet of the coded samples converted from Table 5-1.

4000 samples were obtained from MnDOT and used in this study. These data were equally separated into two groups. The training group was used to derive the deduct-value for each DID for the above 10 type-severity distress. The testing group data was used to check whether the determined deduct-values would reproduce the user-rated PDI. The cubic weight-curve for the PAVER method as recommended in Chapter 3 was used.

5.2.2 Solution of the Deduct-Values

The heuristic Broyden algorithm was employed to determine the 60 deduct-values. A sufficient sample size was first identified, according to random starting points from 1 to 4 (S_{PDI}), and the terminating threshold of 0.04 (1% of S_{PDI}). Three sample sizes (1000,

Table 5-1. Illustration of MnDOT distress survey data for asphalt pavements.

Transverse Cracking			Longitudinal Cracking			Multiple Cracking	Alligator Cracking	Rutting > 0.5"	Patching	PDI (SR)*
Low	Med	High	Low	Med	High					
14**	24	5	38	0	0	0	0	23	0	2.9
34	20	35	35	0	0	60	0	1	0	2.1
12	2	0	11	0	0	87	0	7	0	2.0
8	6	100	0	60	4	25	0	3	0	2.0
52	0	20	4	0	0	0	0	0	0	3.6
20	0	40	0	0	0	0	0	0	0	3.3
24	0	75	93	0	0	0	0	2	0	2.7
24	20	5	16	11	0	0	0	1	0	3.5

Note:Each row is a sample, and each column is a specific distress type-severity; *PDI is called Surface Rating (SR) in MnDOT, it is on a scale of 0 to 4; **values are densities in percentage.

Table 5-2. The Converted MnDOT distress survey data for asphalt pavements.

Transverse Cracking			Longitudinal Cracking			Multiple Cracking	Alligator Cracking	Rutting > 0.5"	Patching	PDI SR
Low	Med	High	Low	Med	High					
3*	10	13	23	0	0	0	0	52	0	2.9
5	9	17	23	0	0	42	0	49	0	2.1
3	7	0	21	0	0	42	0	50	0	2.0
2	8	18	0	30	31	40	0	49	0	2.0
6	0	15	19	0	0	0	0	0	0	3.6
3	0	17	0	0	0	0	0	0	0	3.3
4	0	18	24	0	0	0	0	49	0	2.7
4	9	13	21	27	0	0	0	49	0	3.5

Notes: *each row is a sample, and each value is a distress ID number, ranging from 1 to 60; zero shows no such distress appears in a particular sample.

2000, and 4000) were fed into the Broyden algorithm, and the DV-Tables associated with each sample size were obtained. The errors between the DV-Tables of 1000 and 2000 samples, and 2000 and 4000 samples were plotted in Figure 5-1.

As shown in Figure 5-1, 1000 samples performed very well in approching the solution from 2000 samples. The mean and standard deviation of the errors were 0.03, and 0.12, respectively. However, given some 1000 additional samples, the deduct-values for some DIDs might change as much as 0.69, or a 17-point equivalent on a 0 to 100 scale. This

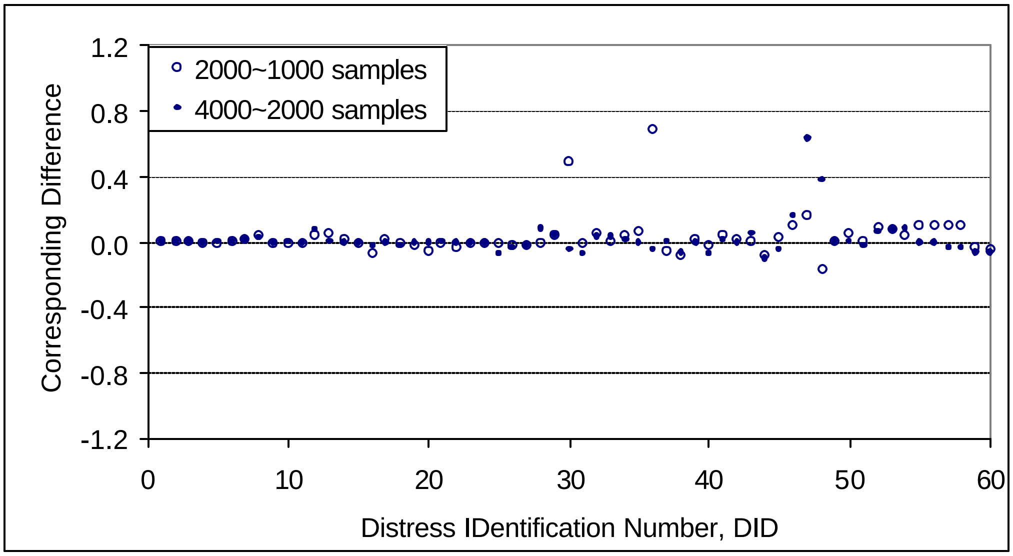

Figure 5-1. Selection of the sufficient sample size for asphalt pavements.

result suggested that the solution from 1000 samples was not stable, and therefore, 1000 was not a sufficient sample size. After the sample size was increased to 2000, the mean and standard deviation of the errors between the two DV-Tables from 2000 and 4000 samples decreased by 88%, and 15%, respectively. This indicated that the solution of 2000 samples approached the solution of 4000 samples better than the solution of 1000 samples did in approaching the solution of 2000 samples. Additional samples beyond 2000 did not help reduce the mean and standard deviation of the error as significantly as they did beyond 1000 samples. The solution from 2000 samples was more stable. However, it is difficult to say that 2000 is a sufficient sample size, because the maximum change between 2000 and 4000 solutions is 0.63, or a 16-point equivalent on a 0 to 100 scale. Due to limited data availability, this study used 2000 as the sample size.

The 2000 training samples were then used to determine the user DV-Table. Three parallel runs with different starting points were conducted to explore the possible influence of the starting points. These included random start I (randomized between 1 to 4) , random start II (randomized between 1 to 4), and all-zero start. The converging processes of the three runs are shown in Figure 5-2. As reported before, different starting points dictate only the unique converging paths of the Broyden algorithm, but do not affect the final objective function value. As the converging curve leveled off when the algorithm terminated, the threshold of 0.04 was a very good choice. The solution from random start I was adopted and tabulated in Table 5-3.

