Streamlining the World Bank's Highway Design and Maintenance Standards Model (HDM-III) for Network Level Application

by

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ABSTRACT

The World Bank's Highway Design and Maintenance Standards model (HDM-III) is increasingly becoming a popular economic analysis "engine" with wide applications within pavement management systems, in particular, the network-level priority programming sector in developing countries. The major disincentives, however, for widespread application of the model in low-income road agencies include the excessive data needs and lack of effective guidelines on local adaptation.

The thesis addresses streamlining the application of the HDM-III model at the network-level priority programming by reducing the model data needs. This was done by screening out the insensitive input variables with respect to an application-specific output.

An advanced statistical experimental design based on the Latin hypercube sampling was formulated to investigate the sensitivity of the link characterization input factors upon several HDM-III outputs – the net present value of net benefits (NPV), the agency life-cycle costs, and the road users' (mainly vehicle operating costs, VOCs) life-cycle costs.

The boundaries of the input space (factor ranges) investigated in this study were determined from field data collected in Tanzania in 1994.

The plausibility of extending the current pool of "default inputs" for task-specific applications was examined. The inactive factors (as determined by the sensitivity study) were replaced by constant values reflective of typical levels for the case study region. The HDM-III model predictions from using the full set of inputs, and those obtained by using default values in place of the inactive factors, were statistically compared.

The research findings confirm the suspected nature of factor sparsity (few active factors) of the HDM-III model. The agency and road users' life-cycle costs were found to be dominated by very few input factors. More importantly, the factor sensitivity is specific to the R&M strategy employed.

Statistical comparison between the HDM-III life-cycle predictions based on default inputs and the predictions based on the full data set found that there was no significant difference. The study demonstrated the possibility of extending the current pool of default inputs for application-specific model output.

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DEDICATION

Kwa mama yangu mpendwa, Mariana Mkandeke Sambuo Mushi,

Kwa upendo wako usiomipaka, kwa sala zako, kwa imani yako, kwa kujimima kwako.

"Nyi'we kuletaana nu mae!"

Kwa mwanangu Donath kwa kulelewa bila baba.

Kwa Ilu,

Kwa Zainabu, mpendwa wa maisha yangu, kwa upendo, subira na uvumilivu.

Kwenu nyote, pokeeni kwa upendo na taadhima kazi hii.

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Chapter 1

INTRODUCTION

1.1 Background

According to a World Bank policy study, the state of the road networks in Sub Saharan Africa (SSA) poses a serious crisis. The networks, which were expanded massively in the post independent boom of the 1960s and 1970s, started crumbling in the 1980s and are presently on the verge of collapsing. Immediate measures are necessary to control the deterioration. The dimensions of the problem in terms of poor network upkeep, its origin and its economic implications are further addressed in Section 2.1.3. An even more serious problem is the lack of economic capability of SSA countries to correct the situation. Economic adversity in the region for the last two decades is only part of the explanation; past mistakes in investment choices played even greater role. However, a large part of the problem is attributable to lack of institutional capacity in the SSA [Faiz 87 and 91, Bank 88].

The SSA road networks were estimated to have an aggregate length of more than one million kilometers in 1988, of which only 11 percent was paved [Bank 88]. Faiz *et al.* estimated that more than 95 percent of the road system consist of low-volume roads, with an average traffic of less than 400 vehicles per day [Faiz 87]. Yet, SSA has the lowest road spatial density (about 5 km per 100 sq. km of land) -- about one half of the global average for developing countries. The ratio of road kilometers per million dollars of gross national product (GNP) is the highest of all regions, at a global average of 3.6 (excluding Nigeria) [Faiz 87]. These figures reflect the vast distances, the dispersed settlement patterns, and the smaller economic base of SSA. The economic importance of these poorly distributed road networks is underlined by the fact that more than 90 percent of land commerce is dependent on roads [Faiz 91]. The main roads in the region cater for up to 80 percent of the inter-urban traffic in the region [Faiz 87].

With the road conditions in the region as given in Table 1.1, the financial implications are staggering. Smith estimated the financing requirements to contain the road maintenance problem in SSA under three categories [Smith 87]. The current backlog of rehabilitation for the main roads alone was valued at approximately US $4.6 billion (at 1984 prices). Annual maintenance to check normal deterioration was estimated at US $0.7 billion. Further, to clear the backlog in 10 years the minimum annual rehabilitation and maintenance financial requirements (over the next ten years) are US $1.2 billion. It should be noted that more than 70 percent of the funds required are in foreign exchange. More conservative estimates have been given elsewhere [Faiz 91, Riverson 90 and 91, Mason 89, Bank 88].

TABLE 1.1 Road Conditions in Sub-Saharan Africa (1984 – 1988) *[Faiz 91]*

Year	Pavement Type	Percent of Roads		
		Good	**Fair**	**Poor**
1984	Paved	47	27	26
	Unpaved	33	32	35
1988	Paved	52	25	23
	Unpaved	29	32	39

To appreciate the magnitude of the problem these figures should be compared with the regional GNP of US $85.5 billion for 1984 at an annual decline of about 1 percent. Measuring the road needs in terms of other social needs of the region [Faiz 87] noted that:

> *"...The expenditures needed to make for past omissions of preventive maintenance in Sub-Saharan Africa are at least 10 times as much as would be needed to provide a continuing supply of textbooks for all elementary schools in the region until year 2000."*

The cross-sectoral economic implications are overwhelming. It is a well-documented fact that the increase in costs to the road authorities is only a fraction of the overall burden resulting from deteriorating roads. Vehicle operating costs on properly maintained roads account for up to 90% of the total transport costs even for medium trafficked roads. On bad roads, vehicle operating costs (mostly in foreign exchange) can easily double, imposing a heavy burden on road users. The higher haulage costs can drastically constrain economic activity and put brakes on economic growth, especially in agricultural production areas. It is worth noting that without efficient transport – which in SSA means, more than anything else, roads – there can be no supply response to support renewed economic growth and sustainable development.

1.2 Nature of the Problem

Current practice in pavement management technology in SSA is such that assessment of maintenance and rehabilitation needs still relies on less than optimal methodologies [Pinard 87, Mason 89, Bank 88, Faiz 89 and 91]. Implementation of rational methodologies is constrained by many factors. They include relatively low level of material and human resources and the lack of institutional and technical capacity to adopt existing comprehensive decision making models [Pinard 87, Faiz 91].

Effective application of tools like the World Bank's Highway Design and Maintenance Standards Model (HDM-III) and the British Transportation Research Laboratory's Road Transportation Investment Model (RTIM3) in investment appraisal requires, among other things, quality detailed data and skilled personnel to maintain the data, prepare the data files and run the model. These relatively high requirements have, in effect, made the models inaccessible to the low-income road agencies of SSA. There is a real need for these road agencies (in Sub Saharan Africa and in developing countries in general) to develop simplified analytical tools for allocating limited resources to rehabilitation and maintenance (R&M) programs in a manner which achieves the highest economic efficiency [Queiroz 92, Kerali 91, 92, ISOHDM 93].

It is hypothesized that road investment appraisal tools currently available (*e.g.*, HDM-III, RTIM3, *etc.*) fail to recognize the special concerns of the low income road authorities of SSA, particularly in relation to data needs and skills to apply these tools. Summing up, the consensus of the inception workshop for the current initiative to upgrade the model [ISOHDM 93] observe that:

> *"It was acknowledged that some institutions in developing countries may generally lack the finance and personnel with skills required to effectively implement all of the facilities in the new model. ... "In particular, there is a need for simplicity and understandability of any model, and for cost effective data requirements."*

This thesis addresses a simplified application of the HDM-III model to network level priority programming by reducing the model data needs. The approach is to identify factors with least impact on the HDM-III predictions and provide surrogate values that can be used in subsequent analyses.

1.3 Basis for a Simplified Pavement Management Analysis Tool for Low Income Road Agencies

The Highway Design and Maintenance Standards Model (HDM-III) was developed by the World Bank to provide highway agencies, particularly in developing countries, a tool for evaluating and analyzing maintenance and rehabilitation options; comparing policies or standards and formulating programs; and to support decision making in road investment in general [Watanatada 87a, Bank 89]. The model estimates detailed pavement deterioration, agency costs and road users' costs for different design and maintenance alternatives and hence provides rational and consistent economic decision criteria for technical planners and policy makers.

[Pinard 87] and [Queiroz 92] discuss in detail the special constraints for implementing pavement management in developing countries as including a low level of technology and limited availability of human and material resources. HDM-III requirements for high quality detailed data and consequently highly trained and skilled personnel to maintain the data, prepare the data files and run the model seem to be beyond the means of the low income road agencies of Sub-Saharan Africa. The social and economic factors derailing road network stabilization in this region is widely published in the literature. The most critical factors include failure to establish sustainable institutions that can effectively and efficiently use the available resources to manage the road networks [Faiz 87 and 91, Bank 88].

The HDM-III model offers an excellent potential for application at the network and sub-network level pavement management for developing countries [Queiroz 92]. However, this potential has hardly been realized in most of the poor countries of Sub-Saharan Africa (SSA). The motivation of the research in this thesis is based on the premise that the major factor hindering wide adoption of the HDM-III model for network-level priority programming in SSA is its excessive data needs and skills to use it.

1.4 Objectives and Scope of the Research

1.4.1 Research Hypothesis

The motivation of the research presented in this thesis is that low income road authorities need to implement more rational methodologies of allocating limited resources to the upkeep of their road networks. The limited supply of skilled personnel and financing available to these agencies limits their ability to effectively make use of the existing investment appraisal tools like the HDM-III in the priority analysis of rehabilitation and maintenance programs. For the same reasons, developing local analysis tools based on technically sound algorithms is generally out of question.

The data requirement for network level application of the HDM-III model is serious concern for the extreme low income agencies of Sub Saharan Africa. The link characterization for a paved road, for example, requires about 41 input attributes including the critical pavement deterioration calibration parameters. Although some of these input requirements are optional (with default values supplied internally by the model) no guide exists in the literature identifying the most sensitive input factors where the user could focus to arrive at reasonable estimate predictions from the model.

The key thesis hypothesis is that for a given model application and a given case study region, only a few active input factors (relative to the total number of input factors) have significant influence upon the relevant HDM-III model output(s). In statistical terms, the model is said to exhibit factor sparsity with respect to a given model response. In other words, for a specific application, such as priority analysis of rehabilitation programs, an acceptable quality of model output criteria could be achieved by supplying relatively fewer inputs than currently demanded. The least sensitive model factors could be fixed as constants, and re-used for similar applications within the same study region. This is the basis for reducing the data needs for regional-specific application of the model.

1.4.2 General Goal

The general objective of the research in this thesis was to streamline the data requirements for network level application of the HDM-III model. The ultimate goal was to develop a framework that could be used to identify the most significant factors for specific applications and develop a set of default inputs. It is expected that this will reduce the need for heavy outlays of human and material resources on detailed data bases that are typically required to effectively make use of the HDM-III model.

It was recognized that the resulting (trimmed down) model may provide less precise quantification of the primary output parameters (compared to the full model). However, it is argued that the trade-off of this lost precision against the prospects of wide adoption in priority analysis (albeit approximate) in SSA outweighs the disadvantage. If the reduced predictive accuracy can be shown to have a marginally low impact upon the technical strategies chosen, then the simplified model will offer tremendous benefits to the regional and national road agencies in SSA. Further, even where quality databases (and necessary skills) exist, a quick approximate analysis can be very handy for preliminary program review prior to full scale studies.

The secondary product of the study, the sensitivity results of HDM input parameters offers several potential applications. For example, for the road agencies in the region that are relatively more endowed in capital resources, it may be necessary to determine which input data values merit higher accuracy, and hence justify increased expenditure in data collection.

1.4.3 Initial Scope and Specific Objectives

The thesis hypothesis and the broad focus of the research were further translated into specific objectives. Tasks to guide and accomplish these objectives were formulated on the basis of which an initial scope of work was established. This initial scope is summarized in the following tasks:

(1) Review and consolidate the literature on calibrating and adapting the model to local applications, in particular for network-level rehabilitation and maintenance programming. Develop a comprehensive calibration guide for the specific application in priority analyses.

(2) Develop an efficient approach to conduct systematic factor sensitivity analysis (including effects of factor interactions) on HDM input variables that influence the decision criteria for priority analysis of rehabilitation and maintenance programs.

(3) Explore the possibility of developing a simplified application of the HDM-III based on regional-specific, application-specific default values for the less sensitive factors in the model.

(4) Test the validity of the simplified model (defaults-based predictions) by statistical comparison of the model response against the full model.

Initially, it was intended to explore the possibility of reducing input data requirements under all the four classes of HDM-III inputs relevant to R&M priority analysis (Figure 1.1). However, as subsequently discussed in, only part of the initial scope was realized.

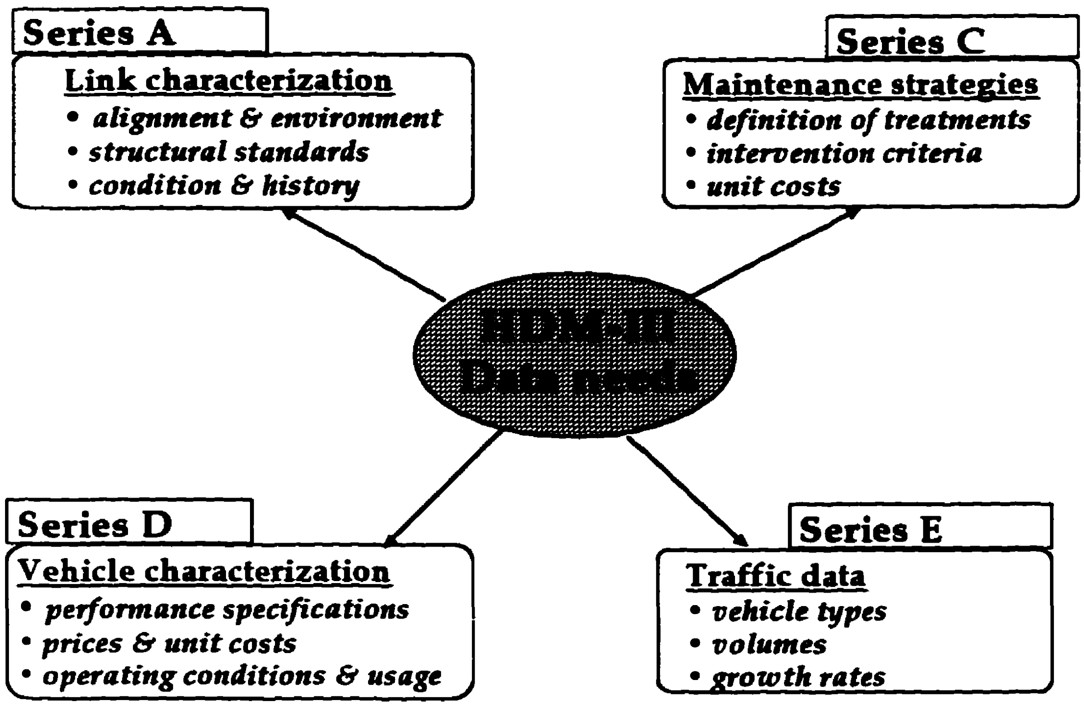

FIGURE 1.1 HDM-III data requirements for R&M priority programming

1.5 Organization of the Thesis

The thesis is organized in a manner closely reflecting the research steps given in the preceding subsection. Following this introduction, chapter two summarizes what the literature has to offer in the various aspects of the study. First, the need for a different approach to priority programming in Sub Saharan Africa is highlighted. Next, the potential of using HDM-III as an analysis engine in a pavement management system is presented followed with the key model limitations making it unpopular in SSA. The chapter also looks into the past efforts to simplify the application of the HDM-III model, including the expectations of the HDM4 initiative. Finally, the chapter reviews techniques used in sensitivity analyses and concludes by highlighting the advantages of experimental design in the exploration of effects of factor interactions upon computer models.

In chapter three, the thesis presents a compendium of the literature on user guide to adaptation and calibration of the HDM-III model for local application in R&M priority programming.

Chapter four presents the key aspects of formulating and developing the research methodology. The background to the research problem and its significance is further highlighted. Initial formulation of one-factor-at-a-time sensitivity analysis is developed. Next, the diversity of choices for relevant criteria (or model response) for prioritizing R&M programs is discussed. Finally, the concept of elasticity as a rational platform for comparing factor sensitivities is introduced.

Chapter five deals with design of the statistical experiment and its application to explore main factor effects as well as effects of factor interactions of computer models.

Chapter six presents the research results, while in chapter seven the concept of regional-specific default inputs as a model simplification strategy is examined.

The thesis concludes with a summary of research findings and recommendations in chapter eight.

Chapter 2

LITERATURE REVIEW

2.1 Approaches to Priority Programming in Low Income Agencies

2.1.1 Role of Priority Analysis in Pavement Management

Priority programming constitutes one of the most important functions of pavement management analysis. The basic function of priority programming both at the project and network levels is to evaluate or compare project alternatives in order to select optimal set of alternatives for implementation. The degree to which the program is optimal is influenced by both the criteria and the analysis technique used. Some agencies may, for example, use simple subjective ranking; some use cost effectiveness as surrogate to an economic index, yet others use direct economic criteria, *i.e.*, cost minimization or benefit maximization. [Haas 94] summarizes the various methods and gives their advantages and disadvantages. Few agencies use complex mathematical optimization procedures to identify true optimal solutions (cost minimization or benefit maximization) taking into consideration effects of project location and timing.

A detailed treatment of the priority programming subject is given elsewhere [Haas 94]. There are a few papers that review the available techniques and tools for priority programming (see, for example, [Haas 85, Hill 91 and Liebman 85]). Figure 2.1 shows the major steps in priority programming. The priority analysis within the priority programming function (shaded area in Figure 2.1) is the subject of the research in this thesis. The intention is to develop a simple tool for priority analysis for agencies with limited resources, in particular where quality data are unavailable.

The priority analysis step can be viewed as consisting of two sub-activities: economic evaluation and optimization analysis. Economic evaluation deals with the bulk of computational procedures to determine economic costs, (and/or benefits) and related indices for each project alternative in each time frame in the program period. The second sub-activity, optimization analysis, uses the results of the economic analysis to select the project list that meets the optimality criterion.