Repeatability is the only way to gauge the reliability of such a result from practical data. Between different runs, the reliable results should either reproduce themselves entirely or

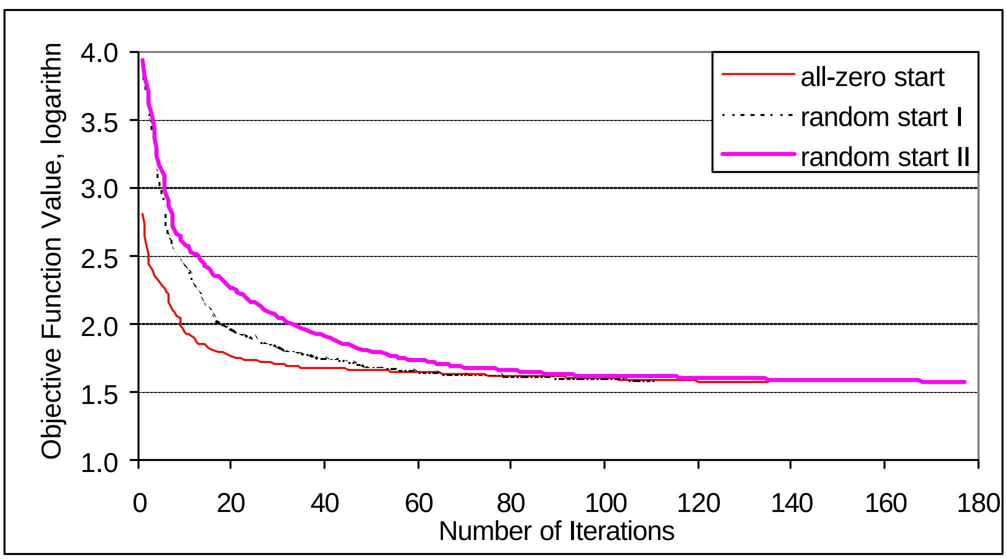

Figure 5-2. The converging process of the Broyden method for the MnDOT asphalt pavement distress data (2000 samples).

Table 5-3. MnDOT DV-Table for asphalt pavements (2000 samples, random start).

Density	DID1	DID2	DID3	DID4	DID5	DID6	DID7	DID8	DID9	DID10
I	0.05	0.05	0.12	0.07	0.18	0.19	0.45	0.09	0.10	0.28
II	0.06	0.11	0.28	0.12	0.19	0.31	0.61	0.46	0.47	0.28
III	0.08	0.28	0.51	0.17	0.19	0.31	0.93	0.73	0.80	0.43
IV	0.09	0.43	0.76	0.25	0.47	0.64	1.23	1.11	1.04	0.43
V	0.12	0.60	1.01	0.38	0.53	0.64	1.62	1.88	1.16	0.73
VI	0.17	0.76	1.52	0.59	1.17	1.48	2.40	2.37	2.02	0.73

with an acceptable variation, say 0.2, or a 5-point equivalent on a 0 to 100 scale. Solutions from the three random starts are compared in Figure 5-3. The comparison revealed that the results were pretty stable for most of the distresses. However, for some type-severity distresses, the discrepancy between different results would be as high as 1.1-points, or a 28-point equivalent on a 0~100 scale. This discrepancy indicated that some of the deduct-values were not reliably determined. These deduct-values included distresses such as density-level VI, medium and high-severity Longitudinal Cracking, density-level V and VI of Alligator Cracking, and all density-levels of Patching.

Why are 2000 simulated samples able to determine 330 deduct-values reliably in the previous chapter, while 2000 real data samples are unable to determine the 60 deduct-values? This dissimilarity may be explained by the biased nature of the samples used. In actuality, some very severe distresses, such as high density Alligator Cracking may not be existent because they will be fixed before they develop to an advanced stage. These kinds of distresses may never reach the high density-level before they are repaired. The practical samples are consequently very biased. Correcting these bias may take thousands of more samples. Because of limited data availability, this research is unable to determine a sufficient sample size for the MnDOT data.

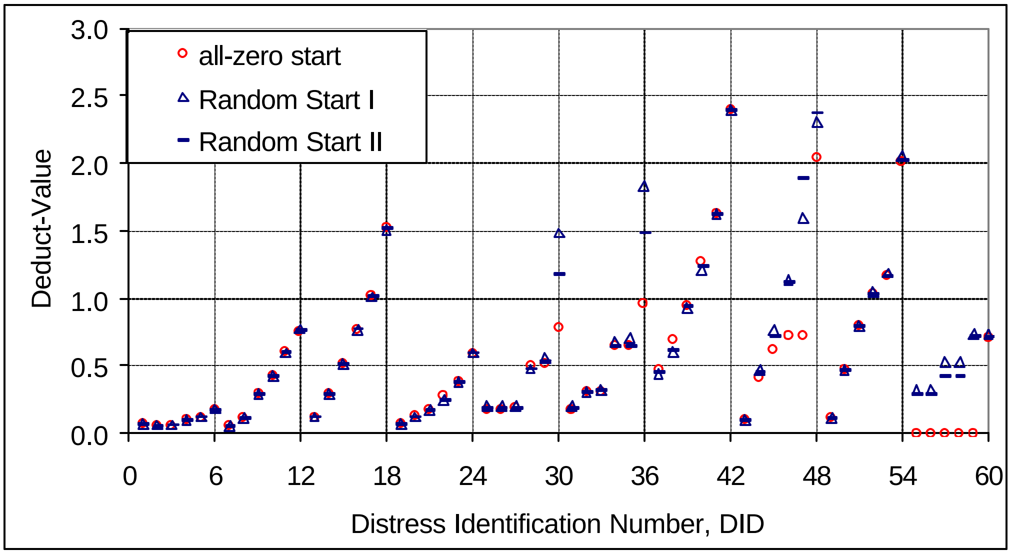

Figure 5-3. The deduct-values from different starting points (2000 samples).

If all the DVs in Table 5-3 are converted to the 0~100 scale, as shown in Table 5-4, the deduct-values are significantly different from those in the PAVER DV-Table, Table 3-2, for similar distresses and density levels. PAVER may therefore not be a good source of deduct-values for the MnDOT PMS. Some types of distresses, such as the Multiple Cracking, do not exist in the PAVER system at all, which contributes to the differences in deduct-values. A highway agency like MnDOT must formulate the PDI and determine all the deduct-values on their own if they elect to use the deduct-value method. Although only 6 discreet points in each weight-curve have been determined by this algorithm, a more precise or continuous weight-curve for each distress may be determined by repeated running of the algorithm with the data digitized differently. Well-selected digitization points may save some efforts.

Table 5-4. The MnDOT DV-Table on a 0~100 scale for asphalt pavements (2000 samples, random start).

Density	DID1	DID2	DID3	DID4	DID5	DID6	DID7	DID8	DID9	DID10
I	1	1	3	2	5	5	11	2	3	7
II	2	3	7	3	5	8	15	12	12	7
III	2	7	13	4	5	8	23	18	20	11
IV	2	11	19	6	12	16	31	28	26	11
V	3	15	25	10	13	16	41	47	29	18
VI	4	19	38	15	29	37	60	59	51	18

5.2.3 Verification of the Performance of the Deduct-Values

The validity of the deduct-values determined by the 2000 training samples is examined in this section. Together with the 2000 testing samples, these deduct-values are fed into the proposed formulation, Equation 3-1, to determine the computed PDIs. The computed PDI is then compared with the existing user-rated PDIs in the testing group data. Statistical and regression analyses are used to verify the agreement between computed and user-rated PDIs. As shown in Figure 5-4, the two PDIs are in very close agreement: the slope of the regression line is 0.99. The detailed statistics in Table 5-5 indicates that 99% of the time, the difference between the two PDIs is less than “0.4”, or a 10-point equivalent on a 0~100 scale. The two PDIs also possess similar mean and variance as supported by the t-test for mean and F-test for variance at a 95% significance level. The analyses show that individual deduct-values as determined by the 2000 training samples can reliably reproduce the user-rated PDI.

It is interesting to note, although deduct-values are different as determined by random start I and the all-zero start, as shown in Figure 5-3, the DV-Table from the all-zero start

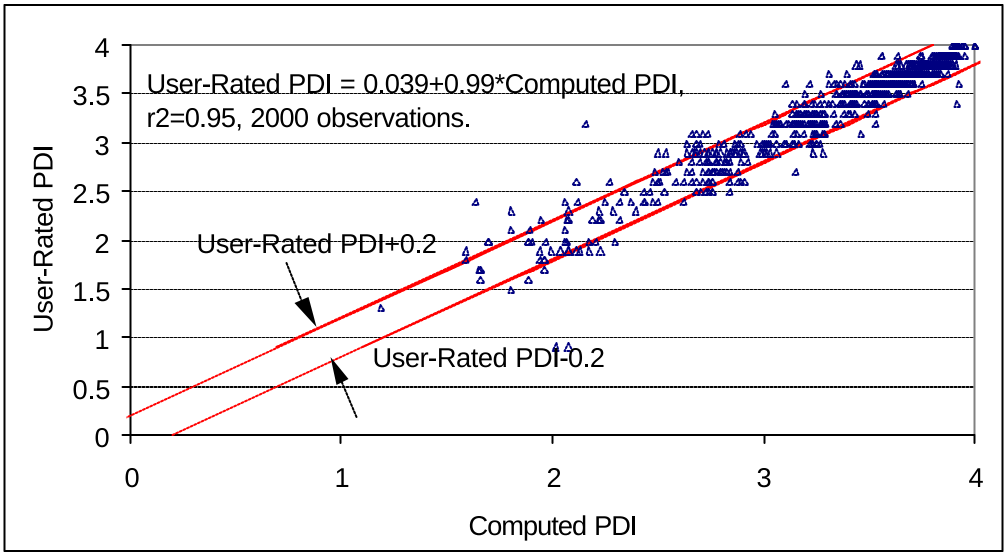

Figure 5-4. Verification of the obtained deduct-values for asphalt pavements, random start results.

Table 5-5. Detailed statistics of the comparison between the derived PDI and user-rated PDI for the MnDOT data.

Items	Asphalt Pavements		Concrete Pavements	
	random start	all-zero start	random start	all-zero start
Mean	0.02	0.02	0.03	0.04
Standard Deviation	0.10	0.10	0.15	0.16
Range, Min./Max.	-1.04/1.18	-0.79/1.48	-1.74/0.35	-1.81/0.46
Error >0.20-point, %	3.45	3.20	6.25	5.90
Error >0.40-point, %	0.45	0.65	2.83	3.07
F-Value	0.96	0.95	1.12	1.16
t-Value	1.21	1.14	2.18	2.50
Sample size	2000	2000	848	848

t-test and F-test critical values: 1.96 and 1.11 is used for t_c and F_c at a 95% significance level, respectively; 2.58 and 1.17 is used at a 99% significance level, respectively.

also similarly, if not better, reproduces the user-rated PDI for the same 2000 training samples. The detailed statistics are tabulated in Table 5-5 and the corresponding PDIs are plotted in Figure 5-5. This result can also be explained to the biased nature of the data used. Some deduct-values, although differently determined did not create any discrepancies in PDI, because they might have never participated in the PDI calculation process. Therefore, caution should be exercised when assessing and accepting the deduct-values from real data, especially those for very severe types of distress, such as Alligator Cracking.

5.3 Case Study for Concrete Pavements

5.3.1 Definition of Distresses

There are 9 type-severity distresses that are collected for concrete pavements in MnDOT.

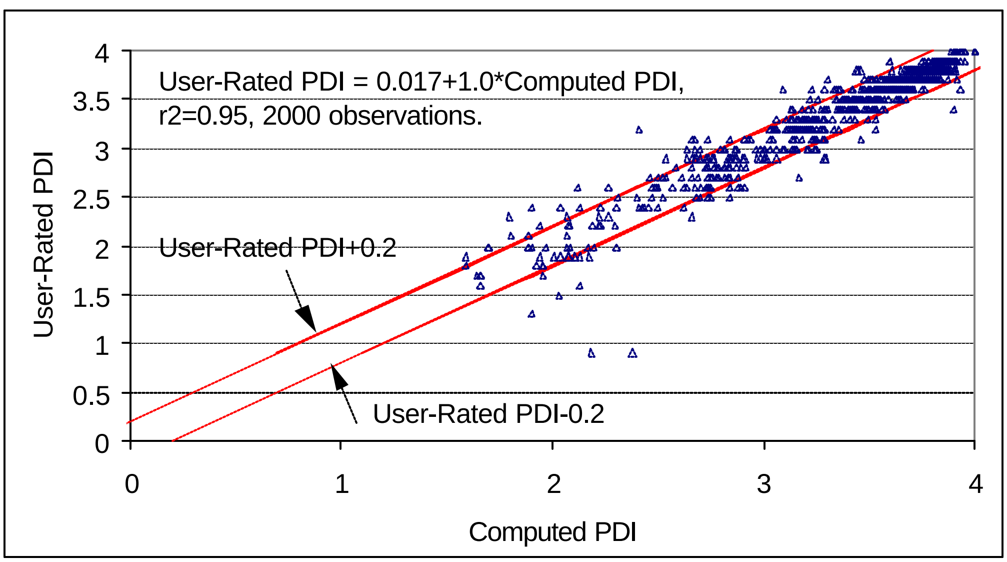

Figure 5-5. Verification of the obtained deduct-values for asphalt pavements, all-zero start result.

These distresses include slight and severe Spalling, Faulted Joints, Cracked Panels, Broken Panels, Faulted Panels, Overlaid Panels, Patches (>5 sq. ft.), and the D-cracking. A sample excerpt of the original distress data is illustrated in Table 5-6. PDI for concrete pavements is defined similarly on a 0~4 scale to that for the asphalt pavements. The density for each type-severity of distress ranges from 0% to 100%. In order to simplify the derivation process, the density of each type-severity distress is digitized into 6 levels, with each level representing a density range of 0~5%, 5.1~10%, 10.1~20%, 20.1~30%, 30.1~50%, and 50.1~100%, respectively. After digitization, each specific type-severity-density state is represented by a DID number. The 9 type-severity distresses produce 54 DIDs in total because each type-severity distress has 6 density levels. Table 5-7 shows an excerpt sheet of the coded samples as converted from Table 5-6.