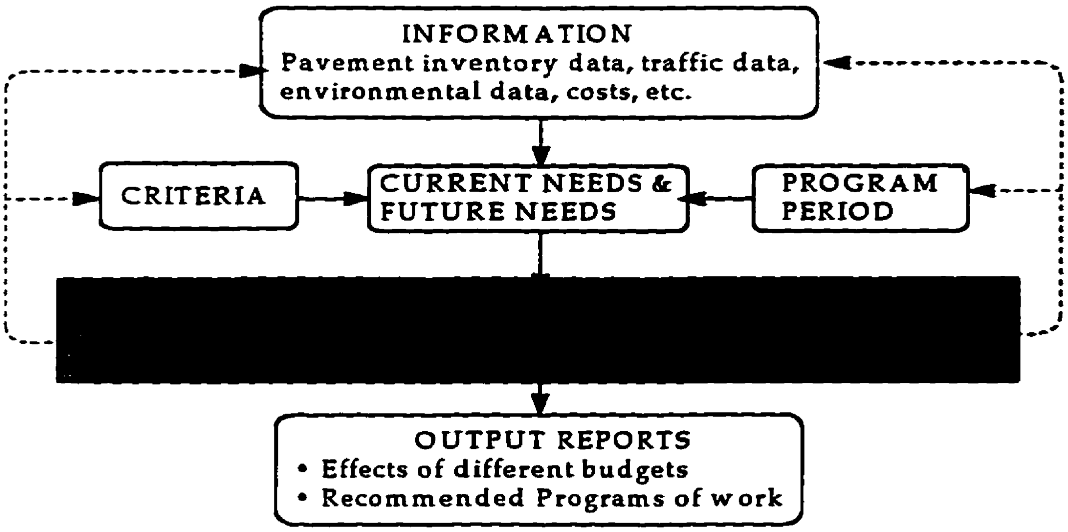

FIGURE 2.1 ***Major steps in priority programming [Haas 85]***

The economic evaluation sub-task (in the context of priority analysis) is generally tedious and computationally intensive owing to the requirement to explicitly consider the primary effects of traffic, link characterization attributes, and pavement standards, as well as the effects of maintenance intervention levels upon the cost streams arising through the life-cycle of a road facility [Parsley 82, Chesher 87, Paterson 87]. This complexity is the basis or the motivation behind analysis software tools like HDM-III (RTIM3, and other proprietary products). These models are primary analysis engines that were intended to provide the basic function of economic evaluations either independently or within larger pavement management processes.

The concept of applying HDM-III as an analysis engine in a network-level PMS has been demonstrated widely; good examples are Brazil [Queiroz 92], and Queensland, Australia [Robertson 94, Howard 94]. In the Brazil application, the model was used in conjunction with the Expenditure Budgeting Model (EBM) which uses a heuristic technique to solve a multi-year budget constraint problem [Bank 89] providing the optimization analysis function. Figure 2.2 shows a schematic of the role of HDM-III and EBM in a PMS analysis. From Queensland [Robertson 94] reports that:

> *"Analysis of road investment upkeep in recent years has focused on strategic studies at the network level. These studies have employed HDM-III and EBM as the economic life-cycle analysis engine within larger software suites which control multiple analysis cycles, and data flows to and from the analysis engine."*

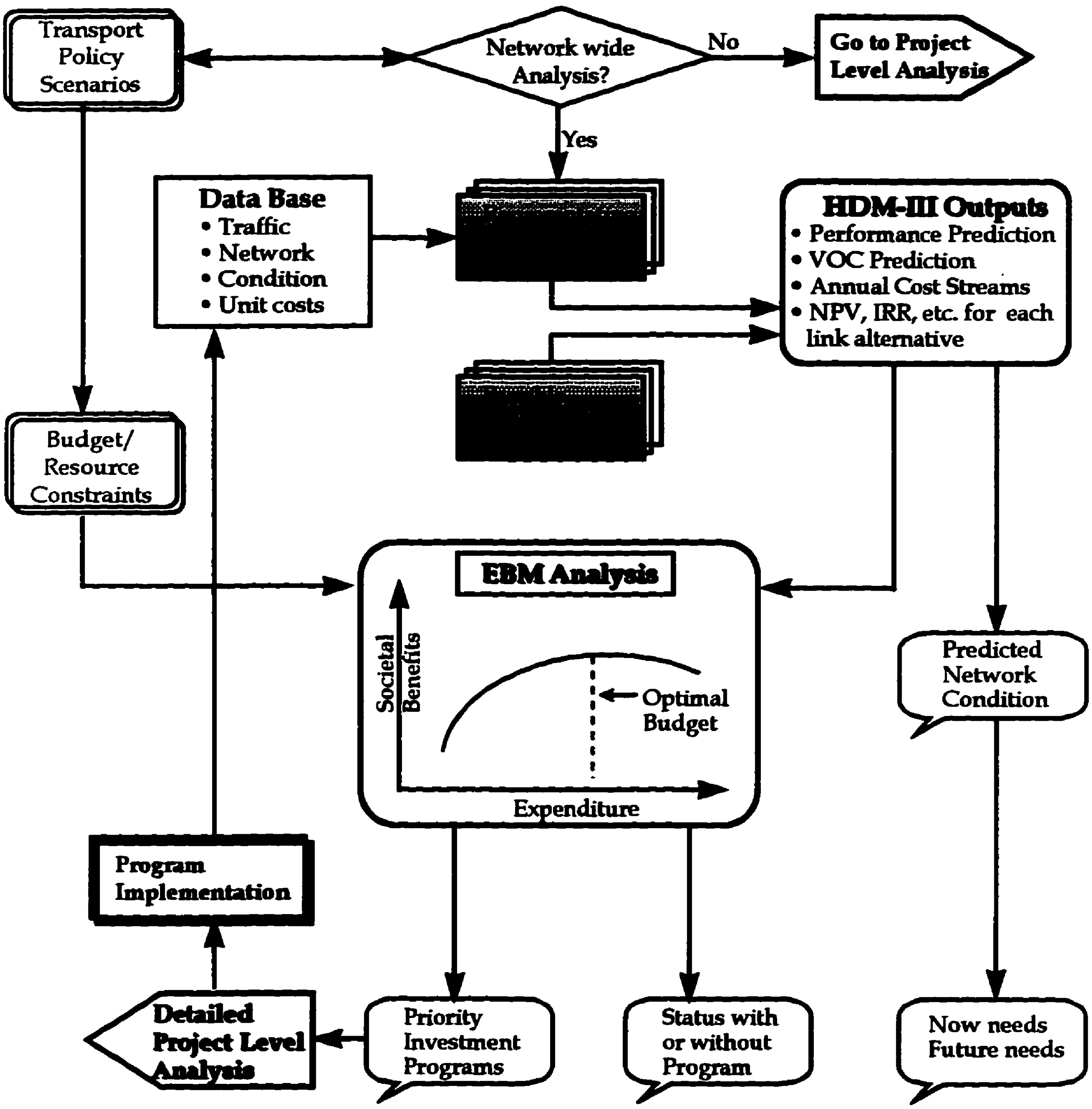

FIGURE 2.2 The role of HDM-III and EBM in a network-level PMS

2.1.2 Diversity of Economic Criteria in Priority Programming

The primary objective of a pavement management system is to achieve the most efficient (optimal) use of available resources such as funds, materials, plant and human resources in providing a road facility which adequately serves the users and the tax paying public [Haas 78, RTAC 77, Lyton 85]. To achieve such an objective the priority analysis has to be based on an economic criterion. Ranking based for example, on judgment, structural adequacy indices, deflection, *etc.*, does not arrive at an optimal solution, and defeats the very purpose of a PMS [Haas 94].

Ranking based on some measure of economic index, the so called parameter based ranking [Haas 94] and the optimization using such indices offer close to optimal solutions and are extensively used in many agencies. The dilemma of what economic criterion is best for comparing alternatives in priority analyses has been around almost from the very advent of pavement technology. At the project level, the literature consistently recommends the use of life-cycle cost (LCC) criterion in evaluating alternatives [Sandler 84]:

> *"Maximizing economic efficiency is the decision criterion implicit in a LCC analysis. Therefore, even though other factors may also be important (and should be considered), the project-alternative with lowest LCC would be the most economically efficient choice."*

Life-cycle cost (LCC) analysis is defined as an economic assessment of competing alternatives, considering all significant costs over the life of each alternative. The five major components of pavement life-cycle costs are, capital construction costs, future maintenance costs, salvage value at the end of analysis period, delay costs during rehabilitation and maintenance work, and users' costs (vehicle operating costs, travel time, accidents, discomfort due to poor condition, *etc.*) [Darter 85].

At the network level the choice of a criterion is not that clear. [Darter 85] for example, discourages the use of the users' costs in priority programming owing partly to the difficulty to estimate them, and mainly due to the controversy still surrounding application of users' costs. Despite some limited efforts to develop simple techniques for users' costs determination (using nomographs) [Lemmerman 84] and more extensive works to adapt the HDM-III user costs relationships to Canadian conditions [Cox 87a and Bein 89, 92a and 92b], the user costs criterion has not been widely adopted in North America. [Riley 95] observes that, *"The total transport cost (TTC) approach departs from traditional pavement design and management techniques. Generally the latter are based on engineering considerations and agency costs and do not directly consider the effects of alternative designs on VOC."*

It is noteworthy that near optimization based on a heuristic marginal cost-effectiveness method is more popular in many agencies throughout North America [Haas 94]. This criterion has been used in Idaho, Minnesota, South Carolina, and in Alberta, Prince Edward Island and Newfoundland.

Another important user cost component that could potentially be used as a criterion in priority analysis is the user delay costs arising at work zones. For high volume facilities, vehicle running costs resulting from traffic interruptions during maintenance and rehabilitation activities can be very high [Haas 94]. Yet, few priority analysis systems use this criterion directly [Hill 91 cited in Haas 94].

2.1.3 Relevancy of Life-Cycle Costs Criterion in Low Income Economies of SSA

The current crisis facing the road network in SSA is widely reported in the literature (see for example [Faiz 87 and 91, Smith 87, Mason 89, Bank 88]). It was estimated that of the entire network of main roads in the region, only about 47 percent were in good condition in 1984 (Table 1.1) [Faiz 87 and 91]. Twenty-seven percent of the said network were in fair condition while over 26 percent were in poor condition requiring immediate reconstruction or major intervention to be serviceable. These figures refer to the paved roads category of the network. The status of the unpaved roads in the region is not much different. Several studies have analyzed the socio-economic background to the crisis [Faiz 87 and 91, Bank 88]. The widespread and ever worsening network deterioration in the region is attributable, among other factors, to the lack of the necessary infrastructure of institutions and trained personnel to administer the networks. This is further compounded by poor policy foundations and meager financial resources [Bhandari 87, Pinard 87]. [Faiz 91] observes that:

"The genesis of the problem lies in the rapid development of the road networks, which expanded much faster in the 1960s and 1970s than did the maintenance budgets and the institutional capacities."

[Faiz 91] further advocates that the only logical approach to alleviating the situation is deep policy reforms based on more consistent, objective methodologies in budget allocation, planning, programming and management of the meager resources.

In the industrialized economies, factors such as high traffic volumes, high values attached to travel time savings, and relatively abundant capital resources have dictated high standards of road design and maintenance. With several thousand vehicles per day, even minute savings in vehicle operating costs and travel time can justify very large expenditures on road alignments and pavements [Watanatada 87a]. [Haas 94] seems to suggest that in general, the total life-cycle costs for rural and urban facilities exhibit a minimum at present serviceability index (PSI) of about 2.0 to 2.5 and 3.0, respectively. Hence, subject to budget constraint, this should be the optimum level of serviceability. However, this proposition, which is dependent on the assumption that at higher levels of PSI the total life-cycle costs rise appreciably because the extra agency costs would not be offset by the savings in vehicle operating costs (VOC), is only valid where the relative magnitudes of agency life-cycle costs and VOCs are comparable.

Competing demands for meager resources in developing countries, much so, in Sub Saharan Africa, dictate that the economic criterion for evaluating different designs, maintenance and rehabilitation options be based, not only on the costs borne by highway agencies, but also on the larger costs of vehicle ownership and operation borne by road users [Bhandari 87, Watanatada 87a]. Programs for road upkeep have to compete with other social programs like education, health, *etc.* which tend to be favored for their political appeal. A ranking criterion based on the societal costs (of providing transportation) becomes preferable in that it gives pavement technologists the advantage of supporting their budget requests in a more understandable language to the political /elected decision making level.

Several other characteristics of the transportation systems in low income economies of SSA include the general low traffic volumes (below 400 ADT) [Faiz 87, Smith 91], the low value associated with travel time savings, the low cost of labor and the relatively high foreign exchange costs of vehicle operation. With these characteristics in mind, the question now is whether the total life-cycle costs criterion is meets the ultimate purpose of the pavement management analysis.

Evidence from this thesis shows that for some price regimes the ratio of the life-cycle VOCs to the life-cycle agency costs, even for moderate traffic levels, is so high that the total life-cycle costs curve hardly rises with PSI. Typically, the life-cycle agency costs of rehabilitation were found to be only about 1.0 and 2.0% of the life cycle VOCs for traffic of 2000 and 1000 ADT respectively. In such scenarios, the total life-cycle cost is dominated by the VOCs component and hence the predicted net present value (NPV) reflects mainly the savings in road users' life-cycle costs. Hence the comparison between investment strategies using the NPV becomes a process of determining an alternative associated with maximum societal savings among the large number of technically feasible strategies.

2.2 Application of HDM-III as an Analysis Engine in Pavement Management

2.2.1 The Role of Economic Analysis in Pavement Management

A pavement management system (PMS) is defined [RTAC 77, Haas 78 and 94] as constituting an efficient and systematic integration of all activities that go into providing roads, so as to achieve the best possible value for the available public resources. This is accomplished by comparing investment alternatives at both the network and project levels, coordinating design, construction, maintenance and evaluation activities, and making efficient use of existing methods and knowledge. The essential requirements of a PMS include the capabilities to be updated, to consider alternative strategies, to identify the optimum alternative, to base decisions on quantified attributes, criteria and constraints and to use feedback information regarding the consequence of decisions. A network level PMS offers the capability to analyze alternative funding programs making it possible to identify the programs that will yield the greatest benefit over the selected planning horizon.

The function of comparing alternatives provides the important basis for ensuring more consistent and optimal decisions. This function can, however, be tedious and is sometimes not feasible owing to the requirement to explicitly consider the primary effects of traffic, pavement strength, age, pavement surface condition and environmental factors as well as maintenance policies on the total life-cycle costs of each viable alternative [Parsley 82, Chesher 87, Paterson 87]. HDM-III offers this computational capability in a very comprehensive manner. The model can, therefore, provide a very handy "plug-in" economic analysis tool in a pavement management system. The analysis can be applied both at the project and the network level of pavement management. Figure 2.3 shows potential application of the HDM-III model, as a life-cycle analysis engine, in network level R&M priority programming based on cost minimization or benefits maximization.

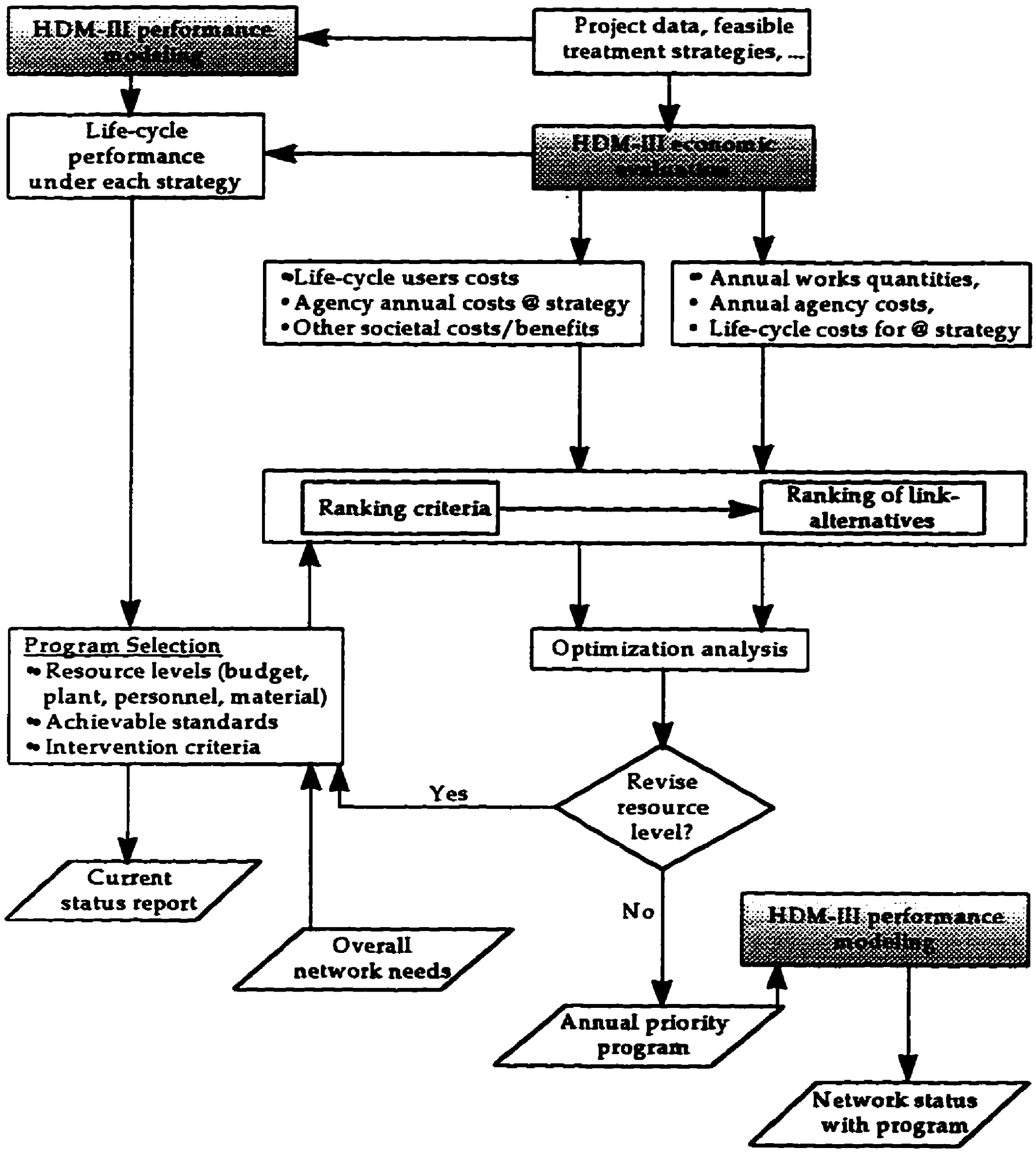

FIGURE 2.3 ***Potential application of the HDM-III model in a network level R&M programming***

2.2.2 Advantages of the HDM-III Model

The Highway Design and Maintenance Standards Model is a result of a series of large scale, international pavement research and experiments between 1970 and 1982 incorporating four environments in developing countries, namely – Brazil, Kenya, India and the Caribbean [Watanatada 87a]. The computer program developed by this World Bank lead initiative, now in its third version, HDM-III, is probably the most comprehensive economic evaluation model for road investments. Its key sub-models of pavement deterioration and user costs were formulated in mechanistic principles and developed from the broad empirical database of the major studies reported above.

The model has subsequently been tested in real applications in more than 40 countries such as Brazil, Guinea-Bissau, Chile, and Indonesia where it has been used in pavement management systems and in highway planning and economic evaluation [Kerali 91, Paterson 92, Queiroz 91 and 92, Alberto 87, Cox 87b]. This gives the model one of its greatest advantages as an economic evaluation tool – a sound economic methodology that can be adapted to diverse geographical and socio-economic environments [Paterson 87]. The concept of using the HDM model as an analysis engine in full scale working pavement management system has been demonstrated widely [Quieroz 91, Robertson 94, Howard 94].

The key advantages of the HDM model can be summarized as:

(1) An efficient pavement life-cycle costs simulation program that can form the basis of an economic analysis engine in a pavement management system based on a variety of cost minimization or benefits maximization or other economic indices.

(2) An adequate body of empirically established relationships among the relevant variables that simulate the complex interrelated effects of traffic, environment, geometry, pavement strength and, maintenance effects upon pavement deterioration. Further, the model provides prediction of the effects of pavement condition upon vehicle operating costs – hence the basis for quantifying the primary benefits of road improvements.