1,848 samples are obtained from MnDOT and used in this study. These data are separated first into training and testing two groups. The training group contains 1000 samples. The remaining 848 samples are used as the testing group. The cubic weight-curve for the PAVER method, as recommended in Chapter 3, is used.

Table 5-6. Illustration of MnDOT distress survey data for concrete pavements.

Spalling Slight	Spalling Severe	Faulted Joints	Cracked Panels	Broken Panels	Faulted Panels	Overlaid Panels	Patches > 5 sq.ft.	D-Cracking	PDI (SR)*
19**	0	0	14	3	0	0	0	0	3.4
16	42	0	0	1	0	0	0	0	2.4
48	10	0	0	1	0	0	0	0	3.8
24	0	24	100	6	0	0	0	0	2.3
17	0	0	0	0	0	0	0	0	3.7
0	3	3	3	0	0	0	0	0	3.8
0	0	0	5	0	0	0	0	0	3.9
0	0	0	0	0	0	0	0	0	4.0

Note:Each row is a sample, and each column is a specific distress type-severity; *PDI is called Surface Rating (SR) in MnDOT, it is on a scale of 0 to 4; **values are densities in percentage.

Table 5-7. The converted MnDOT distress survey data for concrete pavements.

Spalling Slight	Spalling Severe	Faulted Joints	Cracked Panels	Broken Panels	Faulted Panels	Overlaid Panels	Patches > 5 sq.ft.	D-Cracking	PDI (SR)
3*	0	0	21	25	0	0	0	0	3.4
3	11	0	0	25	0	0	0	0	2.4
5	8	0	0	25	0	0	0	0	3.8
4	0	16	24	26	0	0	0	0	2.3
3	0	0	0	0	0	0	0	0	3.7
0	7	13	19	0	0	0	0	0	3.8
0	0	0	19	0	0	0	0	0	3.9
0	0	0	0	0	0	0	0	0	4.0

Notes: *each row is a sample, and each value is a distress ID number, ranging from 1 to 60; zero shows no such distress appears in a particular sample.

5.3.2 Solution of the Deduct-Values

The heuristic Broyden algorithm is employed to determine the 54 deduct-values using the 1000 training samples. As evidenced by the performance of 1000 samples of asphalt pavements, 1000 was assumed to be a sufficient sample size. No detailed study was conducted to identify the "true" sufficient sample size. Three parallel runs with different starting points were conducted to investigate the influence of the starting points. These may include the all-zero start, and the random start I and II (randomized from 1 to 4). These three parallel runs may also help identify the reliability of the obtained DV-Table. The converging processes for different runs are shown in Figure 5-6. The determined deduct-values from random start I are tabulated in Table 5-8.

As shown in Figure 5-6, different starting points converge to almost the same terminal objective function. However, this convergence does not mean that the DV-Table determined by each run is the same. On the contrary, the three DV-Tables are composed of very different deduct-values for some types of distress, such as Broken Panels, Faulted Panels, Overlaid Panels, Patches, and D-Cracking. Refer to Figure 5-7. From different

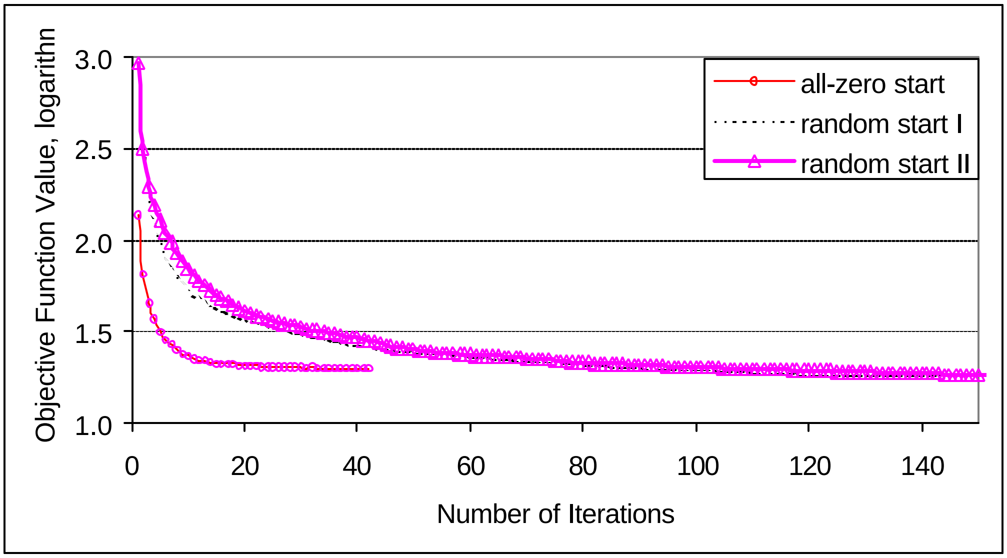

Figure 5-6. The converging process for the Broyden algorithm (1000 samples).

Table 5-8. MnDOT DV-Table for concrete pavements (1000 samples).

Density	DID1	DID2	DID3	DID4	DID5	DID6	DID7	DID8	DID9
I	0.16	0.39	0.22	0.08	0.33	0.00	0.07	0.24	0.30
II	0.29	0.63	0.41	0.10	0.45	0.20	0.08	0.59	0.51
III	0.45	0.93	0.62	0.25	0.57	**4**	0.11	0.95	0.52
IV	0.69	1.42	0.86	0.41	0.67	**4**	0.21	1.04	1.54
V	0.89	1.62	1.30	0.68	0.68	**4**	0.53	**3**	1.74
VI	1.59	2.61	1.67	1.13	**3***	**4**	**3**	**3**	2.00

*: values shown in shadow and bold faces are observed to be never calibrated.

runs, the deduct-value for some types of distress may change from 0.0 to 4.0. This variation indicates that the solution for some types of distress using the 1000 samples is very unreliable. Indeed, according to our observation, some deduct-values in Table 5-8 have never changed during the running process. This phenomenon suggests that some deduct-values may have never been calibrated, and therefore the information contained in the 1000 samples appears to be biased and insufficient for the determination of all the deduct-values.

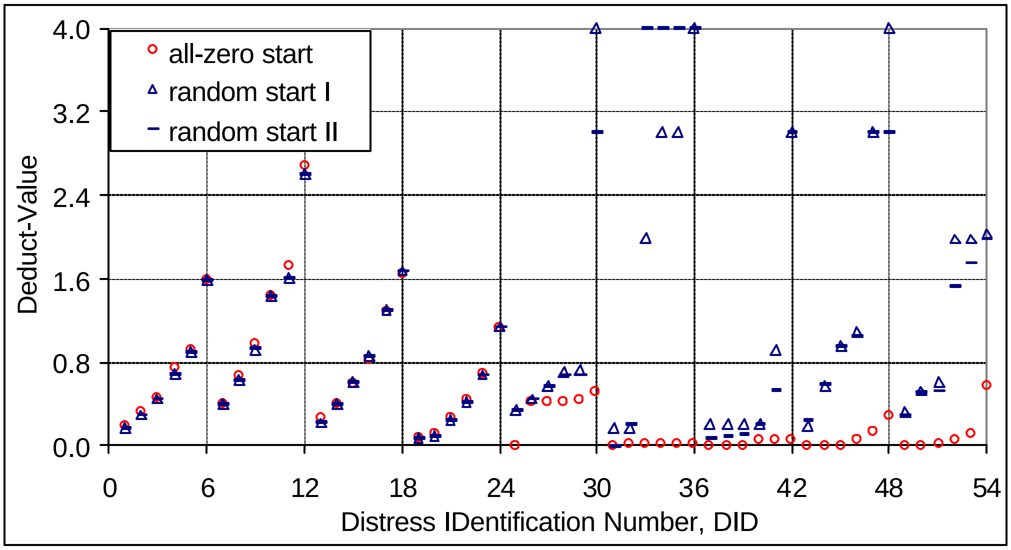

Figure 5-7. Comparison of the DV-Table for concrete pavements from different runs using different starting points (1000 samples).

5.3.3 Verification of the Performance of the Deduct-Values

Together with the testing group data, the determined deduct-values are fed into Equation 3-1 to compute PDIs. The computed PDI is then checked against the existing user-rated PDIs in the 848 testing samples. Interestingly, results from both the random start I and all-zero start produce close agreement between the computed and user-rated PDIs. As it is shown in Figure 5-8, and Table 5-5, the DV-Table from random start I produces a close regression relationship with the user-rated PDI (the slope is 0.84). About 97% of the errors are less than 0.40, or a 10-point equivalent on a 0-100 scale. According to the statistical t-test for mean and F-test for variance, the two PDIs have a similar mean and variance at a 95% significance level. As also shown by Figure 5-9 and Table 5-5, the DV-Table from the all-zero start produces almost the same level of agreement between the two PDIs. According to these 848 testing samples, there is no doubt that individual

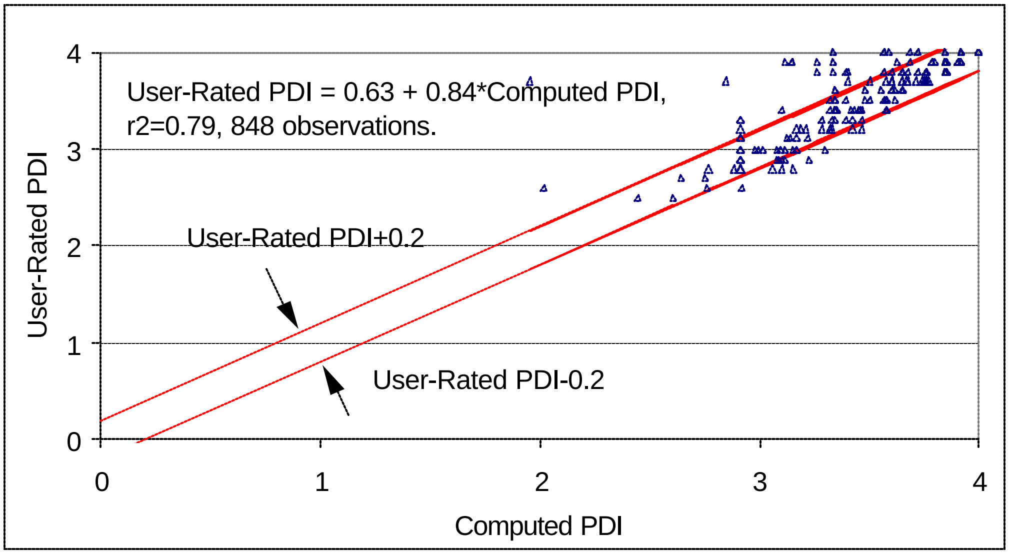

Figure 5-8. Verification of the obtained deduct-values for concrete pavements (848 samples, random start).

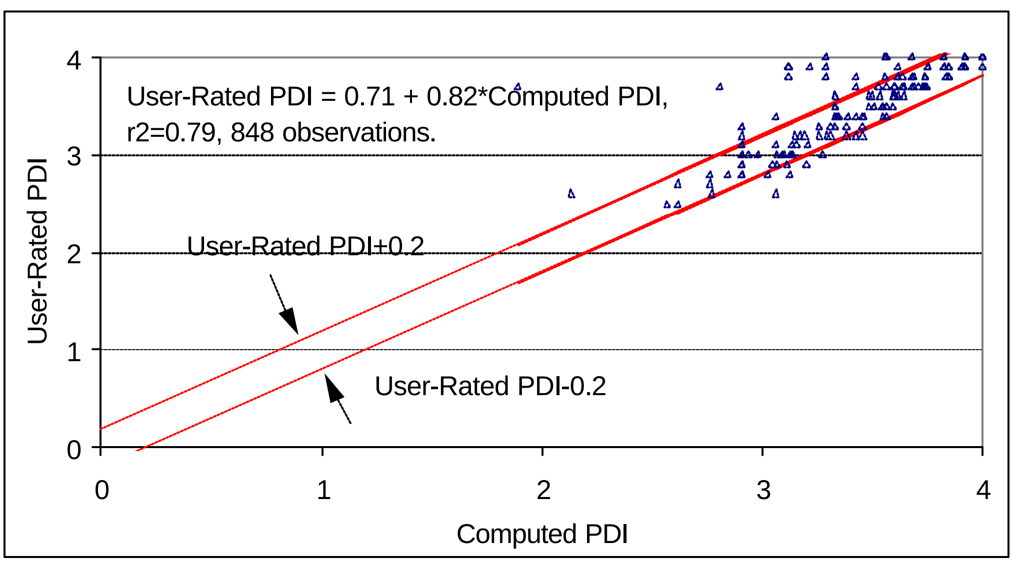

Figure 5-9. Verification of the obtained deduct-values for concrete pavements (848 samples, all-zero start).

deduct-values as determined using the 1000 training samples can reliably reproduce the user-rated PDI.

Because a different DV-Table produced almost the same level of agreement, some deduct-values must have never participated in the PDI calculation process. In other words, some types of distress may have neither appeared in the training samples, nor in the testing samples. One should, therefore, examine the data range before giving credit to the determined deduct-values. As the proposed method is essentially regression-based, it is the practitioner's responsibility to feed sufficient and unbiased data into the algorithm. Abnormal signals from the converging process and the final output should be carefully observed, in order to ascertain the reliability of the solutions.