(3) Generic model forms that can be calibratable at the local level and hence are transferable from region to region.

[Cai 92] discusses other advantages of the model as including the benefit-cost analysis feature that comprises more benefit and cost items than any other model. Further, several economic indicators – net present value (NPV), internal rate of return (IRR) and first year benefits ratio (FYB) can be selected for comparing the alternatives. Moreover, use of HDM-III has become a requisite for projects financed by the World Bank.

2.2.3 Comparison of HDM-III to Other Models

Several other models or tools that are suited for investment appraisal in the road sector (potentially applicable in low income economies) do exist. The most important among them are the Road Transport Investment Appraisal Model (RTIM2 and RTIM3) developed by the British Transport and

Road Research Laboratory [TRRL 86, Parsley 82, and 83, Cundill 95]. Another option is the recent work at Waterloo [Turay 90 and 91]. The key aspects of each of these tools are subsequently highlighted in comparison to HDM-III.

2.2.3.1 The Road Transport Investment Model (RTIM3)

The British Transport Research Laboratory (TRL) developed the Road Transport Investment Model (RTIM) for particular use in economic appraisal in developing countries [Parsley 82 and 83, TRRL 86]. The model simulates road construction and maintenance costs and evaluates benefits (for each investment alternative) in terms of savings in vehicle operating costs and user delay time. In this respect, the model offers most of the features of HDM-III. The model has the advantages of being smaller, and computationally faster.

From its experience of advising on economic appraisals in developing countries, TRL recognized the critical need for simple and easily understood investment tools [Cundill 95]. The latest edition of TRL model (RTIM3) was released in July 1993 to respond to that need while improving on the limitations of the former version (RTIM2). In overall, RTIM3 uses the same equations (with minor simplification) that were incorporated in RTIM2 [Cundill 95]. These relationships were based on studies conducted in Kenya in the early 1970s and later in the Caribbean [Parsley 83, TRRL 86].

However, the most important limitation of RTIM3 is its narrow range of validation. In general, RTIM3 relationships were calibrated for a narrower range of factors than HDM-III. It is reported, for example, that the pavement deterioration sub-model incorporated in RTIM2 was based on data for double surface dressed pavements obtained solely from the Kenyan study [TRRL 86, Parsley 82 and 83]. Also, the vehicle operating cost relationships built into the model were based only on the Kenyan and the Caribbean studies [TRRL 86]. Extension of these sub-models to other types of pavement construction cannot be technically justifiable. It has been shown that vehicle operating costs is a function of such diverse, but regional specific parameters as climatic factors, the road geometric standards, driver skills and behavior, vehicle design and fleet composition, price regimes and the nature of market competition, *etc.* [Chesher 87]. Use of the Kenyan results to model costs in other regions must be treated with caution. Given the limited data base used in formulating the relationships it was not possible to include all the causal factors in the model. As a result, transferability to other regions is highly questionable.

2.2.3.2 The Road Network Improvement System, RONIS

[Turay 90] developed the Road Network Improvement System (RONIS) on the premise that the existing models like HDM-III and RTIM2 were only good as tools for decision making for overall road investments [Turay 90 and 91]. However, as shown in Figures 2.2 and 2.4, using the various HDM-III reports the experienced user can generate status lists, year by year need sections, or use the results in an EBM run to optimize strategies under multi-year and budget constraint situations [Watanatada 87a]. This is considered sufficient for the purpose of priority programming at the network planning level. [Queiroz 92] demonstrated this capability by applying the HDM/EBM models the Brazilian Federal (network-level) pavement management system. It is, therefore, noteworthy that [Turay 90 and 91] argues that these existing models lack appropriate priority sub-systems that could generate network status and need lists, and provide the necessary detailed evaluations for network level priority programming. This could, however, become the case if one goes to the next lower planning level, where detailed evaluation is a valuable process in project realization.

While the RONIS model could provide a potential substitute for HDM-III and EBM, especially as a result of its superior optimization sub-system, it still requires substantial improvements. For instance, the sub-system dealing with generation of maintenance and rehabilitation alternatives for unpaved roads would need more fine tuning before it becomes useable [Turay 90]. More importantly, first time implementation of the RONIS model is not as easy as pulling a ready made system from the shelf. A lot of original model-development work has to be done by the user agency. The net resources involved may amount to several times the effort required to adapt the widely accepted models like HDM-III and RTIM3.

2.3 HDM-III Limitations from Sub Saharan Africa Stand Point

The HDM Model does, however, have several weaknesses and limitations. Ease of use is one area that calls for immediate improvement and is perhaps the key motivation of the current efforts to upgrade the model [ISOHDM 93 and 94a].

An excessively large number of input variables requiring detailed and systematic network data represents the most constraining factor that negates wide spread usage of the model in low income countries. The limited resources of the case study region (discussed in subsection 2.1.3) translate into a serious disincentive of adopting the model in Sub Saharan Africa. The other important weakness, which also has a direct bearing upon its application to pavement management analysis, is the limited and scattered availability of model calibration literature. Chapter 3 provides a review of the scanty literature on the HDM-III Model re-calibration.

It is worth pointing out that the HDM-III is a fairly comprehensive model that is capable of simulating the complex phenomenon of pavement behavior with the interacting factors of traffic loading, environmental factors, the initial pavement design strength, the quality of the subsequent maintenance. The intended application of the model also required it to be capable of relating the diverse vehicle mechanics, engine speed, fuel consumption, tire and parts consumption, driver behavior and management effects, *etc.* with the quality of the traveled road. Such demand on the model's eventual usage implied, of necessity, the need for it to embody causal relationships that involve all relevant factors [Paterson 87, Watanatada 87a]. The inherent complexity of the HDM-III model, including the large number of input factors -- the concern in this thesis, was therefore, born of necessity.

[Watanatada 87a] points out several important limitations of the HDM-III model. First, the VOC equations were based on free flow conditions only; congested traffic could not be simulated. Second, the road deterioration equations for freezing climates as well as rigid pavements were lacking. These three limitations are the central motivation of the HDM4 study to upgrade the model. With inputs from several international efforts from Malaysia (updating technical relationships), Sweden (cold climate models) and Chile (modeling of rigid pavements), the most significant enhancements in HDM4 are likely to address these immediate concerns. Finally, HDM-III does not endogenously model accident costs, other indirect costs or benefits of road improvements, for example, emissions, noise pollution and other environmental impacts, *etc.*

2.4 Past Efforts Towards Model Reduction

2.4.1 General Overview

There have been several attempts to provide the specific strengths and functions incorporated in HDM-III in simpler alternatives or in improved forms for HDM-III users. The most significant ones, as far as this study is concerned, are those of [Kerali 91, Paterson 92, Quieroz 92] and the current efforts initiated by the World Bank itself [Callao 92, Hoban 92]. While the first three articles deal with reducing the problem of data needs in HDM-III applications, the last two papers focus more on user friendliness issues. The following paragraphs review the former set of efforts, while subsections 2.4.2 and 2.4.3 looks at the later attempts to develop more user-friendly tools. Finally, subsection 2.4.4 discusses the expectation of the current international initiative to upgrade the HDM-III model [ISOHDM 93] and its implications to the pavement management technology in low-income economies.

[Kerali 91] developed a simplified computer package based on the HDM-III Model for economic appraisal to determine the traffic level at which it becomes economically feasible to pave gravel roads. Depending on the level of accuracy required by the user the shell package was capable of providing approximate or detailed results. At the simplest operation level, only a few data variables would be required by the package to accomplish a quick analysis giving approximate results.

The interesting feature of this tool is the user interface or front-end program for input data preparation. This front-end facility is used to prepare the data files for the HDM-III model in the form required for the break-even analysis typical of paving decisions. The ease of use is built into the user interface in a way that the user is required to input only a few parameters to run HDM-III. Other inputs are provided in pre-assigned default values from which the user can select low, medium or high ranges.

In a general sense the [Kerali 91]'s approach provides a suitable framework in which the potential of the HDM-III model can be made more available to the novice users in developing countries. The major limitation is the fact that the package provides only a specific use in evaluating paving decisions (*that is,* to pave on not to pave).

It is also important to note that analysis provided by the simplified model is by no means region and task specific. In other words, the results will be applicable only to the region for which the default values reflect the typical values for the corresponding variables. The variables that are likely to be influenced by location are for example, the link characterization data (*e.g.*, precipitation, altitude, subgrade, pavement standards, thickness, calibration factors, *etc.*). Transferability of the reduced model to other geographic regions would only be feasible if the user interface provides for the user to be able to re-calibrate the default values when needed. Kerali's model does not provide such a feature.

[Paterson 92] developed simplified equations of pavement deterioration for asphalt concrete paved roads based on the HDM-III. The major motivation of the study by [Paterson 92] was, however, to improve computational speed of the predictive models in HDM-III for pavement management applications. According to [Paterson 92]:

> *"Application of HDM-III to pavement management for many thousands of pavement sections have been limited by (computing) time requirement. Thus, there is a strong need for simpler algorithms which approximate the primary effects captured by the full (HDM) recursive model, and permit rapid prediction of pavement roughness from small number of primary parameters."*

The methodology described by [Paterson 92] offers a viable option in the reduction of the number of input variables for running the HDM-III model. However, the simplified prediction models developed are useful only for users capable of developing (computer coding, *etc.*) their own analysis "engines" or entire Pavement Management Systems. To the low-income road agencies in SSA this capability is not available. Therefore, the only way to provide this potential methodology is to incorporate it into ready to use (computer) packages. Modifying the HDM-III computer code is not considered a real option from the low-income road agencies' standpoint.

[Queiroz 92] approach in reducing the data problem in the application of HDM-III was to trim down the number of HDM runs by factorial matrix scheme. In their methodology, homogenous sections of the network were grouped into classes, each corresponding to a cell in a factorial matrix. The factorial matrix had four dimensions: with traffic levels, pavement deflection, area cracked and roughness defining the link attributes. Feasible rehabilitation and maintenance options were then defined for each cell of the matrix. Running HDM-III for the cells would then identify an optimum maintenance and rehabilitation alternative for the group of sections in that cell. Running the EBM model for the matrix under a given budget constraint would thus identify priority cells to be implemented in the planning horizon.

However, the [Queiroz 92] approach still requires detailed data for each typical link representing a cell in the factorial matrix. The methodology only reduces the effective number of HDM (and EBM) runs needed to achieve a pavement program for the network. The suggested factorial matrix reduction and the use of acceptability index in the analysis still assume the road agency has the capability to collect and organize the detailed data. (Data are required for all model factors for each cell in the factorial matrix.)

Recently, the World Bank has initiated a number of efforts aimed at developing simpler and easy to use sub-models based on HDM-III. Research has been under-way (starting late 1992) on such prototype modules as HDM Manager, RODEMAN and HDM-VOC [Callao 91 and 92, Deighton 92]. These attempts to model simplifications are further discussed in the following subsections.

2.4.2 HDM Manager

The HDM Manager software is an attempt to provide a user-friendly shell environment for preparing the data set and running HDM-III for specific applications. The HDM manager (designed to work with the HDM-III) offers the following functions: (a) a quicker and easier preparation of HDM-III input files, (b) running the HDM-III model, and (c) collecting the results in an easy to review format [Callao 92].

However, the HDM Manager in its present form has some serious limitations that reduce its usefulness in full scale pavement management applications. First, only a few of the HDM-III features are retained; the module is capable of evaluating only paved roads. Second, and most importantly, it is not capable of evaluating within-project alternatives for more than one link at a time. This is probably the most critical factor with respect to its application in a network-level pavement management. It is worth pointing out that, typically, network level analysis involves hundreds or even thousands of road links. Other omitted HDM-III features include the capability to handle construction options, generated traffic and exogenous costs and benefits.

2.4.3 RODEMAN and HDM-VOC

RODEMAN is a menu-driven personal computer version of the Road Deterioration and Maintenance sub-model of HDM-III that produces the same detailed results as HDM-III [Deighton 91, Paterson 92]. It also includes simplified vehicle operating cost and other cost functions, which enable it to calculate the main economic parameters, although in less detailed manner than HDM-III. The important user-friendliness features achieved in RODEMAN are: comprehensive system-to-user communication, structured menu system, context sensitive on-line help, and decimal numbered menu items to speed access to functions (jump facility).

These advantages make the RODEMAN a much easier to use model. Also, the sub-model is useful for simulating road performance and deterioration independent of the other HDM-III sub-models. However, the technical demands of the RODEMAN (in terms of detailed data preparation and skills to correctly use it) are still the same as for the full HDM-III model. In addition, as discussed in 2.1.3, decision making in network-level pavement management requires not only performance prediction, but also the cost streams associated with each project-alternative. For this reason, the RODEMAN will have very limited applications at network-level pavement management in SSA in the near future. It is considered, however, to have a strong potential for project-level pavement management studies in which detailed analysis of each design alternative has to be quantified in terms of performance and costs.

The HDM-VOC is another key HDM-III sub-model made available separately. The program predicts the various components of vehicle operating costs (VOC) using input information on the roadway, vehicle characteristics and unit costs [Callao 91]. The computations are based on the Brazil relationships derived from the World Bank's Highway Design and Maintenance Standards Study. The program computes vehicle speeds, physical quantities of consumption: fuel, parts, *etc.*; and individual VOC components as well as total VOC for each vehicle type. The program seems to incorporate all the features of the relationships in HDM-III, including the range of default variables provided by the model. Most of the default input parameters provided are in relation to vehicle characteristics. Out of the 65 input variables required by the model, the user would need to input only a fraction of them to run the program unless accuracy of results demands more detailed input information.

Again, like the sister sub-model RODEMAN, HDM-VOC is much easier to use but has only limited advantages in the area of network-level pavement management. It can be very handy in specific project studies like user charge assessments and research in transport economics, but it offers no real incentives for adopting it for network level PMS applications in SSA.

2.4.4 The HDM4 Study and its Expectations

2.4.4.1 Broad Objectives and Goals of the HDM4 Initiative

The fundamental objective of the HDM4 initiative is the development of a new software tool for highway appraisal that will ultimately supersede the HDM-III model [ISOHDM 93 and 94a, Bennett 94, Kerali 94]. The underlying motivation for the new initiative is the recognition that the existing model (HDM-III) has several key limitations as an analysis tool for works programming in the road sector [ISOHDM 93 and 94a]. The following trends have contributed to the renewed need to recast the framework of HDM-III.

- There is increased demand for expansion of network capacity while on the other hand resources for public investments are dwindling.
- Higher traffic loads are underlying the move towards stronger pavements (including concrete pavements).
- More diverse maintenance and other treatment types have emerged since the last HDM study.
- Growing global pressure for more detailed assessment of environmental impacts of road projects.

In addition, there is a need for a harmonized system approach to road management, with adaptable and portable software tools that are user-friendly and more oriented to graphical communication. A strong need has been recognized for a standardized set of highway appraisal tools that will be applicable in a wider range of environments in developing countries and in industrialized countries as well [ISOHDM 94b].

2.4.4.2 HDM4 Study Approach

The new initiative will not involve a major factorial study. Rather, it will mainly rely on "desk study" to derive, extend or improve the relationships incorporated in HDM-III on the basis of recent (completed or in progress) research findings available world wide [ISOHDM 93]. In a way, the initiative undertakes to pool together the existing industrial strength that has evolved since the initial HDM study. It is anticipated that from the recent literature and some specific project reports it will be possible to extend or improve some of the HDM-III technical relationships.

The study has recognized that in addition to HDM there are a number of other highway appraisal models such as RTIM that perform some of the tasks required in the proposed model. It is intended, therefore, that the universal relationships for the models will be developed from a synthesis of recent international research together with the experience gained from existing models.

The key sub-models will, however, be based on the fundamental framework and principles of HDM-III, with enhancements in three major areas:

(1) Technical content will focus on improving the existing relationships for pavement performance and vehicle operating costs. Possible new relationships are expected for congested traffic flow, rigid pavements, effects of new maintenance types, drainage, road safety and environment.

(2) A highly improved user-interface catering to all levels of users and for the major computer operating systems.

(3) A framework for specific applications of the models to planning and budgeting, work programming and project design and evaluation.

2.4.4.3 Expected Deliverables from the HDM4 Study

There is strong evidence to suggest that the new model will evolve substantially from HDM-III. The scope of the HDM4 initiative is reflected in [Bennett 94]. The study philosophy can be summarized as finding the areas where HDM-III needs the most improvements and how can this best be achieved with the available resources. The greatest improvements or changes are expected in two areas: introduction of new relationships and major facelift on computing framework. These are subsequently discussed under technical improvements and user interface respectively.

2.4.4.3.1 Expected Technical Improvement

Improvement to the technical content will be reflected by the introduction of new relationships as well as extensions to relationships currently used in HDM-III. The objective will focus on such concerns as the modeling VOC for traffic congestion, the incorporation of recent research on VOC, wider range of pavement types (*e.g.*, concrete, penetration macadam, *etc.*) maintenance effects, safety implications and relationships for wide range of environments. More specifically, the following enhancements to the technical content are expected:

- **Congestion:** The capability to model VOC for congested traffic flows in both rural and urban areas.
- **Rigid Pavements:** New relationships for performance prediction of rigid pavements and effects of new maintenance treatments and new pavement types derived from recently completed studies.
- **Freezing Climates:** Additional relationships for predicting pavement performance in a wide range of environments, particularly for modeling freeze-thaw effects are expected.
- **Vehicle Operating Costs:** Enhancement in the existing VOC relationships to reflect the changes in automotive technology, particularly for fuel, tire wear, parts consumption and depreciation.
- **Safety, Environment and Drainage:** New relationships are expected for evaluating the effects of road improvements on accidents and safety, the impact of vehicle emissions and noise pollution and for predicting the effects of drainage on pavement performance.

2.4.4.3.2 User Interface

Given the general recent trends in micro-computer technology towards more graphic user interface (GUI) and menu driven software architecture, the new HDM model will most likely see a major improvement in the user interface. More specifically, the following changes are seen as achievable within the scope of the present initiative [ISOHDM 94a, and 94c]:

(1) **Computer Platform:** A user friendly front-end employing "graphical user interface" (GUI) and menu system under Windows environment is envisaged. The resulting package will be used primarily on personal computers, but will probably be available on other platforms at a future date.

(2) **Modular Software Architecture:** An integrated modular structure is envisaged where it should be possible to use individual modules for specific tasks independently. Further, it is likely that users will be able to modify or replace individual modules or relationships.

(3) **Interface with Other Systems:** HDM4 proposes to develop an interface to enable data exchange with external systems, such as existing pavement management systems, *etc.*

2.4.4.4 The HDM4 Scope Versus the Sub Saharan User Concerns

The list above represents the major enhancements that are considered achievable within the scope of the current HDM4 initiative. It is, therefore, projected that the emphasis of the technical improvements in the new model will mainly be in the areas of cold climate pavement performance, congested traffic VOC relationships and rigid pavement performance equations. Most of the technical relationships in the current HDM-III, especially those relating to pavement performance and VOC prediction in tropical Sub Saharan Africa are likely to remain unchanged.