5.4 Conclusions

A real application of the proposed procedure using actual data from MnDOT was illustrated in this Chapter. Distress definitions from MnDOT and data from direct distress survey were used to customize the proposed procedure. The Broyden algorithm successfully extracted deduct-values for all the defined distresses. Using the customized DV-Table, together with the testing set of data, the user-rated PDI can be reproduced with reasonable accuracy. The computed PDI and the User-Rated PDI have a similar mean and variance at the 95% significance level. Over 97% of the absolute difference between the two PDIs is less than 0.40, or a 5-point equivalent on a 0~100 scale. The same process was also found to be applicable for other facilities such as concrete pavements.

This application verified the validity and applicability of the proposed procedure: PDI may be formulated by fixing the relatively stable weight-curve and customizing the individual deduct-values only. However, as real distress survey data is very biased in nature, caution should be exercised in adopting the deduct-values for some very severe type of distresses, such as Alligator Cracking. Unbiased data should be entered into the algorithm in order to obtain a reliable deduct-value for every type of distress.

Chapter 6 Summary

6.1 Recapitulation

PDI is one of the most important indexes common to almost all PMS. By nature, it is a subjective characterization of pavement conditions based on objective measurements of individual distresses. At the initial stage of its development and implementation of PMS, every agency has to formulate its own PDI in order to ensure the system's responsiveness.

Almost all of the existing PDI formulation procedures are faced with a dilemma. On the one hand, PDI formulation has to allow for the free choice of distress definitions; on the other hand, the costly formulation process just produces a definition-specific model. The fact that distress definitions may change even within an agency aggravates the situation. This dissertation established and assessed a customizable procedure based on human rating behavior, or the relationship between the individual deduct-values and their corresponding weight. The method developed herein enables the easy procurement of deduct-values based on user-specific distress definitions by eliminating the iterative PDI formulation process common to most of the previous studies such as PAVER and Sun and Yao (1991).

This study proposed a generic PDI formulation as the maximum PDI value in a user-defined scale minus the Total Deduct-Value (TDV), which is the sum of the product of each individual deduct-value and its corresponding weight. The weight is defined as a function of DV-percentage, i.e. individual deduct-value over TDV. Because it is extremely difficult to obtain this function using field data, the function is obtained by approaching the existing studies based on a least squared optimization setup. The weights are identified when the squared sum of the difference between the user-rated PDI and computed PDI for a series of samples is minimized. The simplest and yet effective weight function, called weight-curve, is found to be a 3rd degree polynomial. Because the weight-curves extracted from the two independent studies, PAVER and Sun and Yao (1991) are very similar in function form, the extreme difference in PDI caused by interchanging the curves in the proposed formulation is less than 9-points on a 0~100 scale. One can conclude that the weight-curve itself is portable and may be used as the basis for PDI formulating PDI.

By fixing the weight-curve initially, the customization of deduct-values is accomplished by a non-linear programming technique, the Broyden algorithm. Deduct-values for user-defined distresses are determined when the summed squared difference between the computed PDI and the user-rated PDI for a series of samples is minimized. The weight-curve can be recalculated by the same optimization setup using the newly determined deduct-values when one deems it to be absolutely necessary. A software package was developed in Visual Basic® 5.0 to fully automate the customization process.

As a case study, the proposed customizable procedure was implemented to formulate a PDI using direct distress survey data from MnDOT. Deduct-values were successfully identified for each distress as defined by MnDOT for both asphalt and concrete pavements. It was determined that these deduct-values are capable of reliably reproducing the user-rated PDIs when similar pavement conditions occur. The 3rd degree polynomial weight-curve from the PAVER method is applicable for both asphalt and concrete pavements.

6.2 Contributions

The proposed methodology can facilitate the formulation of the PDI for agencies that are implementing a PMS. First, this procedure is based on reasonably stable human rating behavior. This feature enables the proposed procedure to be easily customized to different distress definitions because the painstaking iterative process common to most conventional procedures is eliminated.

Second, the proposed formulation is superior to that of the existing methods. There is a clear physical meaning for each part of this formulation. This formulation is also mathematically friendly, which enables easy identification of both the weight-curve and deduct-values. By comparison, verifying the stability of the correction curves for the PAVER method would be extremely difficult. Deriving the deduct-values based on the step-wise formulation in the China method is also very difficult. In addition, the modeling concept of the proposed procedure proves to be better suited for rating bad pavements than the concept embedded in PAVER. The proposed procedure models every component in a sample, beyond just the total deduct-value.

Third, the proposed procedure allows the direct use of samples with mixed distresses from the distress survey in the formulation process, while it produces deduct-values with the same physical meaning as those in PAVER. This capability, though adopted from the previous studies, is significant, because it relieves the workload of field data collection during PDI formulation.

In addition, the proposed procedure encourages the adoption of a default weight-curve, which is far more meaningful than adopting an entire default model. It eliminates the possible incompatibility problem inherent to adopting default models, and ensures the maximum responsiveness of a PDI with the least amount of effort from the agency. More importantly, the proposed procedure enables an agency to adapt actively to its own needs. For example, this procedure makes it easier for an agency to update its DV-Table in response to the introduction of a new data collection method, equipment, or a new maintenance standard.

6.3 Limitations

Theoretically, both weight-curve, and deduct-values are unique to each agency. Adoption of a default weight-curve can definitely introduce discrepancies. In the proposed procedure, such discrepancies are borne entirely by the determined deduct-values, so that the integrity of PDI is not compromised. As a result, the values of these deduct-values may deviate from those in PAVER by as much as 15-points on a 0 to 100 scale. It should be noted that actual pavement performance curves should be used as additional constraints to identify these deduct-values, if they are also employed for the development of individual distress indexes.

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APPENDIX

Appendix User's Guide to the Visual Basic Programs

1. Introduction

This appendix is the user's guide to the non-linear programming algorithms developed in this study for the determination of both weight-curve and individual deduct-values. All codes are written in Visual Basic Professional Edition 5.0 (VB5.0). There are three major functions in the developed programs. The first one is the determination of the shape of weight-curve based on given sample files. The next function is the determination of the continuous weight-curve by regression analysis. And the third function is the derivation of deduct-values for individual distress based on a given initial DV-Table, and sample data files. According to the three functions, the graphic user interface is separated into 6 frames, namely the INPUT MODULE FRAME, CALCULATION MODULE FRAME, WEIGHT-CURVE FRAME, WEIGHT-CURVE DISCREET POINTS FRAME, DEDUCT-VALUE TABLE AS DETERMINED FRAME, and the FRAME for the display of objective function value. The user-interface is shown in Figure A-1. The following is a frame by frame description of the program.