The research in this thesis identified the following limitations of HDM-III as being of more immediate concern to Sub-Saharan Africa:

a) Data intensive – hence high requirements in technical and financial resources.
b) Complicated procedure for input data preparation – implying extensive experience and skills.
c) Lack of user friendly features.
d) Complex and excessive number of outputs – not convenient for network appraisal.
e) Lack of standard guideline for calibrating to local conditions, and
f) Lack of standards criteria for assessing quality of outputs for known precision of inputs.

The subsequent paragraphs highlight some of the items and how the limited scope of HDM4 is unlikely to address the special concerns for Sub-Saharan Africa.

▪ **Data intensive:** First, the demand for higher reliability or precision of outputs will continue to dictate a need for more parameters in the modeling approach. Secondly, "universal transferability," which seems to be a major goal in the HDM4 study [ISOHDM 93], will imply both extending the existing and adding new relationships. The possible net effect is therefore an increase still in the total number of input parameters required to apply HDM4.

▪ **Standard guidelines for calibrating to local conditions:** The approach to be adopted for this need is likely to be limited to the improved documentation on the model; again universal to all users. In our view, such universal guidelines will still be too general. A more appropriate approach would be to provide regional specific calibrating guidelines, since different regions will always have different needs, concerns and backgrounds.

▪ **Criteria for assessing quality of outputs:** It would be desirable, for example, to be able to quantify the loss in optimality associated with the chosen R&M treatments (using HDM-III outputs) for any given level of input precision. This is not likely to be given sufficient weight in the proposed HDM4 study. Initial approach to sensitivity analysis for HDM4 seems to focus on individual sub-model outputs as objective functions, for example, initiation of cracking, progression of cracking, change in VOCs, total VOCs, *etc.* The limitation of such an approach is that at the network-level programming the interest is, for example, the factor sensitivities upon a decision criterion (NPV, IRR, *etc.).*

The above concerns remain very real for road agencies planning to use the strengths of HDM-III (or HDM4) for network-level programming. The research described in this thesis is, therefore, an attempt to respond to these special concerns.

2.5 Conventional Approaches to Sensitivity Analysis

2.5.1 Overview of the Thesis Methodology

The motivation for this thesis is based on the hypothesis that the HDM-III model can be streamlined by screening out the least sensitive input variables with respect to an application-specific output. It is argued that, for any given application of the model, *e.g.*, R&M programming, there are only a few active input factors influencing the output(s) of interest. As long as the user can provide these active inputs with reasonable precision, the model will yield sufficiently reliable results specific to that region and task. The rest of the inactive input factors, once identified, can be fixed at constant values and re-used in similar tasks as region-specific defaults.

The methodology of the thesis is, therefore, centered at developing efficient approaches to sensitivity analysis that can be used to screen and quantify the influence of individual HDM-III input parameters. The next subsections look into traditional approaches to sensitivity analysis, and then review earlier works on sensitivity analyses on HDM-III and their relevance to the present study. More robust techniques of sensitivity analysis are presented in Chapter 5.

2.5.2 Traditional Sensitivity Analysis

Traditionally, sensitivity analysis has been used as a tool for assessing whether some input factors to a decision making process require further careful examination so as to reduce uncertainties associated with the decision taken [Little 74]. [Ashley 80], in an article investigating the influence of factor errors in traffic forecasting models, points out why sensitivity by computer simulation is sometimes inevitable. The article observes that an exact analytical solution often requires one to derive partial derivatives of fairly complex inter-relationships, mostly of iterative nature (very common in transportation engineering). This difficulty in theoretical approach negates its applicability to efficient investigation of computer based models.

The approach developed in this thesis is not about risk testing *per se*, rather the objective is to determine which input factors dominate the choices taken in a set of alternatives. This objective requires investigation of both main factor effects and the influence of factor interactions. It is always desirable, for example, in strategic planning, network priority programming, *etc.* to know to what extent the quality of the decision criterion is compromised if some input factor(s) were missing or were known to be unreliable to some degree. Unfortunately, the literature outside advanced statistics journals, does not provide much in the area of multi-factor sensitivity analysis of computer based models. Yet, such models, of which HDM-III is an example in point, are becoming almost indispensable routine tools in most engineering practice.

The traditional method of investigating factor effects in a model is to change only one factor at a time, the so called *ceteris paribus* method. In search of efficiency, an alternative method was developed. The factorial design allows all levels of a factor to be combined with all levels of other factors in a planned fashion that enables determination of factor effects as well as their interactions.

Factorial experiments were shown to be more efficient in that they yield more reliable estimates of the (main) effects of the factors, and moreover, they give estimates of the interactions among factors. The differences between *ceteris paribus* and factorial experiments are summarized in Table 2.1.

TABLE 2.1 Motivation for Factorial Experiments

Ceteris paribus **experiments**	**Factorial experiments**
Defined: Experiments in which only one factor at time is varied; all other factor are kept constant	Defined: Experiments which combine all levels of one factor with all levels of all other factors
• Can be inefficient (require a large number of runs)	• Efficient (minimum variance of measured effects)
• Not capable of detecting factor interactions	• Capable of detecting factor interactions
• Requires detailed knowledge of phenomenon to enable an informed search	• Experiment size reduction is possible
• Can be useful if the model has few factors, and the assumption of small joint-effects is valid	• Easy to implement and analyze

The critical limitation of *ceteris paribus* experiments is the misleading nature of the results when factor interactions are present. Figure 2.4 illustrates this limitation. Suppose a test is conducted for a particular variable, say x_1, while all the other factors, say x_2, x_3, ..., x_n are fixed at level 1 and the effect of x_1 on the response is determined. If factor interactions are present, repeating the test for x_1, but at different levels of the other factors (x_2, x_3, ..., x_n at level 2) will yield a different value for the effect of x_1 (Figure 2.4 b). In other words, the results of factor effects are influenced by the "state" of the other input factors. Therefore, sensitivity results are meaningless without reference to the "base case" levels of all the variables used in the investigation.

The obvious advantages of the "*ceteris paribus*" techniques (in particular for simple models and where factor interactions are not important) notwithstanding, the limitations discussed above (Table 2.1) motivate a search for more robust techniques investigating factor effects of complex models. These newer techniques are presented in Chapter 5. The remainder of this chapter reviews past works on sensitivity studies on HDM-III.

(a) No factor interaction

(b) Presence of factor interactions

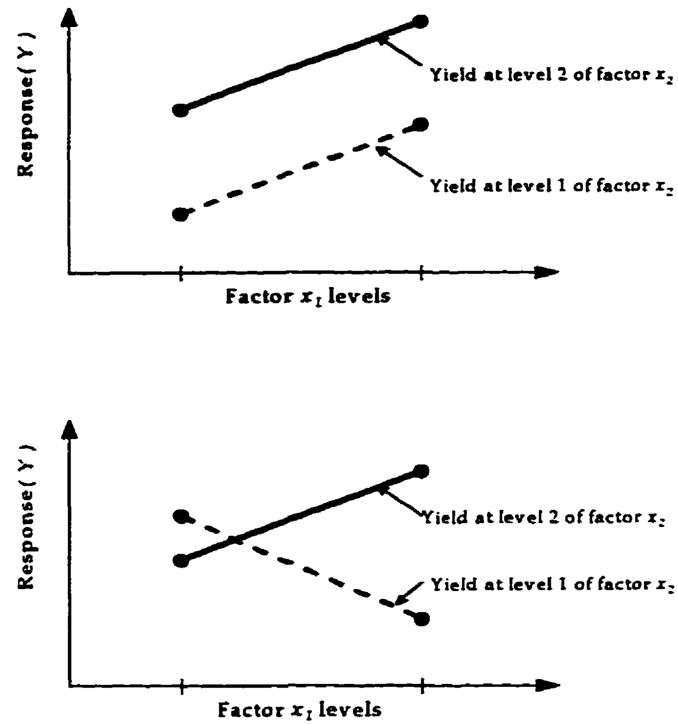

FIGURE 2.4 ***Hypothesized effect of factor interactions at two experimental states***

2.5.3 Past Sensitivity Studies on HDM-III Model

[Cai 92] investigated the sensitivity of gravel road upgrading decisions with respect to a set of input factors. The *ceteris paribus* study was based on analyzing the net present value (NPV) as the model response variable. In HDM-III, net benefits of road improvements are defined as savings of the total life-cycle costs of one alternative over a do minimum alternative [Watanatada 87a]. [Cai 92]'s idea was to compare the benefits of a paving alternative (chip seal) against retaining a gravel road (as the null alternative). The NPV index, representing the difference in the total transport costs between the two alternatives was, therefore, the response parameter of interest while a number of input factors were varied in a "one-at-a-time" fashion. Although based on prevailing unit costs and other physical attributes in a mid-state province of China, [Cai 92]'s work demonstrated that the NPV predicted was sensitive to only a few of the many input factors. Further, this work showed that the individual effects of the active factors vary greatly from one factor to the other.

A key lesson for this thesis from [Cai 92]'s work is that the assumption of factor sparsity (few active factors) is valid for HDM-III. This would generally be the case for many large and complex engineering models involving a large number of variables. This assumption underpins the research hypothesis that the model is reducible (by screening out inactive factors), at least for specific applications.

While the findings of [Cai 92] shed some light upon which variables to further focus on, in the present study, several precautions are in order. First, the base case scenario used in [Cai 92]'s study may not correspond with situations in other study regions. As it is later argued by [Mrawira 96a] in a paper arising from this thesis, the absolute sensitivity of the active factors in the NPV output may not be applicable in other scenarios. For the sensitivity factors to apply, the values selected for base case scenario should reflect the typical values in the case study region. Furthermore, the relative changes in input parameters simulated in the sensitivity analysis should reflect the true upper and lower boundary limits of the variables typical for the study region. Secondly, the R&M strategy investigated in the [Cai 92] looked only at upgrading a gravel road to a chip seal surface. While this may constitute one of the many strategies in a typical PMS analysis in Sub Sahara Africa, the thrust of the thesis is to expand the scope of investigation to screen active factors in a range of R&M strategies applicable in priority programming in the case study region.

The literature contains a few more studies on sensitivity of HDM-III parameters, including those of [Kerali 91, Queiroz 91 and Bank 88]. However, most of these studies were focused, like that of [Cai 92], on investment decisions on upgrading gravel roads. It was a motivation, therefore, for this thesis to expand the scope of sensitivity study accomplished by Cai and others.

Chapter 3

CALIBRATION OF HDM-III MODEL TO LOCAL CONDITIONS

3.1 Introduction to the Chapter

The World Bank's Highway Design and Maintenance Standards Model (HDM-III) is by any measure the most common and acceptable analysis tool for supporting decision-making in the road delivery sector in developing countries [Riley 94]. It provides a robust methodology for life-cycle cost evaluations of road construction, rehabilitation and maintenance alternatives, and hence sound economic criteria for comparing investment options. However, there are no standard, comprehensive user guidelines on how to collect the necessary data, calibrate the model for local conditions and how to go about the important aspects of setting up the model to determine optimum strategies [Riley 94 and 95, Mrawira 96a].

It can be concluded that the literature on calibration is not readily available to the end user, and has so far mainly focused on improving predictive capabilities of individual deterioration equations; it does not offer much in terms of generic guidelines to the calibration problem.

The current HDM-III documentation [Watanatada 87a, 87b, and Bank 89], for example, points out a number of analysis questions for which the model can potentially be used. The user manuals provide a very limited guide on the best methodology for applying the model in any of those potential areas. Several case studies supplementing the HDM documentation [Bank 89, Callao 94a, and 94b] exist, but none of them provide a comprehensive guide on the process of applying the model at a local level.

This chapter draws together the experiences of model users worldwide as reported in the literature to provide a compendium of "user guide" to the key aspect of adapting the HDM-III model for local implementation. The focus is more specific to applications in the area of priority programming at the network or strategic planning level.

The following two sections look into the challenge surrounding the need for model calibration and calibration data needs, respectively. The remainder of the chapter reviews the three levels of calibration – adapting the performance predictions, the user costs models, and generating suitable and cost-effective intervention strategies.

3.2 The Need for Model Re-calibration

Before applying the HDM-III model in any analysis there is a need to review whether the model will require calibration, and if so, how to implement such a calibration.

The modeling relationships in HDM-III are categorized into two main classes:

- Prediction of pavement deterioration under the combined impacts of traffic, aging or environment impacts and maintenance interventions.
- Prediction of road users' costs under given pavement conditions, other road attributes, traffic interactions, and the socio-economic factors.

Issues underlying the need for calibration are given by [Watanatada 87c], as summarized below:

- Geographical location affects climate/weather related parameters, road design standards, operators' fleet management policies, driver behavior, *etc.*
- Effects of large changes in vehicle technology, economic circumstances over time and over space.

Calibration of the model therefore involves three main steps:

- Adjusting the pavement performance parameters to approximate local pavement deterioration.
- Adjusting the VOC model parameters so that the prediction is close to observed users' costs.
- Formulating rehabilitation and maintenance (R&M) strategies that reflect local practice.

All three steps may be necessary to improve the reliability of the model outputs. This chapter reviews the calibration process under the above three levels.

One point to note is that different model applications would have different priority for calibration. This is obvious since, for network status study for example, pavement performance prediction is the important output criterion, while for R&M priority programming or any other economic analysis, the NPV prediction is the focus. In the former, calibration priority is on fine-tuning performance prediction; in the latter, the focus is reliable life-cycle costs predictions. For the investigation in this thesis, the primary interest is on calibrating the model for priority programming at network level.

On one side of the re-calibration question, the literature argues that the HDM-III Model is quite robust, particularly with respect to some of the model relationships. [Watanatada 87c] points out that the HDM Study was more successful with some types of data and therefore it was possible to develop relationships embracing all relevant, significant variables. Example of such cases are the speed and fuel models in the VOC equations. On the other hand, sufficient data were not acquired from the HDM Study for the tire wear model. Consequently, the equation is considered less transferable.

The vehicle annual utilization relationship is also highly region-specific; likewise, the vehicle maintenance cost model is also sensitive to local conditions. Except for the exponent of the annual cumulated kilometers of travel (in the parts model), the spare parts consumption variable and the vehicle repair labor equations are suggested [Watanatada 87c] to be reasonably stable across borders.

In relation to adaptation of the VOC models to local conditions [Watanatada, 87c] summarizes by three important observations:

- The mathematical forms of the models are generally adequate and need not be changed except for special reasons (*e.g.*, to incorporate a new policy variable).
- The vehicle attributes which appear as explanatory variables in the models should generally be determined for the local situation.
- Some parameters are obviously more sensitive to local conditions than others.

Based on these considerations [Watanatada 87c] recommends parameters to which re-calibration can be applied. [Watanatada 87c] argues that a decision on whether or not to re-calibrate a parameter should be based on three key inter-acting factors – locational sensitivity, parameter impact on model output, and the effort required to re-calibrate it.

However, the problem still remains that no attempt has been published quantifying the impact or the sensitivity of each calibration parameter on the model output. [Mrawira 96a] presents results of a study aimed at quantifying the sensitivity of the pavement deterioration factors upon NPV as a ranking criterion in an R&M options analysis at the network-level. Despite the fact that the sensitivity results of [Mrawira 96a] were based on one–factor–at–a–time approach, they remain invaluable in shedding light on where to put emphasis in the calibration process. A more comprehensive approach to factor sensitivity analysis is developed later in this thesis. Chapter 5 presents the methodology, while the results are outlined in Chapter 7.

3.3 Data Requirements for Calibration

The calibration-related data include primarily longitudinal-section data that relate observed attributes over time. Historical data on, for instance, pavement performance under a known maintenance strategy, are needed to calibrate the deterioration equations. In this regard [Howard 94] notes that effective calibration of performance prediction requires reliable and representative historical data that relate a known past pavement environment (the combination of structure, climate, traffic, and maintenance activity) to pavement deterioration over a substantial period. The calibration of the user costs relationships requires appropriate data on vehicle resource consumption covering a wide range of road conditions, vehicle types/makes, age distributions and utilization degrees. Efforts can and should be made in the factorial sampling to include all possible range of key factors and vehicle characteristics representing the local traffic composition. However, it is generally very difficult, for example, to associate a particular vehicle operation with one route or road with constant conditions or geometric standards.

In most cases, with respect to pavement performance, it is possible to assemble a number of reasonably reliably known as-built pavement data, but in general an adequate history of progression of roughness or other distress parameters is not available. More often all that is available is, for example, an estimate (based on the knowledge of the construction process) of as-built roughness, and a measure of current roughness and cracking.

It is generally acknowledged that reliable data are a major problem, particularly in low income economies in which the practice of modern PMS is at its very infancy. It should be emphasized that any attempt to calibrate the model must therefore be critically evaluated against the data constraint. The validity of the calibrated model will primarily depend on the assumptions or approximations put forward by the consultant or researcher. It is important that the eventual model user evaluate the relevancy and sufficiency of any such assumptions used in re-calibration. [Howard 94] concludes that,

> *"... a highly controlled calibration study may not always be possible. Calibration of performance, even though based where possible on the back calculation of observed performance, (more often than not) relies on a judgment of the reasonableness of predicted outcomes in the light of local experience."*

On the same note of the general lack of sufficient calibration data [Robertson 94] concluded that calibration of the HDM-III relationships eventually relies on one of the three options:

(1) Adoption of some default parameters where it is considered that the default assumption will not have a significant bearing on the analysis;

(2) Calibration from historical data, *i.e.*, fitting the predicted performance to "snapshot" observations of pavements of different ages; or

(3) Calibration from experience - based judgment of expected performance *i.e.*, based on knowledge base of experienced pavement engineers.

It has been suggested, and in fact most users rely on, calibrating the HDM performance relationships based on scatter analysis of "snapshot" or "window observations" of pavements at various ages instead of the much difficult to come by actual life-cycle or time series observations [Rohde 94]. Scatter analysis is based on collecting several "one-time" condition data on various "similar" pavements at different ages and traffic loading levels. These different pavements then provide different points on the deterioration curve for the particular design and traffic intensity. In essence, this process implies the fundamental form of the individual predictive relationship is acceptable, and that "scaling" rather than change of model form is sufficient.

This approach can achieve reasonable results where the as-built records as well as traffic loading history and environment records exist. Again this assumption is important in that the use of a one-time survey is valid to the extent that the performance from as-built condition through to the point of the "one-time" observation has been subject to continuously uniform factors as reflected in the given factorial class. It also assumes that a sufficient sample that spans (and is balanced over) the age spectrum can be obtained from the network for each pavement design class and traffic intensity combination.

3.4 Sources of the Calibration Literature

The primary guide on calibration is the user manuals and the accompanying volumes collectively called the Highway Design and Maintenance Standard series [Watanatada 87a, 87b and 87c, Paterson 87, and Chesher 87]. The most notable recent contribution to the HDM-III calibration literature is found in the Proceedings of the International Workshop on HDM-4 [ISOHDM 94d]. Several other individual studies also exist which contribute to the calibration literature in varying degrees [*e.g.*, Sršen 94, Riley 95, Kannemeyer 95, and Mrawira 96a]. This subsection identifies the most useful pieces of the HDM-III calibration literature and highlight the key lessons learnt from each.

At page 29-34 [Watanatada 87a] discusses the general validation of the model and the model areas requiring further research. Subsection 1.4.2 outlines the basic construction of the model, broad strengths and weaknesses and key aspects that need be considered in adapting the model. This section also introduces the transferability issues and applicability of the equations in diverse physical and economic environments. The philosophy behind the model formulation and its suitability for adapting to different locations is highlighted. The subsection also points to other parts of the HDM-III documentation where calibration guidance is given. Chapter 13 (pp. 317-335) of [Watanatada 87c] is referred to as the primary guide for calibrating the vehicle operating costs models, while chapter 10 (pp. 373-397) of [Paterson 87] is pointed out as the primary guide for pavement performance.

Chapter 4 (pp. 87-148) of [Watanatada 87a] describes in great detail the computational logic for pavement performance in the model, the structure of the equations and highlights the quality of estimation of the several model factors. This is considered an invaluable source of guidance for understanding the model before setting out to calibrate or modify the relationships.

Subsection 4.1.8 (pp. 84) of [Watanatada 87a] mentions the role and the basic approach of using "deterioration factors" to calibrate the pavement performance equations. On the question of factors to be given priority in a local calibration, the subsection argues that, "It is expected that cracking, raveling, and pothole models are the most likely to require local adaptation." However, as it was argued in [Mrawira 96a] the priority for re-calibration should also be based on sound factor sensitivities relevant to the analysis criterion. The results given later in this thesis suggest a different calibration priority.

Subsection 4.3 (pp. 109-128) in [Watanatada 87a] addresses the important role of maintenance intervention upon paved road deterioration and outlines a procedure of formulating R&M strategies in the context of HDM-III. The effects of maintenance interventions for unpaved roads and considerations in defining appropriate strategies are given in subsection 4.5 (pp. 144-148) of [Watanatada 87a]. Good understanding of the concepts of intervention criteria and hierarchy of maintenance activities, for example, is essential and crucial in formulating a proper model application. Although [Mrawira 96a] recognized and strongly recommended careful formulation of

R&M strategies as an important step in model calibration, most of the calibration literature does not fully address this subject.

Chapter 5 of [Watanatada 87a] discusses the basis, formulation and the validation of the vehicle operating costs equations in HDM-III. The considerations of choosing the set of model relationships and vehicle types for representing local traffic compositions is given in subsection 5.1.2 of [Watanatada 87a]. The Appendix to chapter 5 [Watanatada 87a] also provides a very useful guide in selecting the appropriate vehicle types to model local traffic composition. More detailed specific guidelines on how to design an investigation to calibrate the VOC relationships are given in chapter 13 of [Watanatada 87c].

[Paterson 87] is the most comprehensive guide to pavement performance modeling not only for understanding and applying the HDM-III model but also for the general application to pavement management. Chapter 10 of [Paterson 87] is referred to in [Watanatada 87a] as a primary guide for calibrating the performance relationships. This important source provides an extensive summary of the strengths underlying the performance prediction equations, the quality of the database used to estimate the model parameters and hence reliability of the model and the areas warranting higher priority for local re-calibration, *etc.* However, the guide to calibration contained therein is general in nature and again lacking the "how" contribution.

Chapter 13 (pp. 315-335) of [Watanatada 87c] provides a well structured guideline on calibrating the VOC relationships to the local settings. Individual model parameters are discussed, subjective assessment of their relative impact upon the predicted VOC, as well as the nature of data or experiment and the effort required to calibrate it. It may be pointed out that the guidelines are more or less general in nature. There is a need for more specific detailed case application guidelines.

Among the various papers on model calibration given in [ISOHDM 94d] the most interesting contributions are those of [Robertson 94, Howard 94, Riley 94, Rohde 94, and Kannemeyer 94]. A sketch of the content in each of these works is subsequently given.

In Queensland performance calibration efforts focused on the roughness and cracking models for the most common types of pavements – surface treatment on granular base (SD/GB), and asphalt concrete on granular base (AC/GB), and surface treatment on cement treated base (SD/CB)

[Robertson 94]. For the cracking model, the data available was of low quality, hence experience-based calibration was recommended.

In the Queensland study it was found that the ratio of cracking initiation factor, *Kci*, to the age at which wide cracks start manifesting was influenced by the traffic level. From this observation two recommendations were made. In calibrating the cracking model it was recommended to start with the initiation factor, *Kci* before the progression factor, *Kcp*. Second, the cracking initiation factor should be calibrated separately for each traffic – environment category. Table 3.1 shows the cracking calibration factors recommended for Queensland using an experience-based calibration [Robertson 94].

TABLE 3.1 Recommended Cracking Calibration Factors for Queensland

Pavement type	Cracking initiation factor	Cracking progression Factor	Wide Cracks initiation age	Cracking progression Rate (%)
AC/GB	0.40	0.55	7 - 10	0 - 30 in 6 years
SD/GB	0.30	0.55	7 - 8	0 - 30 in 6 years
AC/CB	0.05	0.38	8 - 10	0 - 33 in 4 years
Full depth AC	0.40	0.55	8 - 10	0 - 30 in 6 years

Notes: Source: [Robertson 94]; AC/GB = asphalt concrete on granular base; SD/GB = chip seal on granular base; AC/CB = asphalt concrete on cement treated base

The calibration experience from Philippines [Howard 94] goes beyond the normal interpolation of the model relationships to predict existing pavement types. The feasibility of extending the equations to concrete pavements and to high traffic volumes of up to 10,000 AADT was demonstrated.

[Howard 94]'s approach to extending the HDM-III performance prediction to concrete pavements was investigated by a carefully designed calibration of the corresponding AC pavement equations. Appropriate calibration factors were determined by trial and error for a range of cases representing low to very high traffic loading (*ESALs*) and normal to poor quality concrete bases. Occurrence of ruts and raveling was suppressed by setting $Kvi = 0.0$ and $Krp = 10$. Table 3.2 shows the range of calibration factors recommended by [Howard 94] for modeling concrete pavements in Philippines.

TABLE 3.2 Calibration Factors for Modeling Concrete Pavements in Philippines

Factor	Symbol	Recommended Range	Remarks
Cracking Initiation	*Kci*	0.1	
Cracking Progression	*Kcp*	0.1-0.6	varies with ESALs and constr. quality
Roughness- age/environment	*Kge*	0.2	
Roughness Progression	*Kgp*	3.6	
Pothole Progression	*Kpp*	0.13	
Rutting Progression	*Krp*	0.0	to suppress rutting
Raveling Initiation	*Kvi*	10.0	to suppress raveling

Source: [Howard 94]

Apart from the calibration contribution, [Howard 94] also presented an interesting experience gained in the application of the HDM-III model as an analysis engine in a network level pavement management. For example, to extend the HDM-III deterioration equations to AC overlaid rigid pavements [Howard 94] modeled the before and after overlay cases as separate pavement sections, and then combined the relevant parts of the predicted performance and cost streams as a post-processing task (outside HDM-III) before performing the optimization analysis (using EBM).

[Riley 95] provided an example of model adaptation for a mountainous terrain, low volume road network in Nepal. The pavement standards in Nepal are granular base with AC surfacing, mostly penetration macadam or thin premixed asphalt. Generally, construction quality involves "hand laid" pavements implying relatively high initial roughness levels. Use of a back calculation method of estimation was employed since as is generally the case, historical data were not available.

Given the high roughness levels tolerated in Nepal [Riley 95] suggested an interesting measure; the internal upper roughness limit permitted in the HDM-III source code was modified from 11.5 IRI to 20 IRI. Similarly, the rutting limit was revised to 10 mm by manipulating the HDM-III source code.

In a study to evaluate the applicability of HDM-III on South African national roads [Kannemeyer 94 and 95] demonstrated another interesting case of calibrating the model.

On the roughness model [Kannemeyer 94, and 95] recommended the approach of calibrating the environmental-age factor (*Kge*) first and then calibrating the roughness progression factor (*Kgp*) based on the *Kge* calibrated model. The environmental-age roughness factor is estimated by first determining an estimate for the environmental index, *m* based on Thornthwate moisture classification of the region. The details of this technique are given under Subsection 3.5.3. Using this technique

[Kannemeyer 94] obtained *Kge* values ranging from 0.39 to 0.89 for semi-arid to humid conditions in South Africa respectively. These values suggest that the pavements studied are about one half less susceptible to environmental degradation compared to the default HDM-III predictions.

Table 3.3 gives a summary of other pavement performance calibration factors recommended from the [Kannemeyer 94] study. For roughness progression, potholes and raveling equations the default HDM-III prediction (*Kgp* = *Kpp* = *Kvi* = 1.0) was found adequate. It is interesting to note that the default prediction generally over-predicted the cracking rate by more than twice. It is also noted the significant difference in the cracking behavior between overlays and reseals compared to original pavement surfaces. This underscores the need for more studies on performance modeling of rehabilitation treatments – an area which is noted in the literature as lacking sufficient empirical data.

TABLE 3.3 Range of Calibration Factors for South African National Roads

Pavement Type	Cracking Initiation, *Kci*	Cracking progression, *Kcp*	Rutting progression, *Krp*
Original surfacings	1.0 - 1.5	0.1 - 0.3	1.5 - 1.8
Overlays & Reseals	0.4 - 0.8	0.4 - 0.8	1.0

Source: [Kannemeyer 94]

3.5 Calibration of Pavement Deterioration Models

3.5.1 An Overview

In HDM-III, both the initiation and the rate of pavement deterioration have an important impact on the life cycle maintenance and rehabilitation costs as well as determining or predicting road users' costs. To ensure that the pavement deterioration sub-models in HDM-III predict or simulate realistic pavement performance for a given region the model performance prediction needs to be carefully calibrated by comparing predicted conditions with observed performance.

The calibration of the performance prediction equations in HDM-III is effected by including in the input data a set of linear multiplier factors, referred to as *deterioration factors*. The set of deterioration factors is determined so that it accounts for region-specific factors such as, material properties, rainfall intensity, temperature, construction practices and quality, plant, *etc.* If it is considered desirable to calibrate the performance models for a given distress type, then the model user will need to develop deterioration factors for each type of distress and for each link or set of links.

The calculation procedure for determining the deterioration factors is simple in theory. A deterioration factor is a simple ratio of the rate of progression (or the time to initiation) of a given distress predicted by the uncalibrated model to that observed locally. Other approaches have used simple trial and error method to determine the calibration factor, yet more rigorous numerical methods have been suggested, see for example [Kannemeyer 94 and 95].

The approach to the question of the need to re-calibrate the HDM-III performance models recommended from this study is a trade-off between the effort required to calibrate the parameter (cost, data, and skills) against its sensitivity on the model output. To decide on parameters that merit local re-calibration this study proposes a ranking of the parameters based on factor sensitivities with respect to the analysis criteria. A ranking of the HDM-III pavement performance calibration factors based on their sensitivity to the output criterion can be assembled and used to prioritize the need for calibration.

3.5.2 Choice of Pavement Distress Modes to Re-calibrate

In HDM-III deterioration of flexible pavements is predicted separately by five distress modes, namely, roughness, cracking, raveling, potholes and rutting. The mechanism of *surface distresses* is characterized by two phases [Paterson 87, Watanatada 87a]: initiation phase and progression phase. HDM-III uses separate equations for predicting initiation and progression phases of surface distresses. Roughness and rutting, are referred to as *'deformation distresses'* as they relate to movement in the pavement structure. The mechanism of a deformation distress is single phased and it is therefore sufficient to model it using one equation.

Consequently, there are seven *deterioration factors* used in calibrating the performance models in HDM-III: Cracking initiation and progression factors (*Kci, Kcp*), Potholes progression factor, *Kpp*, Rutting progression factor, *Krp*, Raveling progression factor, *Kvi*, and Roughness progression and age-environment factors (*Kgp, Kge*).

It has been suggested that the surface distress modes of cracking, raveling and potholing are more likely to require local adaptation [Watanatada 87a]. The other two deformation distresses, rutting and roughness are relatively less sensitive to locational attributes. However, sensitivity results indicate relative importance of these parameters that suggest a different priority in the need to calibrate. The *ceteris paribus* study reported in [Mrawira 96a] showed that a more comprehensive set of factor sensitivities presented later show a different priority based life-cycle cost components. Raveling and rutting factors have the least significance upon the NPV output.

3.5.3 Specific Considerations on Calibration of Performance Prediction

3.5.3.1 Calibration of Cracking Initiation and Cracking Progression

Pavement cracking is modeled using two equations; one for predicting the time from construction /rehabilitation when cracking initiates, and the other for predicting the rate of increase in extent and severity once the cracks have appeared on the pavement.

The form of the equation for the time it takes a new or rehabilitated pavement to show signs of cracking for flexible pavements is given by [Paterson 87]:

$$TYcra = Kci\ (Fc \bullet TY + CRT) \qquad \text{... (3.1)}$$

where, $TYcra$ = time to start cracking in years,
Kci = calibration factor for narrow cracking initiation,
Fc = occurrence distribution factor,
CRT = cracking retardation time due to maintenance, and
TY = mean age of surfacing at initiation of cracking.

TY is given by different equations for different pavements and is a function of modified structural number, annual traffic loading, excess binder content, construction quality, resilient modulus of soil cement, mean Benkelman deflection, and effective surface thickness.

Cracking (wide and narrow) models have been shown to be functions of five primary variables:

- pavement layer thickness (hence modified structural number, *MSN*),
- resilient modulus of cement stabilized material,
- Benkelman beam deflection,
- annual traffic loading in *ESALs*, and
- a linear calibration factor, *Kci*.

Four of these variables can be obtained from construction records, and from condition and pavement evaluation surveys. The only factor requiring calibration here is the *Kci* parameter. For cases like in Tanzania where sufficient data to carry out cluster analysis or time series analysis was not available a viable approach to estimate *Kci* was to draw on the engineering experience of the local practitioner. An average estimate of the time it took a pavement of a given standard to start developing cracks was established from field personnel.

A generic, yet simple procedure of determining a calibrating factor is to run HDM-III with the default *Kci* under the level of maintenance anticipated and observe the predicted time to initiation of cracking. This prediction is compared with the local data to decide on what extent to scale the *Kci* factor. An iterative process may be needed to approach the best value. The local experience in the Tanzanian study for example, showed that a new pavement took about 5 to 7 years to start cracking. Under similar conditions HDM-III predicts cracking initiation after 9 years. The predicted time required calibrating to $Kci = 1.2$ (default $Kci = 1.00$).

The relationship governing the annual rate of progression of cracking has three major variables: namely, the current condition (severity and extent), the pavement age, and the progression calibration factor, *Kcp*. The calibration of this equation again involves only the factor *Kcp*. The default value of $Kcp = 1.0$ under minimal R&M strategy will predict complete surface disintegration in 5 years after the initiation of cracks for a surface dressing (SD) on a stabilized base road. If this is close to the observed trends in the local pavements then the range of *Kcp* at 1.00 to 1.20 can be kept. Otherwise, the factor has to be adjusted to predict the performance approximating the local pavements. Figure 3.1 shows the results of cracking model calibration for a typical link with an initial traffic of 2020 ADT.

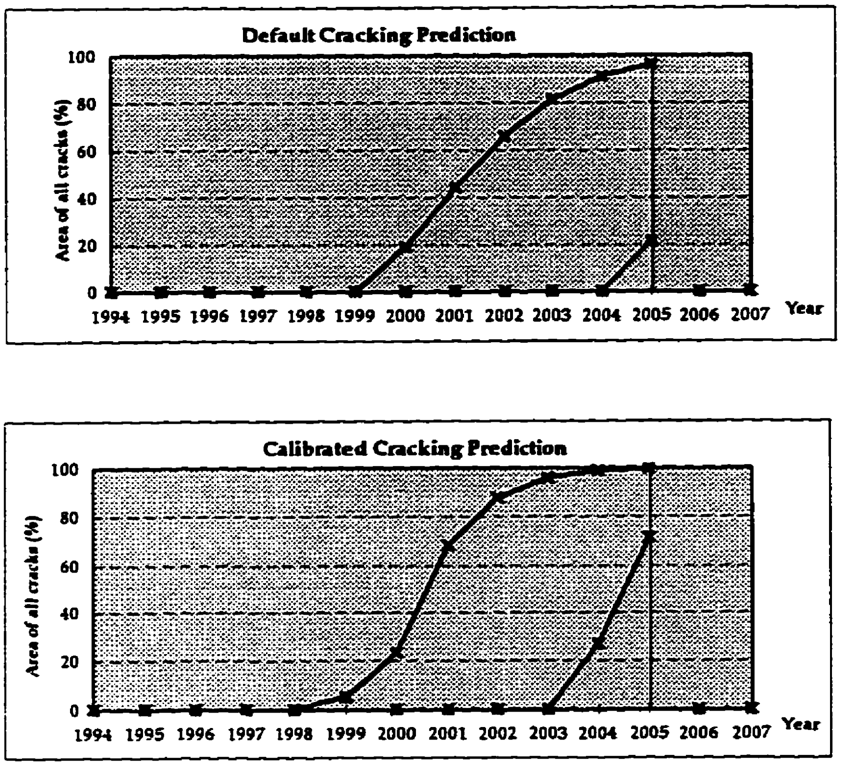

FIGURE 3.1 Cracking calibration for a typical link from Tanzania (ADT = 2020)

3.5.3.2 Raveling Initiation and Progression Parameters

Raveling is defined as the loss of surfacing material from a pavement. It is more common in surface dressed and gravel roads where the binder in the wearing course has lost its effectiveness. It may also occur in AC wearing course, for example, where oxidation is excessive or where aggregate-to-binder bond was questionable at construction. But this later type of occurrence is less significant and was not modeled in the HDM study [Watanatada 87a].

The phenomenon has two phases that requires different equations: the time to first occurrence and the rate of progression. HDM-III provides separate prediction equation for three types of surface, *i.e.*, surface treatments, slurry seals on SD or AC surfacing, and for cold-mix asphalt or cold-mix overlays. Raveling is modeled for hot-mix asphalt concrete surfacing.

Both the initiation and progression of raveling are functions of five key variables:

- Surface type,
- Construction quality,

- Traffic loading (total passage of all axles per lane per year),
- Retardation effects of R&M treatments,
- A user specified deterioration factor, *Kvi*.

Calibration of the two raveling equations involves adjusting the deterioration factor, *Kvi* which is common to both equations.

The *ceteris paribus* sensitivity results showed that the raveling calibration factor is the least sensitive relative to all other calibration factors upon the predicted NPV. Its effects are less than half a percent of the roughness progression factor. Consequently the study in Tanzania recommended that it was not worth attempting re-calibration of the raveling model. This recommendation is further validated by the comprehensive sensitivity results reported later in this thesis.

3.5.3.3 *Calibration of Initiation and Progression of Potholes*

The mechanism for potholes occurrence in pavements is a complex phenomenon, interacting with spalling, wide cracking, raveling and even roughness [Watanatada 87a, Paterson 87]. Furthermore, potholing is centrally influenced by the type of pavement surface and base layers. While drainage and localized damages have been known to have a significant impact on pothole initiation and progression, they all complicate modeling of this phenomenon.

Potholes progression is modeled as a function of the base type, the modified structural number, *MSN*, the current condition (in terms of wide cracks and raveling), and a calibration parameter, the potholes progression factor, *Kpp*. Calibration of this equation involves adjusting the *Kpp* factor to achieve close to locally observed pothole rates.

The study in Tanzania could not acquire sufficient data on development of potholes. Noting that the relative significance of the pothole progression factor was low compared to other input variables it was recommended to keep the model default for the *Kpp* factor.