2. THE WEIGHT-CURVE FRAME

The main function of this frame is to display the initial and possible later-on update of the coefficients for the weight-curve, according to the user-specified degree of the weight-curves. The existing coefficients, as shown in Figure A-1, "3.27", "-5.96", and "3.65" is the default value of the proposed model. The later-on updates may come from multi-linear regression analyses, which are activated by the WEIGHT-CURVE button in the CALCULATION MODULE FRAME. The credibility of the regression analysis is indicated using the two text-boxes, R-SQUARED VALUE, and F-STATISTICS. The sample data file name is specified by the SAMPLE FILE NAME text-box in the INPUT MODULE FRAME. Users may specify the degree of the polynomials through the DEGREE OF POLYNOMIAL combo-box. The maximum degree of the polynomial is set as seven (7). The minimum degree of the polynomial is set as three (3). The corresponding text-boxes will appear/disappear according the specified degree of polynomial.

3. DEDUCT-VALUE TABLE AS DETERMINED

DEDUCT-VALUE TABLE AS DETERMINED is a DBGRID in VB5.0, which bounds with an ACCESS database table. It is also called the DV-Table. Each row of this DBGRID displays the Distress IDentification (DID) number, while each column displays the discreet density level for a specific type of distress. Each number displayed is the corresponding deduct-value for that specific type-severity-density state of distress. For example, the value of “98” at the up-left corner of the DBGRID is the deduct-value as determined for DID number “1”, and the first density level. The value of “93” at the lower-right corner of the DBGRID is the deduct-value for DID number “6”, and density level “6”.

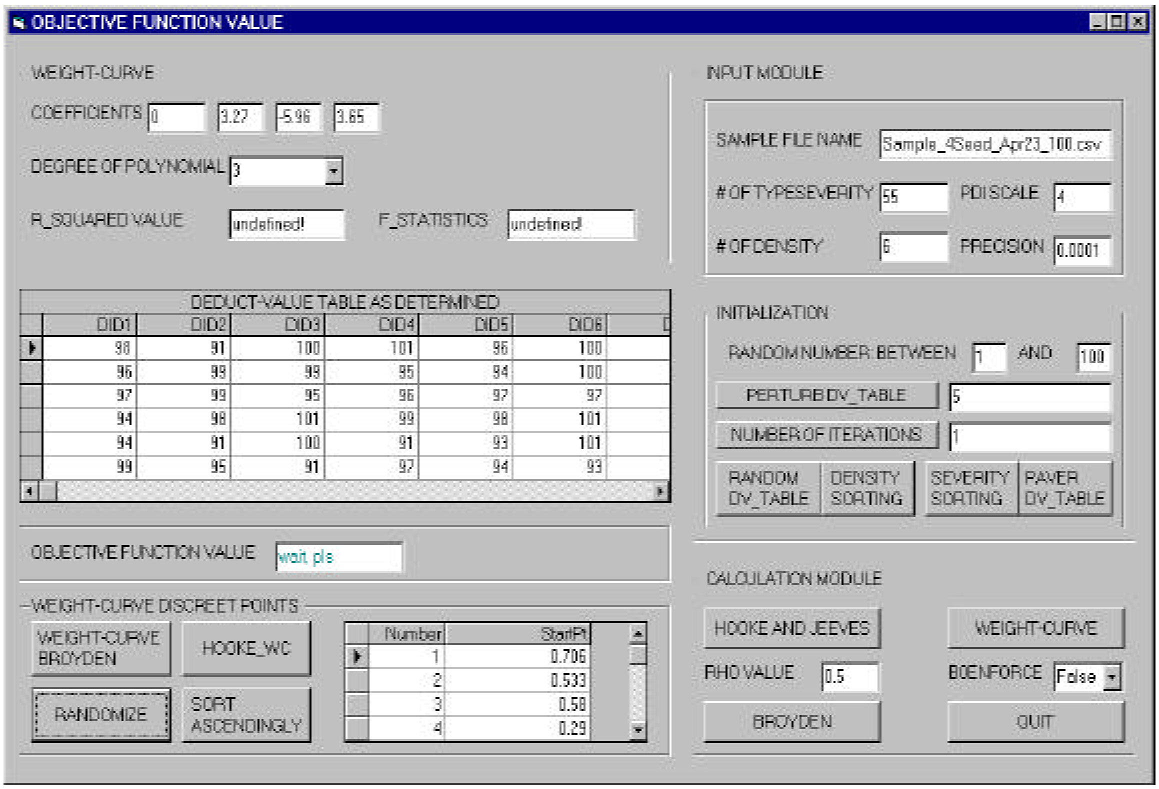

Figure A-1. The Graphical user interface of the program.

This DBGRID provides the initial input to start the Broyden algorithm. It also stores the final output of the program. Before the user start to compute individual deduct-values, this DBGRID should be initialized. Several schemes are available for the initialization process. The first scheme is to use the default PAVER DV-Table, which is activated by the PAVER DV-Table button in the INPUT MODULE FRAME. Another scheme is to initialize the DBGRID randomly, using a pair of user-specified random numbers. The random number is intended to be between "0" to "100". However, the user may ignore this limitation, because even a negative number will also work. The DBGRID also allows manual editing, which may be considered as an additional scheme in initializing the DBGRID.

When the program terminates, the DBGRID will be updated. This is the final result of the deduct-values as determined. A backup text-file will be generated at the same time. The file name is dependent on the calculation algorithms employed. For example, "BROYDEN.txt" will be generated when the button BROYDEN has been pressed for the computation purpose. A file named "HK.txt" will be created when the Hooke and Jeeves algorithm is chosen.

4. THE OBJECTIVE FUNCTION VALUE FRAME

Objective function value is defined as the squared sum of the difference between the given PDI in the sample file and that calculated using the proposed model based on the current DV-Table and weight-curve. This value will update each time when the program terminates. It may act as an indicator on how well the current DV-Table is performing. For example, if the value for the objective function is “16,000” for “1,000” samples, then the average difference between the two PDIs is $\sqrt{16{,}000/1{,}000} = 4$-points, assuming the difference is equal for each sample. This is the primary indicator for the user to judge the performance of the algorithms and the determined DV-Table.

5. THE INPUT MODULE FRAME

THE INPUT MODULE FRAME includes two frames. The first one encompasses 5 text-boxes. The SAMPLE FILE NAME text-box stores the user-input file name. The file should be in ASCII text file format, with either fixed width for each field, or comma delimitation. The PDI SCALE box indicates the scale the user prefers for its PDI. A value of “4.0” implies a PDI-range of 0.0~4.0 (4.0 for the best pavements). In addition, this value also dictates the final range of the deduct-values, i.e. the contents in the DBGRID when the program terminates. The user should pay attention not to use a random range beyond the PDI scale to initialize the DV-Table. Otherwise, this will cause unnecessary computation load to the program without producing any better results as verified by this study. # OF TYPESEVERITY text-box stores the maximum number of distress DID, that is considered by the user. Similarly, # OF DENSITY text-box indicates the maximum number of density the user wish to discretize. It is suggested that the user use 6 density levels as defined in the algorithms. A larger value will cause unnecessarily slow-down of the program. PRECISION text-box is used to stipulate the precision level intended for a run of the program. The precision refers to the precision of the model of the gradients.