3.5.3.4 *Roughness Calibration Factors*

Pavement roughness is one of the most sensitive variables in the HDM-III deterioration sub-model. It is used as the primary predictor or trigger level for scheduling most maintenance and rehabilitation treatments. It should also be noted that roughness is the primary road parameter that impacts heavily on the VOC resource consumption equations [Watanatada 87a].

Other studies have indicated that the ranking or choice of maintenance or rehabilitation options is very sensitive to roughness [Cai 92, Kerali 91]. Consequently roughness must be given special attention in calibration of the HDM-III model.

The roughness model for paved roads requires calibration of two parameters, the roughness progression, *Kgp*, and the roughness - age /environment factor, *Kge*. The sensitivity results on the calibration factors showed that the former must be given a higher priority; the NPV function output being about at least four times more sensitive to the roughness progression factor than the roughness - age factor. Ironically, the data requirements for calibrating the former are much higher than the later. While it is relatively easy to acquire rainfall and temperature data from the local meteorological stations, the corresponding data for roughness progression is almost non existent.

The recommended approach is to calibrate the environment-age factor, *Kge* first and then using the results of predicted roughness to calibrate the roughness progression factor, *Kgp*. It is an obvious logical approach since calibration of *Kge* aims at reflecting the effect of age and environment factors and could therefore be estimated directly from climate data. Again here it is assumed that the model form (with respect to effects of climate–aging) is acceptable, and that as long the climate input is accurately determined then the model prediction is good enough. The environmental–age calibration factor, *Kge* is estimated from the appropriate climate-moisture index, *m* using the relation:

$$Kge = m \,/\, 0.023 \qquad \text{... (3.2)}$$

The climate-moisture index, *m*, is defined in [Paterson 87] generally as representing an annual average effect of all non-traffic-related environmental factors, including daily temperature changes, seasonal and drainage-related moisture variations, subgrade movements, *etc*. As such, the value of *m* could not be explained by micro-climatic factors (such as local rainfall). Recommended values for the coefficient, *m* were estimated for various climates and given in [Paterson 87]. Estimating a value for local use based on [Paterson 87] requires classifying the local climate into a factorial of the four moisture-categories — arid, semiarid, sub-humid and humid-wet; and three temperature classes — tropical, subtropical nonfreezing, and temperate freezing.

As an example, one part of southern Tanzania consists of a region situated between the highlands of Njombe (mild temperatures, high rainfall) and the plains of Songea (warm temperatures, high rainfall). This location would be classified as humid-wet in the moisture category, and tropical to subtropical on the temperature category. Therefore a logical estimate for the *m* constant would be 0.025 to 0.040. The corresponding *Kge* factor then computes to 1.0 to 1.70. Table 3.4 presents estimated *m* values and the corresponding *Kge* factors from a study in Tanzania based on local climate data [Mrawira 95a].

TABLE 3.4 Estimated Roughness – Age Parameter for Select Regions in Tanzania

Region	Rainfall (mm/year)	Temperature range (°C)	Temperature/ moisture[1] classification	Environmental index (estimate), *m*	Calculated *Kge*
Morogoro	800 - 1400	4 - 6	Tropical – Humid	0.030	1.304
Iringa	400 - 1600	4 - 6	Tropical – Humid/Subhumid	0.027	1.174
Mbeya	500 - 1600	over 4 - 6	Subtropical – Humid/Subhumid	0.035	1.522
Ruvuma	1000 - 1200	over 4 - 6	Tropical/Subtropical – Humid	0.035	1.522
Kilimanjaro	500 - 1200	4 - 6	Tropical/subtropical – Subhumid	0.023	1.000
Tanga	500 - 1200	4 - 6	Subtropical – Semiarid/Subhumid	0.023	1.000
Kagera	1000 - 1400	below 2	Tropical – Humid	0.030	1.304
Mwanza	700 - 1000	2 - 4	Subtropical – Semiarid/Subhumid	0.023	1.000
Shinyanga	700 - 1200	2 - 4	Subtropical – Semiarid/Subhumid	0.023	1.000
Lindi	800 - 1400	2 - 6	Tropical – Subhumid	0.030	1.304
Mtwara	800 - 1400	2 - 6	Tropical – Subhumid	0.030	1.304

Source: [Mrawira 95a]

The HDM-III roughness prediction (after calibrating for environment/age factor) shows that a medium traffic asphalt concrete road will take 6 years to deteriorate from 2500 to 4000 mm/km BI[2]. Comparison to local observations suggests that the roughness rate is on the lower side. The default value of roughness progression factor in the model was therefore calibrated to 1.2. Figure 3.2 compares roughness prediction before and after model calibration for a typical link.

[1] *Approximate temperature-moisture classification according to [Paterson 87].*

[2] *BI = Bump Integrator. The TRRL fifth wheel towed (at 32 km/hr) bump integrator roughness index.*

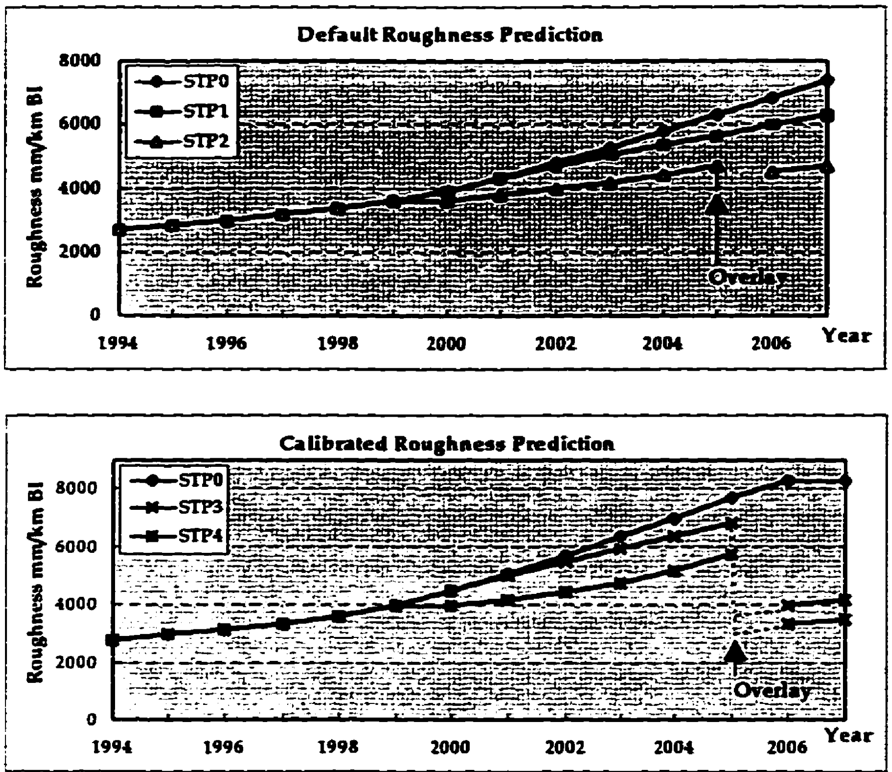

FIGURE 3.2 Roughness calibration for a typical link from Tanzania (ADT = 2020)

3.5.3.5 Calibration of Rut Depth Relationship

The HDM-III equation for modeling rut depth is common to all pavement types. The key variables to this equation are the annual traffic loading in *ESALs*, pavement strength in modified structural number, *MSN* (or Benkelman beam deflection), base layer strength (in degree of compaction), current level of cracking, annual rainfall, and a calibrating factor, *Krp*.

The maximum rut depth in HDM-III is fixed by default at 50 mm. Improved prediction suitable to local conditions may need amendments of this upper limit in the HDM source code. Again, an initial boundary condition does exist in the model which generates initial rut depths of the order 1.5 to 2.5 mm [Watanatada 87a]. These may differ substantially from local observations in which case adjustment may be required to enhance the prediction. However, the difficulty with this recommendation is it requires modifying the HDM-III source code.

The second relationship for rut depth is the standard deviation (*RDS*) which is given by a separate equation. This predictor of performance is also an important input to the roughness model where it appears as a variable in the roughness equation. The important implication of this observation is that calibration of the rut depth model should be concerned more with the change in the standard deviation over time and not the actual magnitude of standard deviation. A deficiency in prediction of the actual value of the rut depth standard deviation will not have a significant effect on the economic analysis.

Again it should be noted that an upper limit for the rut depth standard deviation, *RDS* is set at the mean rut depth. Whether this agrees with the local observation or not it is another question requiring attention in the calibration process.

The sensitivity study on calibration factors under settings applicable in Tanzania showed that the calibration of rut depth model has a relative impact of less than 5 percent of the impact of the roughness progression factor upon the NPV function. With this in mind, and the fact that no data was available for the calibration process, it was recommended to retain the default value.

3.6 Calibration of User Costs relationships

3.6.1 Overview

As previously discussed, the need for calibration of the VOC relationships arises from the fact that the statistical basis of the equations (*i.e.*, the databases from the Brazil, Kenya, India or Caribbean studies), may not be applicable to the local situations on account of technological change across time and/or space, disparity in economic environments, standards and policies, *etc.* Further, it has been documented that owing to the physical realities existing during the HDM Study, it was not possible to acquire sufficient, statistically designed samples for all causal variables in the mechanistic models.

In planning a study to calibrate the VOC relationships it is important to note that, with respect to R&M priority programming for weak pavements (*i.e.*, structural number less than 3.5), the most sensitive equations in the HDM-III are:

- prediction of vehicle repair costs with respect to change in road riding quality, and
- prediction of change in riding quality with a given maintenance treatment.

The parts cost equation in HDM-III is given by [Watanatada 87a, 87c] as:

$$PC = \begin{cases} CKM^{k}.COSP.\exp(CSPQI.QI) & \text{if QI} < \text{QI0SP} \\ CKM^{k}(a_0 + a_1.QI) & \text{if QI} > \text{QI0SP} \end{cases} \qquad \dots (3.3)$$

where: CKM = mean age of vehicle group in cumulative vehicle km of travel since new,
k = the age exponent
$COSP$ = constant coefficient in the equation
$CSPOI$ = Roughness coefficient in the exponent of the equation
$QIOSP$ = threshold roughness (in QI) at which the $PC - QI$ equation becomes linear, and

$$a_0 = COSP \,.\exp\left(CSPQI \,.\, QIOSP\right)\left(1 - CSPQI \,.\, QIOSP\right)$$

$$a_1 = COSP \cdot CSPQI \,.\exp\left(CSPQI \,.\, QIOSP\right)$$

Vehicle repair labor costs constitute another important component of the VOC. The labor hours are estimated from the parts costs by the equation [Watanatada 87a]

$$LH = COLH \cdot PC^{CLHPC} \cdot \exp\left(CLHQI.QI\right) \qquad \text{... (3.4)}$$

where LH = vehicle repair labor hours per 1000 km.
$COLH$ = constant coefficient in the $LH - PC$ equation
$CLHPC$ = the exponent of parts costs in the $LH - PC$ equation
$CLHQI$ = the roughness coefficient in the exponential component of the $LH - PC$ equation.

Although inconclusive, the *ceteris paribus* factor sensitivities results (see Chapter 6) indicate the role of both equations (3.3) and (3.4) to be highly significant.

This is obvious from the following two reasons:

(1) VOC contribute a relatively large share in the total life-cycle costs for this class of roads.

(2) the spare parts component in the total VOC is substantial.

Hence the role of vehicle repair policies in the local economy needs to be carefully investigated to enhance the quality of VOC predictions. Likewise, the effects of maintenance intervention upon road condition, particularly, riding quality need to be accurately reflected in the pavement performance sub-model prior to VOC calibration.

3.6.2 Choice of VOC Model

HDM-III provides four alternate sets of equations for modeling vehicle resource consumption, namely, the Brazil, Kenya, Caribbean, and India relationships. Among these, the principal set of relationships are those derived from the Brazil study. The choice of the appropriate set of VOC relationships for local application is an important initial step in adaptation of the model to the local situation. Once the appropriate set of relationships have been selected, the next step is to select vehicle types from the standard HDM vehicle types that can best represent the local traffic composition (at the link level).

From the case study in Tanzania [Mrawira 96a] only the Brazil and Kenya set of relationships were potential choices for simulating the traffic and vehicle characteristics in Tanzania. It was previously argued that Kenyan relationships was the appropriate choice for Tanzania because the study was undertaken in settings, geographically and economically, very similar to Tanzanian conditions. However, the Kenya VOC equations are generally considered to be inadequate. As mentioned earlier, the most important weakness is the narrow range of the predictive capability of the model [Watanatada 87a]. The Brazil set of relationships is generally recommended for users outside the three host countries to the alternative relationships in HDM-III. The range of model parameters (in the Brazil relationships) allows for more responsive calibration to suit many diverse situations than any of the alternative model forms.

3.6.3 Choice of Appropriate Vehicle Types

The Brazil equations for VOC modeling are recommended for most local application. The Brazil VOC relationships provide 10 standard vehicle types from which the user is to select the types that can best represent the traffic composition on the road link being studied. [Watanatada 87a] summarizes the important characteristics of the vehicle types used for modeling VOC in the Brazil study. It is necessary to conduct a careful comparative investigation of the vehicle characteristics between HDM types and the typical vehicles in each class in the local traffic.

It should be noted that, since traffic composition changes from one link to the next, and even from one year to the next, the best way to represent this variation of composition over a road network and time is to define several traffic categories. A link can then be assigned a different category from one year to the next as needed. In this spirit, the vehicle classification finally adopted should aim at representing the entire spectrum of vehicles in the region to be studied as well as the projected period of analysis (where traffic composition is expected to change over time). Traffic volumes and growth data will then need to be tailored to match this vehicle classification. In most cases the traffic data available locally will need to be modified to match the HDM-III vehicle types for VOC predictions.

The Tanzanian study observed that the most important limitation of the HDM-III VOC sub-model is the outdated truck characteristics incorporated in the model. In the past fifteen years or so the truck technology has changed so much that even developing economies like Tanzania have seen a significant increase in gross vehicle weights, payloads, engine power, *etc.* The technological trends have consistently moved towards increased engine power, higher gross vehicle weights, improved engine configurations and better fuel efficiency. Further, tire technology, suspension and braking systems have changed tremendously. These changes pose a serious challenge to the HDM-III VOC relationships. The present VOC model is considered inadequate for simulating resource consumption especially for vehicles in the categories of medium, heavy and articulated trucks. It is hoped that the current efforts to update HDM-III [ISOHDM 94] will examine this deficiency.

The criterion for selecting the appropriate HDM-III vehicle types is to simulate vehicle resource consumption that approximates the average values observed for that vehicle class in a given traffic composition. In other words, an ideal vehicle type (selected in HDM-III) should be such that the predicted resource consumption is equal to the average value for the vehicle class which it represents in the traffic. The key vehicle characteristics affecting resource consumption are fuel type, engine size, gross vehicle weight (GVW) and axle loads and configuration. Comparison between these factors for the typical vehicle in a traffic class and the available standard HDM-III vehicles have to be made to determine the most appropriate representation.

Seven vehicle types were recommended as suitable to characterize the traffic mix in Mwanza region in Tanzania [Mrawira 95a]. The average vehicle characteristics given were derived mainly from a local guide on VOC [MoW 94a].

The current traffic counting forms in use by most regions in Tanzania classify the traffic into eight groups. Cars, utilities (light goods vehicles) cover the smallest units. Small buses and small trucks classify traffic in the lower end of sizes, whereas, large buses, heavy trucks semi-trailer and full-trailer trucks represent traffic in the high end of sizes. A small bus is defined as one with passenger capacity less than 25, whereas, light truck is defined as one with less than 5 tons payload capacity.

The MoW traffic classification for buses and trucks has the advantage of capturing a better axle loading representation. On the other hand the advantage of counting semi-trailer and full-trailers separately cannot be explained in similar terms. It is however possible that such break down of the articulated truck class may enhance VOC predictions as resource consumption is likely to differ significantly for semi- and full trailers. Unfortunately no research has explored this possibility.

3.6.4 Decision on Parameters to Re-calibrate

Table 3.5 lists the model input cards for the variables relating to re-calibration of the Brazil VOC relationships. [Watanatada 87c] recommends (Table 3.6) that the final choice of candidate parameters to re-calibrate at the local level should be based upon the key factors – locational sensitivity, impact on model output of interest, and calibration effort required (or available). However, this recommendation needs to be reviewed because it was mainly based on subjective assessment of the three factors.

TABLE 3.5 VOC Calibration Related Input Variables

HDM Symbol	Description of the Variable or Data Required	HDM Card Number
PAYLOAD	Average payload for the typical vehicle in each class	D301
HPDRIVE	Used driving power per vehicle class (equiv. the SAE maximum rated power)	D304
HPBRAKE	Used braking power (see *HPDRIVE*)	D305
VDESIROPV	Desired speed (no effects of width, gradients, curvature, roughness)	D311
RECAP COS	Tire re-treading cost (as a fraction on new tire price)	D318
NR0	Base number of recaps (average per vehicle class)	D320
C0TC	Constant term of the tire consumption model	D321
CTCTE	The tire Circumferential wear coefficient	D322
C0SP	The constant term in Parts – Roughness equation	D323
CSPQI	The roughness coefficient in the exponent of the Parts – Roughness equation	D324
QI0SP	Transition roughness at which the Parts – Roughness equation becomes linear	D325
C0LH	Constant term in the Labour Hours – Parts Costs equation	D326
CLHPC	The exponent of Parts Costs in the Labour Hours – Parts Costs equation	D327
CLHQI	Roughness factor in the exponent of the Labour Hours – Parts Costs equation	D328
DEPRECIATE	Average depreciation rates for the typical vehicle in each class	D501
KM DRIVEN	Annual vehicle kilometres of travel (*VKmT*)	D503
VEH LIFE	Average economic life of typical model in vehicle class	D504
HR DRIVEN	Annual number of hours	D505
HURATIO	Average utilisation ratio (actual time of usage to total time)	D506

The literature does not offer any quantitative guide on the locational sensitivity of model parameters, nor their relative impact on the model output (*e.g.*, NPV). The scope of factor sensitivity analysis for this class of input factors was only limited to the *ceteris paribus* study. The results (Chapter 6) indicate that the parameters of the parts-roughness ($PC - QI$) equation and the labor parts ($LH - PC$) equation should be given highest priority in an exhaustive sensitivity study to determine their role. Factor sensitivity is recommended as a standard procedure for all local adaptation.

TABLE 3.6 Recommended Re-calibration of the VOC Models *[Watanatada 87c]*

Prediction Model	Parameter Description	Symbol	Locational Sensitivity	Impact on Ranking	Calibration Effort	Calibrate (yes/no)
Speed	Used driving power	*HPDRIVE*	high	med - high	low	yes
	Used braking power	*HPBRAKE*	med - high	low	low	yes
	Desired speed (width ≥ 5.5m)	*VDESIR*	high	low - med	med	yes
Fuel	Fuel efficiency factor	*ALPHA1*	med	med - high	low	yes
	Fuel adjustment factor	*ALPHA2*	med	low	high	no
Tire wear	Cost ratio of re-treading to new tire	*RECAP COS*	high	high	low	yes
	Base number of recaps	*NR0*	high	med - high	med	yes
	Constant term in tire wear equation	*COTC*	med - high	med - high	med	yes
	Circumference tire wear coefficient	*CTCTE*	med - high	med - high	med	yes
Vehicle utilisation	Base number of hours driven	HRD_0	high	high	med	yes
	Base utilisation	AKM_0	high	high	med	yes
	Base elasticity of utilisation	EVU_0	med - high	high	med	yes
Repair Parts	Constant term in the $PC - QI$ eqn.	*COSP*	high	high	med	yes
	Roughness factor in the exponent	*CSPQI*	med	high	high	no
	Age exponent in the $PC - QI$ eqn.	k	low	med	high	no
Repair labour	Constant term in $LH - PC$ eqn.	*COLH*	high	high	med	yes
	Exponent of PC in $LH - PC$ eqn.	*CLHPC*	low	high	med	no
	Roughness factor in the exponent	*CLHQI*	high	med	high	no

Symbols according to the Glossary; eqn. = equation; med. = medium.

3.7 Generating Appropriate Intervention Strategies

3.7.1 General Approach

The HDM Model requires the user to define a set of maintenance actions applicable to a road section, that will be used to simulate the life cycle of each individual project alternative. Formulating the maintenance standards requires a careful process involving local experience as well as a knowledge of the HDM-III model computational logic. The local experience is important in selecting R&M options that are practical, feasible and compatible to the local materials, environment and technological base. The proposed R&M alternatives must be based on local practices, conditions, policies or standards, and the local availability of materials and plant. Again, to estimate the effects of these maintenance options upon subsequent pavement deterioration requires local expertise. Sufficient knowledge of the effects of the each treatment upon pavement performance is necessary in order to achieve realistic life cycle cost analysis.

Defining an R&M strategy in HDM-III is constrained by the fact that only fixed building blocks can be used. All strategies are defined as a combination of one or more activities from twelve pre-defined HDM-III unit operations. There are eight operations for paved roads and four for unpaved roads [Watanatada 87a, 87b]. A maintenance standard is formulated by selecting one or more of these basic operations. Further, a trigger criterion has to be specified. The trigger defines when an operation is to be applied or repeated. The trigger criterion can either be a fixed interval, or an intervention based on cumulative traffic or the predicted deterioration level of one or more distress modes.

Another serious limitation of the HDM-III model is the inflexibility of defining trigger levels for different maintenance interventions. While, for instance, pavement patching can be prescribed either by the area per km to be patched annually, or the proportion of total damaged (or pothole) area to be patched; preventive sealing (sand or slurry) can only be triggered by fixed time interval between applications or initiation of cracking or raveling. On the other hand surface treatment (chip resealing), hot mix overlays, and total re-construction can be triggered by roughness level, or by fixed time intervals only. It was noted that while in some cases it would be desirable for purposes of staged construction (fairly popular in developing economies) to schedule overlays by cumulative traffic loading, the model does not provide such an option.

3.7.2 A Sample of R&M Standards Applicable in Tanzania

The following R&M standards were first formulated in a project to implement HDM-III for Mwanza region [Mrawira 95a]. After consultation with the local engineers, a set of ten maintenance alternatives were configured, five each for paved and unpaved roads. These were considered representative of most scenarios from which the practicing engineers would normally choose annual programs for their region. Given the similarity of road design and construction standards in Tanzania, the set of R&M alternatives proposed for Mwanza can generally be applied for many cases in the country with minor modifications. Table 3.7 summarizes the recommended maintenance standards for Mwanza region in Tanzania.

TABLE 3.7 A Sample of R&M Strategies from the Tanzanian Study

Code	Routine	Potholes Patching	Resealing frequency	AC overlay	Reconstruction
STP0	included	30%	-	-	not included
STP1	included	100	-	-	not included
STP2	included	100	12 mm every 6 years	-	not included
STP3	included	100	-	50 mm every 15 years	not included
STP4	included	100	12 mm every 5 years	50 mm at 5.5 m/km IRI	not included
	Routine	**Grading Frequency**	**Spot Regraveling**	**Gravel Resurfacing**	**Reconstruction**
STU0	included	once per year	-	-	not included
STU1	included	once every 180 days	-	-	not included
STU2	included	every 20,000 veh. passes	-	-	not included
STU3	included	once every 180 days	30% material loss	-	not included
STU4	included	every 20,000 veh. passes		150 mm when t < 25 mm	not included

NOTES: all strategies include routine (off-carriageway) maintenance, e.g., drainage, vegetation control, shoulder repair, road furniture, etc. AC = hot mix asphalt concrete. Resealing consist of patching all damaged area and 12 mm hot mix surface dressing.

Note that STP0 and STU0 are set as the "do minimum" options against which economic comparison of the other alternatives is based. Net benefits computed by the model are therefore savings over these "do-minimum" alternatives.

The strategies summarized in Table 3.7 are not uncommon in the literature. A recent study in Queensland determined optimum roughness intervention levels as a function of traffic level. The study found that optimum roughness intervention for paved road ranges from 5.0 IRI for AADT less than 500 to 3.0 IRI for AADT greater than 10,000 [Robertson 94]. The most favored treatments, according to [Robertson 94] were reseals at low traffic and thin AC overlays for high traffic.

Similar maintenance strategies for paved roads were also recommended in Nepal [Riley 95]. The work in Nepal emphasized the need to consider maintenance strategies as comprising of two components – a long term, regular periodic intervention policy, and a series of different immediate treatments to be applied in conjunction with the long term policy. The resulting R&M strategies were very comparable to those in Table 3.7.

In a case study to determine cost-effective intervention policies in Mali [Bhandari 87] proposed 31 and 10 treatment alternatives for paved and unpaved roads respectively. The unpaved road strategies consisted of routine off-the-carriageway maintenance and various combinations of: (a) up to 30% material loss regraveling, (b) blading at frequencies ranging from every 2000 to 8000 vehicle passes, and (c) gravel resurfacing whenever the remaining gravel falls below 50 mm.

The paved road strategies consisted of off-the-carriageway routine maintenance and various combinations of: (a) patching annually 50% or 100% of all potholes, (b) resealing 25%, 50%, or 75% of all damaged area, (c) 40 mm or 80 mm AC overlay at roughness levels of 3.5, 4.2 or 5.0 m/km IRI, and (d) reconstruction whenever the roughness level exceeds 8.5 IRI.

It should be pointed out that the blading frequencies investigated by [Bhandari 87] and those proposed in Costa Rica [Bank 88] are on the higher side compared to typical practice in low-income road authorities. [Bhandari 87 and Bank 88] found that for the Costa Rican conditions the optimal blading frequencies (maximizing the NPV) ranged from once every 4000 to 7000 vehicle passes. They further showed that this optimal grading frequencies remained fairly stable over the range of traffic levels investigated (25 to 300 ADT). HDM-III analysis is normally applied to unpaved roads with traffic levels ranging from 100 to 250 vehicles per day. For such facilities, the blading frequencies of 2000 to 8000 vehicle passes proposed in [Bhandari 87 and Bank 88] would translate to between five and over 45 bladings per year. The present practice in most low-income road authorities is 1 to 3 bladings per year [Liautaud 95].

In another recent application in Germany [Sršen 94] adopted R&M strategies very similar to those proposed by [Bhandari 87 and Bank 88] for paved roads. Despite the fact that the pavement design standards investigated in Germany were much higher (*SN'* ranging from 3 to 9) and the commercial vehicle traffic was only up to 700 vehicle per day, the most cost-effective strategies recommended were mostly 80 to 140 mm AC pavement strengthening followed by overlaying at 3.5 to 5.0 IRI.

3.7.3 Selecting Cost-effective R&M Strategies

Once an appropriate list of feasible, technically viable intervention strategies have been formulated for the investigation at hand, the HDM-III model is run on the project data and a large series of output reports obtained. The question then becomes how does one make use of the model output reports to develop an optimal investment program? The current HDM-III documentation does not provide sufficient guide on how to identify cost-effective strategies. The literature offers some contributions to this subject, the most notable sources are [Bhandari 87, Bank 88, and Riley 94 and

95 and Liautaud 95]. The subsequent paragraphs conclude the chapter by discussing the bare essentials of the technique of selecting cost-effective strategies after these articles.

Identifying the most cost-effective preservation program in a life-cycle analysis framework is critically important, particularly under the budget constraint situations facing almost all road authorities today. The most commonly accepted technique seems to be the use of economic efficiency frontier based on the tradeoff between the total life-cycle costs and the agency cost of implementing the given investment strategy [Bhandari 87, Bank 88, Riley 94 and 95 and Liautaud 95]. The underlying motive in this technique is to identify the R&M strategy, among the several viable options (within the budget ceiling), that maximizes the return on investment. The return on investment can be measured in a number of slightly different ways. More often, the savings in the total transport life-cycle costs (the NPV), or the savings in the users' life-cycle costs, or even the relative reduction in the road roughness is used [Liautaud 95].

Figure 3.3 shows an example (hypothetical) of efficiency frontier that can be developed from life-cycle predictions by the HDM-III model. The following discussion refers to this figure to illustrate the technique of selecting cost-effective strategies. The acronyms STP0, STP1, STP2, *etc.* stand for codes for technically feasible intervention treatments or R&M strategies.

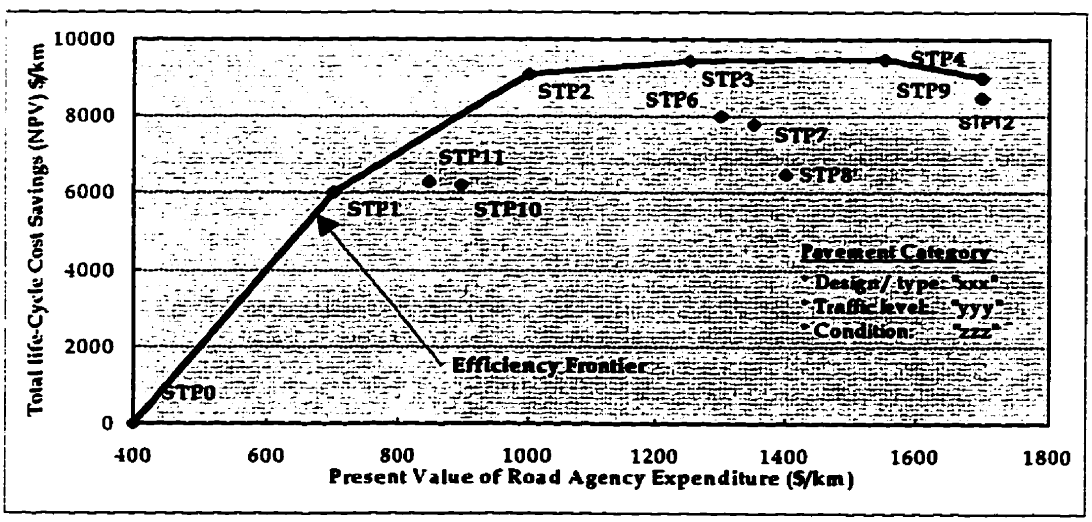

FIGURE 3.3 ***Determination of optimal investment strategies by use of the efficiency frontier***

One efficiency frontier is normally plotted for each category of pavements grouped by surface type (and/or design standard), traffic level and current condition. The plotting proceed by sorting out strategies with positive net benefit (NPV) and plotting the sorted NPV versus the per kilometer cost of each strategy. The efficiency frontier curve corresponds to the line connecting the points of maximum NPV for any given level of agency expenditure. In theory, any R&M strategy that lies below the efficiency frontier (*e.g.*, STP6, STP7, STP8, *etc.*) can be substituted for by a more cost-effective strategy with the same cost implication to the road authority.

Strategies STP3 and STP4 in Figure 3.3 represent high-cost high benefit strategies. The intervention level denoted by STP4 is thus the most-cost effective for the road links depicted by Figure 3.3. Strategies STP6, STP7, STP8, STP10, *etc.* represent inefficient allocation of intervention expenditure, since they can be replaced by other strategies at the same agency cost but with higher savings in total life-cycle transport costs.

In many cases it may not be possible to implement the most-cost effective strategy (*i.e.*, STP4) over the total number of kilometers in the analysis category due to limitations on funding. The next lower cost strategies lying on the efficiency frontier, STP3, and STP2 provide reasonable substitutes for STP4 that can significantly reduce the agency expenditure with only marginal losses in the total life-cycle costs savings. [Bank 88] demonstrated how to employ a combination of two strategies to achieve any given expenditure level while operating on the efficiency frontier. For example, in Figure 3.3 the inefficient strategy STP11 which carries an agency expenditure of about $850/km would be replaced by using strategy STP1 on about one half the total number of kilometers and strategy STP2 on the remaining kilometers in the analysis category.

Under increasing budget constraint the agency expenditure would be pushed further and further to the left of the frontier (*i.e.*, strategies STP2, STP1, STP0). Generally the slope of the efficiency frontier becomes steep in this zone, implying a massive loss of total transport life-cycle savings for even small cuts in agency expenditure. It is desirable for road authorities to establish local policy criterion on the minimum intervention level that safeguards against premature pavement failure and undue excessive costs of reconstruction. Such a policy criterion could be based, for example, on a threshold maximum slope of the efficiency frontier. [Riley 95] proposed a threshold maximum slope of 2. However, it is obvious that this cutoff efficiency frontier slope is dependent on many factors, including the relative unit costs of maintenance operations and vehicle running costs, pavement standards, traffic levels, *etc.*, and therefore it cannot be generalized.

Chapter 4

A FRAMEWORK FOR *CETERIS PARIBUS* INVESTIGATION AND OTHER IMPORTANT ASPECTS OF THE RESEARCH

4.1 Chapter Overview

The ultimate goal of the research, as defined in Chapter 1 (sections 1.2 and 1.4), is to develop a simplified model for pavement investment analysis which will provide decision making support at the network level for road agencies with a limited level of resources. The focus is to make the results of the major international research efforts incorporated in HDM-III more readily available to the poor institutions of SSA. Providing more regional-specific default values than are currently incorporated in HDM-III and are more reflective of the specific conditions in the region is considered an important step towards adaptation and realistic integration of the model in PMS analysis in the region. If this goal is achieved, then the simplified model would provide an indispensable and a timely "therapy" (at least in part) to the current road maintenance crisis in SSA.

The hypothesis underlying the study, and the specific objectives for this thesis, were presented in section 1.4. To achieve the research objective required innovative thinking, experimenting with new techniques (some of them not conceived at the time of the proposal), and continuously revising the approach at a number of stages during the implementation of the research. The purpose of the present chapter is to outline the research process with a view of highlighting some of the key elements learned in the evolution of the research methodology.

A major effort of the study was expended in search for a more efficient and robust technique for investigating the input factor sensitivity upon key HDM-III output criteria. The key motivation was to develop a method that could achieve three aspects: (1) capable of investigating effects of multi-factor interactions, (2) comprehensive results independent of base case input values, and (3) capable of exploring the full range of input space for a given model application. However, prior to the experimental design approach used in the later stages of this research, a substantial amount of work was already done using the "*ceteris paribus* technique." This Chapter looks into the lessons learned in relation to the development of a practical approach to the "*ceteris paribus* technique." The experimental design approach is presented in chapter 5.

The Chapter is organized into six sections. Section 4.2 introduces the computational framework underlying the HDM-III economic analysis. Section 4.3 highlights the link between the maintenance and rehabilitation strategies and the objective function. The key considerations in developing the *ceteris paribus* experiments are discussed in 4.4. Next, the thesis' concern of how best to present results of sensitivity analysis and how these results could be used to screen out the inactive input factors is addressed. Finally, the Chapter concludes by looking at the role of data in this research and the lessons from the field work.

4.2 The HDM-III Economic Analysis Framework

The primary objective of the HDM-III model is to provide a tool for making comparisons between alternatives or strategies in road improvements (alignment, capacity, *etc.*), construction, maintenance or rehabilitation. Relationships to be borne in mind in this sort of comparison are those governing construction standards and maintenance operations in determining the quality of a road link (over its lifetime) and the impact of this quality upon the operating costs of vehicles using that road link.

The basis of model comparison is the difference in costs between one alternative and the other. In other words, the economic evaluation is normally an evaluation of one link-alternative relative to a base case. The "Do minimum" (also called "Do nothing") alternative (*e.g.*, STP0 in subsection 4.2.1) is normally used as the base case such that any extra expenditure on the road represents an improvement which needs to be justified economically. The subsequent paragraphs outline the model procedure for each cost component.

4.2.1 Road Annual Costs

- Physical quantities are predicted by other sub-models on per link, link-alternative and per year of analysis basis. The principal sub-model here is the road deterioration with traffic and age/environmental factors. Vehicle operating costs comprise the other key sub-model (discussed in subsection 4.2.2). The first type of physical quantities are road construction and maintenance resources.

- The quantities are multiplied by their unit prices and the resulting cost components are classified as either capital or recurrent costs. This classification is only relevant in case of further budget analysis where different constraints are applied to capital and recurrent items.

- Cost difference between alternatives for any link in a given year is calculated by:

$$\underline{\text{Road Capital Cost}}:\quad \Delta CAP_{(m\text{-}n)} = CAP_m - CAP_n \qquad \text{... (4.1)}$$

$$\underline{\text{Road Recurrent Cost}}:\quad \Delta REC_{(m\text{-}n)} = REC_m - REC_n \qquad \text{... (4.2)}$$

where,

$\Delta CAP_{(m\text{-}n)}$ = road capital cost difference of alternative *m* relative to alternative *n*
$\Delta REC_{(m\text{-}n)}$ = road recurrent cost difference of alternative *m* relative to alternative *n*
CAP_m = total road capital cost for alternative *m* (on the given link, and year)
REC_m = total road recurrent cost for alternative *m* (on the given link, and year)

4.2.2 Road Users' Benefits and Costs

The principal road users' benefits considered by the HDM-III Model are vehicle operating costs savings and travel time savings resulting from a superior R&M alternative over a base case. Each of these benefits are calculated on per analysis year basis and since slightly different relationships are used for normal and generated traffic these are calculated separately for each category of traffic. The computational logic is as follows:

- VOC savings for normal traffic for alternative *m* relative to alternative *n* for a link and year:

$$\Delta VCN_{(m\text{-}n)} = \Sigma\, TN_j\,(UC_{nj} - UC_{mj}) \qquad \text{... (4.3)}$$

- VOC savings for generated traffic for alternative *m* relative to alternative *n* for a link and year:

$$\Delta VCG_{(m\text{-}n)} = \Sigma\, \tfrac{1}{2}(TG_{mj} + TG_{nj})(UC_{nj} - UC_{mj}) \qquad \text{... (4.4)}$$

- Vehicle travel time savings for normal traffic for alternative *m* relative to alternative *n*:

$$\Delta TCN_{(m\text{-}n)} = \Sigma\, TN_j\,(UT_{nj} - UT_{mj}) \qquad \text{... (4.5)}$$

- Vehicle travel time savings due to generated traffic for alternative *m* relative to alternative *n*:

$$\Delta TCG_{(m\text{-}n)} = \Sigma\, \tfrac{1}{2}(TG_{mj} + TG_{nj})(UT_{nj} - UT_{mj}) \qquad \text{... (4.6)}$$

where,

$\Delta VCN_{(m\text{-}n)}$ = VOC savings due to normal traffic of alternative *m* relative to alternative *n*,
$\Delta VCG_{(m\text{-}n)}$ = VOC savings due to generated traffic of alternative *m* relative to alternative *n*,
$\Delta TCN_{(m\text{-}n)}$ = travel time savings due to normal traffic of alternative *m* relative to alternative *n*,

$\Delta TCG_{(m\text{-}n)}$ = travel time savings due to generated traffic of alternative m relative to n,
TN_j = normal traffic for vehicle group j,
TG_{ji} = generated traffic for vehicle group j due to alternative i relative to the baseline,
UC_{ji} = average VOC per vehicle trip over the link for vehicle group i under alternative j,
UT_{ji} = average travel time cost per vehicle trip for vehicle group i under alternative j.