However, for the Hooke-Jeeves direct search method, it indicates the distance between the final two sought points (step length).

The INITIALIZATION MODULE is the second frame in the INPUT MODULE FRAME. It consists of 6 command buttons, and 4 text-boxes. The two RANDOM NUMBER BETWEEN text-boxes accept user-input about the range within which the DV-Table will be randomly initialized. Note this number should not be larger than the specified PDI scale as cautioned above. The PERTURB DV-Table button is used to perturb the deduct-values in the DV-Table. The amount of this perturbation is determined by the value of the corresponding text-box beside it. The perturbation process will add a random value between 1 and the value in the text-box to all the deduct-values in the DV-Table. This process is found to be effective in re-initializing the algorithm, when it is stuck (the objective function value stops to drop significantly). The NUMBER OF ITERATION text-box has a default value of “1”. However, the maximum number of iterations is not “1”, and it is not used as the terminating criteria for this program. Instead, this program employed the minimum change in the objective function value between two consecutive iterations. The minimum change is set as 0.011 in our experiment, and may be adjusted based on sample size, and stage of the progress of the program.

RANDOM DV-Table button activates the process of the random initialization of the DV-Table. DENSITY SORTING and SEVERITY SORTING buttons will sort the existing DV-Table according to the density and severity levels of the distress, respectively. The underlying concept is that a higher density and/or severity distress should have higher deduct-values. DENSITY SORTING is found to be extremely beneficial in speeding up the converging process. PAVER DV-Table buttons, once pressed, will initialize the DV-Table using the default PAVER DV-Table.

6. THE CALCULATION MODULE FRAME

This frame undertakes the computation function of the program. HOOKE AND JEEVES button will activate the Hooke and Jeeves direct search algorithm once pressed. The current DV-Table in the DBGRID, the RHO VALUE, PRECISION, and NUMBER OF ITERATIONS text boxes will provide input for this algorithm.

RHO VALUE is the parameter for algorithm convergence control. It is a multiplier for the search step in the direct search algorithm, and is between 0 and 1. A default value of 0.5 is found to be quite robust. Smaller values of RHO correspond to bigger step-size changes, which make the algorithm run more quickly. However, there is a chance (especially with highly nonlinear functions) that these big changes will accidentally overlook a promising search vector, leading to nonconvergence. On the other hand, larger values of RHO correspond to smaller step-size changes, which force the algorithm to carefully examine nearby points instead of optimistically forging ahead. This improves the probability of convergence. The step-size is reduced until it is equal to (or smaller than) PRECISION. The number of iterations performed by Hooke-Jeeves is determined by RHO and PRECISION: $RHO^{(number\_of\_iterations)}$ = PRECISION. However, in this program, the minimum change, say 0.01, in the objective function is used to determine whether the search will continue. As the converging process for the direct search method is very much slower than the Broyden method, it is suggested that the Broyden method be applied first. The BROYDEN button will activate the BROYDEN variable metric optimization algorithm. The initial DV-Table, PRECISION, and NUMBER OF ITERATIONS are its essential inputs.

WEIGHT-CURVE button starts the regression analysis for a new weight-curve. The sample file, and the existing current DV-Table will be used as input. The regression coefficients will be displayed in the COEFFICIENT text boxes. The value of the DEGREE OF POLYNOMIAL combo box will determine the independent variable number in the regression analysis. The value of B0ENFORCE combo-box indicates whether the intercept will be enforced to zero. Because each weight-curve is enforced to cross the origin, so most of the time, it is advisable to give a TRUE value for the B0ENFORCE combo box.

QUIT button will cause the program to terminate. However, "Ctrl+Break" is needed to cause termination while the program is still running.

7. THE WEIGHT-CURVE DISCREET POINTS FRAME

The primary function of this frame is to determine the discreet points on a weight-curve using optimizing algorithms. There are four command-buttons and one DBGRID in this frame. The WEIGHT-CURVE BROYDEN button is actually not activated, because the derivative for this objective function is non-existent. The main calculation function is performed by the HOOKE_WC button. Once pressed, this button will accept input from the user-specified sample file in the SAMPLE FILE NAME text-box, and initialize the program using values in the DBGRID, and start to compute. This search will terminate until the minimum change for the objective function value between any two consecutive searches drops below “0.01”. The RANDOMIZE button will randomize the DBGRID using random values between “0.0” and “1.0”, inclusive. The SORT ASCENDINGLY button will sort the existing values in the DBGRID ascendingly. This is to ensure some better form of initial values for the search algorithm. There are two columns in the DBGRID. The first column is the DV-percentage in integer format, and the second column is the initial and also the final mapped weight. For example, the value “1”, “0.706” in the first row means a DV-percentage of 1% will correspond to a weight of “0.706”. The shape of the weight-curve is determined by these discreet points using curve-fitting algorithms.

VITA

Zhongren Wang was born in Changtu County, Liaoning Province, China on January 27, 1967. He graduated from Tongji University, Shanghai in 1985 and 1992 with his B. Sc and M. Eng., respectively, both in Highway, Urban Road and Airport Engineering. After graduation, he joined the Highway Research Institute (HRI) of the Ministry of Communications (MOC) in Beijing, China, where he worked as a consultant and project manager for 5 years. His working areas include pavement design and evaluation, freeway roadside safety appurtenance design and research, and freeway traffic management system design and implementation. He played a major role in the development of a Computer Aided Design (CAD) system for freeway roadside safety appurtenance system, which was sponsored by the MOC.

He is married to Weili Zhao on April 22, 1996. Half a year later, he was awarded a scholarship to further his studies at the National University of Singapore (NUS), where he expanded his research areas to traffic flow theory and traffic operations. He also implemented artificial intelligence techniques, such as Genetic Algorithms, Neural Networks, and Machine Vision in his research projects. In early 1999, he received his M. Eng. in Transportation Engineering from NUS.

Early the same year, he entered the Transportation Program for his Doctorate Education at the University of Tennessee, Knoxville (UTK). He participated in several projects from the Tennessee Department of Transportation (TennDOT), and contributed to the development and implementation of the PMS for TennDOT. He developed a customizable procedure for the formulation of pavement distress index.

Interests and Expertise:

- Pavement design, evaluation and management
- Traffic flow theory
- Traffic operation and control
- Application of artificial intelligence techniques in transportation