Throughout these equations the summation, Σ, is over all the vehicle groups specified by the user.

4.2.3 Exogenous Benefits and Costs

The principal costs and benefits associated with road capital and recurrent costs on one hand, and VOC and travel time savings on the other do, in most general cases, represent the lion's share of the total societal costs and benefits of implementing road improvements. However, it must be recognized that other important costs may come to play in different scenarios, in particular, costs related to road accidents, environmental impacts *e.g.*, noise and emissions, and other congestion related impacts.

In such instances the model user may want to include in the analysis the effect of these exogenous costs or benefits. The model computation logic when dealing with this option is as follows:

$$\Delta EXB_{(m\text{-}n)} = EXB_m - EXC_m - EXB_n + EXC_n \qquad \text{... (4.7)}$$

where,

$\Delta EXB_{(m\text{-}n)}$ = difference in net exogenous benefits of alternative m relative to alternative n;
EXB_j = exogenous benefit for alternative j for the given link and given year;
EXC_j = exogenous cost for alternative j for the given link and given year.

4.2.4 Economic Analysis and Comparisons

For each pair of link-alternatives to be analyzed the model calculates year by year the total cost savings of one relative to the other, combining road capital and recurrent costs, VOC and travel time costs, and exogenous costs differences. Thus, for any link or group-alternative k in year y, the net cost savings are computed as:

$$\begin{aligned}\Delta NB_{ky(m\text{-}n)} = \; & \Delta VCN_{ky(m\text{-}n)} + \Delta VCG_{ky(m\text{-}n)} + \Delta TCN_{ky(m\text{-}n)} + \Delta TCG_{ky(m\text{-}n)} \\ & + \Delta EXB_{ky(m\text{-}n)} - \Delta CAP_{ky(m\text{-}n)} - \Delta REC_{ky(m\text{-}n)}\end{aligned} \qquad \text{... (4.8)}$$

where, $\Delta NB_{ky(m\text{-}n)}$ = net economic benefits of alternative m relative to alternative n in year y for the link k.

The net present value of alternative m relative to alternative n, $NPV_{k(m\text{-}n)}$, is computed as:

$$NPV_{k(m-n)} = \sum_{y=1}^{p} \left(\frac{\Delta NB_{ky(m-n)}}{(1 + 0.01r)^{y-1}} \right) \qquad \text{... (4.9)}$$

where,

r = the annual discount rate

p = the user defined analysis period in years.

The internal economic rate of return, denoted by r^* in percent, is the discount rate at which the net present value as defined by equation (4.9) equals zero, *i.e.*,

$$\sum_{y=1}^{p} \left(\frac{\Delta NB_{ky(m-n)}}{(1 + 0.01 r^*)^{y-1}} \right) = 0 \qquad \text{... (4.10)}$$

Equation (4.10) is solved for r^* by evaluating the NPV at 5% intervals between -95 and +500 percent, and determining the zeros of the equation by linear interpolation of adjacent discount rates with the NPV values of opposite signs. Depending on the nature of the net benefit streams ($NB_{ky(m-n)}$,) solving equation 4.10 may give one solution, multiple solutions or none at all. So the IRR output stream from a typical HDM-III run normally contains some results printed "none" and "many." This is probably the main reason why the NPV output is favored in HDM applications compared to the IRR criterion.

4.3 Significance of the R&M Strategies in the Analysis

In sensitivity analysis we are seeking to investigate the factor effect of an input variable upon a model output (the objective function). As seen in section 4.2, the HDM-III outputs are inevitably defined in relation to two R&M strategies — a "do minimum" and an "alternate" strategy. In other words, any sensitivity analysis results cannot be discussed independent of the "recipe" underlying the R&M strategies used in the analysis. The chosen R&M strategies are thus very central to the findings of the investigation.

[Mrawira 96a] describes a general approach in formulating appropriate R&M alternatives for applying the HDM-III economic analysis. Chapter 3 (Section 3.7) gives details on factors and constraints that need to be addressed in defining the strategies to be investigated by the HDM model. Table 3.7 shows a sample of R&M strategies first applied in a study in Tanzania [Mrawira 95b] and reproduced in [Mrawira 96a]. This set of R&M strategies, having been formulated in consultation with experienced local engineers, were considered adequate and typical for the case study region, and therefore worth retaining for the sensitivity analysis.

The paved road R&M alternatives used throughout the sensitivity analyses are as defined earlier in Table 3.7 and summarized as follows:

STP0: *Do minimum:* Annual routine off carriage way maintenance activities (drainage, vegetation, signs, *etc.*) plus patching 30% of all potholes annually.

STP1: *Low maintenance intervention (1):* Annual routine off carriage way maintenance activities plus patching 100% of all potholes annually.

STP2: *Low maintenance intervention (2):* Annual routine off carriage way maintenance activities, patching 100% of all potholes annually plus a 12 mm surface treatment every six years.

STP3: *Medium maintenance intervention:* Annual routine off carriage way maintenance activities, patching 100% of all potholes annually plus 50 mm AC overlay every fifteen years.

STP4: *High maintenance intervention:* Annual routine off carriage way maintenance activities, patching 100% of all potholes annually, 12 mm surface treatment every six years and a condition responsive overlay (50 mm hot mix AC overlay at 5.5 m/km IRI roughness level).

Note that the surface treatment, also commonly called "chip seal" or "surface dressing," (in strategies STP2 and STP4) was estimated, from the local practice, to achieve a structural strength, (AASHTO layer coefficient) of 0.25 per inch. Again, the high-level maintenance intervention also carries extra constraints of minimum and maximum overlay frequencies of not less than 8 years and not more than 15 years interval between overlays. It was estimated that the AASHTO structural number gain by a typical overlay would be 0.30 per inch.

4.4 Framework of the *Ceteris Paribus* Experiments

The primary role of sensitivity analysis in the research was to identify the inactive input factors (in comparison the most sensitive or active ones) with respect to model output(s) commonly used in priority programming for the particular region. The case study focused on rehabilitation and maintenance (R&M) programming needs for the low-income road agencies of Sub-Saharan Africa. This focus dictated four key considerations:

(1) Defining R&M strategies or alternatives that are commonly applied in the case study region,

(2) Generating a set of base case inputs that is as representative of the case study region as possible,

(3) Identifying an appropriate objective function (for the analysis) among the various HDM-III output(s) that are commonly used as a ranking criterion in the region, and

(4) Choosing an appropriate discount rate and an analysis horizon.

The considerations in choosing maintenance and rehabilitation (R&M) strategies for the sensitivity study was discussed in section 4.3. The formulation of the *ceteris paribus* technique is subsequently discussed in relation to the last three requirements befitting this role of sensitivity analysis.

4.4.1 Base Case Inputs

The *ceteris paribus* method of sensitivity analysis relies on investigating a model response by changing one input parameter at a time while all the other input factors are kept at constant levels, called the base case state. A first requirement of this approach is to decide on the base case levels (or state) for all the input factors. Typical values for the case study region *e.g.*, the mean, or median values are commonly used as base case state. For this thesis, the base case values were selected primarily as the mean values for the case study region based on field data from Tanzania [Mrawira 95a]. However, in a few instances the base case values for some input factors had to be estimated from the author's personal experience since the field work was not successful with these data types.

The HDM-III was set up to run on batch mode for a group of six road links each of length about 26 to 27 km. The six links represented characteristics typical of the case study region (Tanzania) again based on the [Mrawira 95a] study. Use of the link group intended to achieve a wide range representation in the link attributes simulated in the *ceteris paribus* analysis. The design/construction standards, pavement conditions, geometric attributes, environmental factors, *etc.*, for the six links were chosen to provide as wide as practical coverage of the varying pavement standards in Tanzania. The traffic levels on these links were also selected to represent the typical range and composition in the case study region. Tables 4.1 to 4.3 show the typical range of link attributes, the traffic levels applied to the road links and the typical vehicle characteristics used in the *ceteris paribus* investigation respectively.

TABLE 4.1 Paved Road Link Characterization Data from Tanzania

Card #	HDM Card Name	Variable Description and Symbol	Observed Range[3]
A202	Environment	Average monthly rainfall, *MMP*	5 - 300 mm/month
		Altitude, *A*	0 - 3000 m
A203	Geometry	Rise plus fall, *RF*	0 - 120 m/km
		Horizontal curvature, *C*	0 - 700 degree/km
		Carriage-way width, *W*	2.5 - 12 m
		Super-elevation, *SP*	0 - 10 %
		Shoulder width, *WS*	0 - 3 m
		Effective Number of lanes, *ELAN*	1 - 4
A204	Surface	Surface type code	1, 2, 4, 5, 7[4]
		Thickness of new surface layers, *HSNEW*	5 - 300 mm
		Thickness of old surface layers, *HSOLD*	5 - 300 mm
A205	Base/Subgrade	Base type code	1, 2, 3[5]
		Resilient Modulus of soil cement, *CMOD*	0 - 30 GPa
		Thickness of base layers (total), *HBASE*	5 - 1000 mm
		Relative Compaction, *COMP*	85 - 100 %
		Subgrade CBR, *SNSG*	2 - 50 %
A206	Strength parameters	Structural number, *SN*	0.5 - 6
		Benkelman beam deflection, *DEF*	0.1 - 5 mm
A208	Deterioration factors	Cracking Initiation, *Kci*	0.2 - 4
		Cracking progression, *Kcp*	0.5 - 3
		Raveling initiation, *Kvi*	0.2 - 4
		Roughness-age term, *Kge*	0.8 - 2
		Pothole progression, *Kpp*	0.2 - 4
		Rut depth progression, *Krp*	0.2 - 4
		Roughness progression, *Kgp*	0.8 - 2

[3] *Practical range for input variables were determined mainly from the data from the field study in Tanzania, but also to a lesser extent, estimated based on local experience and engineering judgment [Mrawira 95].*

[4] *Surface type codes: 1 = Surface treatment (SD); 2 = asphalt concrete (AC); 4 = Reseal on surface treatment (RSST); 5 = reseal on asphalt concrete (RSAC); 7 = asphalt overlay, or slurry seal on asphalt concrete.*

[5] *Base type codes: 1 = Granular base (GB); 2 = Cement stabilized soil (CB); 3 = Bitumen stabilized base.*

TABLE 4.1 Paved Road Link Characterization Data from Tanzania (continued)

Card #	HDM Card Name	Variable Description and Symbol	Observed Range
A209	Condition	Area of all cracks, *ACRA*	0 - 80 %
		Area of wide cracks, *ACRW*	0 - 60 %
		Area raveled, *ARAV*	0 - 60 %
		Area of potholes, *APOT*	0 - 30 %
		Mean rut depth, *RDM*	0 - 50 mm
		Standard deviation of Rut depth, *RDS*	0 - 40 mm
		Roughness, *QI*	1.2 - 12 m/km IRI
A210	History	Age of preventive treatment, *AGE1*	0 - 30 years
		Age of surfacing, *AGE2*	0 - 30 years
		Age from last re-construction, *AGE3*	0 - 30 years
		Cracking retardation time, *CRP*	0 - 3 years
		Raveling retardation factor, *RRF*	1 - 4
		Area of previous all cracks, *ACRAb*	0 - 80 %
		Area of previous wide cracks, *ACRWb*	0 - 60 %

TABLE 4.2 Paved Roads Traffic Levels Used in the Sensitivity Study

Link Code	Car	Utility	Bus	Light Truck	Medium Truck	Heavy Truck	Articulated Truck	ADT
T703	25	83	32	47	21	15	27	250
T704	108	80	78	96	62	18	58	500
T705	220	190	148	182	116	34	110	1000
T706	354	258	184	322	200	32	150	1500
T707	355	451	240	424	265	60	225	2020
R301	960	1006	13	960	250	6	5	3200

Source: [Mrawira 95a]

The practical variable range was determined as the 95 percent confidence intervals for the factor where numerical data was available. However, there were relatively few cases in which this approach to range determination was feasible. In some cases *e.g.*, condition data, rutting, cracking, *etc.*, the data was categorical (not scalar), yet in other cases, the records available were indices.

Typical types/values for categorical factors, for example, surface type, gradation of gravel, base and sub-base materials, type of base/subgrade material (volcanic, quartz, laterite, *etc.*), applicable R&M

treatments, vehicles types in the traffic composition, *etc.* were selected using local experience and engineering judgment. Others were obtained by direct measurements during the field study. Once determined, the typical (*i.e.*, the base case) values were kept unchanged throughout the investigation.

TABLE 4.3 Characteristics of Representative Vehicle Types in Tanzania

	Vehicle Type or Class Name						
	Car	**Utility**	**Bus**	**Light Truck**	**Medium Truck**	**Heavy Truck**	**Trailer Truck**
HDM-III Vehicle Type Number	**2**	**4**	**5**	**7**	**8**	**9**	**10**
Engine power (HP)	90	120	180	140	180	200	250
Gross vehicle weight (ton)	1.0	2.3	17.9	14.0	21.0	35.5	46
Average Payload (ton)	0.4	1.0	8	5	7	12	25
Average (class) *ESAL* per vehicle	0.00	0.006	2.520	1.610	3.360	6.720	11.870
Number of axles (and tires)	2 (4)	2 (4)	2 (6)	2 (6)	2 (6)	3 (10)	6 (22)
Type of fuel	gas	gas	diesel	diesel	diesel	diesel	diesel
Annual Utilisation: (VKmT)	18,000	39,000	94,000	50,000	67,000	80,000	80,000
Hours driven per year	1500	2200	2800	2600	2900	2900	2800
Estimated vehicle life in years	10	8	6	5	5	5	5
Current Replacement cost (*Tsh*[1] 1000)	5,000	9,654	36,406	23,000	27,500	49,000	55,000
Current tire cost (*Tsh* 1000)	15.0	19.5	133.7	27.9	79.3	141.9	141.9

Notes: Source: [Mrawira 95a]. Tsh = Tanzania shilling (approximately US $1 = Tsh 500 in 1994). HP = horsepower; the imperial unit of power equivalent to 745.7 watts. Ton = metric ton, equivalent 1000 kg.

4.4.2 Choice of the Objective Function

The net present value of NPV based on total life-cycle costs savings of the strategy in question over a "the null" alternative was retained as the model response for the *ceteris paribus* investigations. As mentioned earlier, the strategy STP0 representing all annual off the carriageway maintenance plus 30% patching of potholes annually was defined as the null alternative. All the results from the *ceteris paribus* experiments are based on the NPV criterion as defined above.

As mentioned earlier, the focus of sensitivity analysis in this study was specific to the application in priority programming. It is therefore imperative that only those HDM outputs that are directly or potentially used as ranking criteria in priority analyses in the case study region were investigated. Traditionally, the internal rate of return (IRR) has been used for evaluating investment alternatives in profit oriented projects as well as public sector investments, whereas net present value (NPV) is equally a common criterion for public investments. Among the several HDM-III outputs, the NPV, calculated as the net worth of the total life-cycle savings of an alternative compared to a "do minimum" alternative is more often preferred because (unlike IRR) the model produces an NPV value for each alternative. In solving equation (4.10) the model may find one, many or no solutions at all in some cases, hence the IRR values are not consistently generated for each alternative in analysis.

For the objective function (in the sensitivity analysis) chosen above, the NPV criterion required further refining. The HDM-III model output includes an NPV value for each link-alternative and for each discount rate selected for the analysis. So, the dilemma was what link-alternative should be used, and further, what discount rate would be ideal? To resolve this dilemma it was necessary to look into the role played by these factors in priority programming.

The link-alternative in HDM-III represents a user-specified technically feasible investment option. The function of the HDM-III analysis is to enable the user to choose, compare or rank the alternatives so that an optimal strategy can be recommended for implementation. The strategy recommended for a given link is influenced by many factors, *e.g.*, the standard and performance of the existing pavement, the traffic intensity, the performance of the treatment (the composition of the proposed strategy), *etc*. So, for any given scenario, the best alternative cannot be chosen *a priori*. It was, therefore, recognized that using the NPV for only one link-alternative as the objective function for the sensitivity study would narrow the validity of the results to only that particular strategy [Mrawira 96a].

To circumvent the above limitation it was decided to use the sum of NPV for three best alternatives as the objective function in the *ceteris paribus* studies. This means that the HDM-III model was run to evaluate the five link-alternatives (defined in 4.2.1); the NPV results obtained for the four strategies (STP1, STP2, STP3 and STP4 relative to STP0 as the base case) were ranked and the best three values were summed to obtain the objective function.

The use of the sum of NPV values for the three best alternatives has the advantage of cushioning or attenuating the dependence of the NPV criterion upon the "recipe" of the R&M alternatives. In other words, if the NPV for only one link-alternative was used then the resulting sensitivities would be specific to the particular pair of "do nothing" and the chosen alternative. It is argued that the sum of the NPV values for the three best link-alternatives will provide an objective function more representative of common strategies for the region. Since the formulation of the said maintenance alternatives comprises a wide range, starting from very low level of maintenance efforts to very high level of standards, it is hypothesized that the sum of the NPV values will capture a more representative range of optimal strategies applicable in the case study region. For this reason, the objective function adopted for the sensitivity in this research can be argued to be more general and representative.

It should be pointed out that the above objective function will still be dependent upon the base values assumed for the rest of the input factors. In other words, use of a group of links and sum of the best three NPV values may achieve a general representation of the case study region, however, the sensitivity results cannot be discussed without reference to the base case inputs used. It is possible that changing, for example, the composition of the link-alternative, the link characteristics, *etc.*, would change the NPV predicted for a given strategy. Unfortunately, this weakness arises from the very nature of a *ceteris paribus* experiment and represents the single most important disincentive for using this technique.

4.4.3 Choosing the Discount Rate and Analysis Period

Selection of the analysis period and the discount rate to use in the sensitivity analysis was another area requiring careful consideration. Different maintenance treatments have different re-application frequency, some ranging from as short as several times a year (*e.g.*, grading of high traffic unpaved road), to as long as once every ten or more years (*e.g.*, overlay, or pavement reconstruction). A short analysis period may include none or only a few of the long frequency treatments and, therefore, misrepresent the long term effect of such treatments upon the life-cycle agency costs. An R&M strategy consisting of such long cycle treatments (say an AC overlay every 12 years) applied to two road links at different ages (say 5 and 15 years old) may generate very different NPV values since the younger pavement will require two overlays before re-construction (at age 30 years) while the older pavement will require only one overlay before reconstruction.

The sensitivity studies in this thesis, both the *ceteris paribus* and the experimental design investigations, used an analysis period of 30 years, the maximum allowed in HDM-III.

The role of discount rate in a life cycle cost analysis is to introduce the time value of a capital resource. "A discount rate is used to reduce future expected costs or benefits to present-day terms," [Haas 94]. In profit oriented investments the discount rate is a reflection of the cost of borrowing money, and it is referred to as interest rate. Sometimes we talk of the discount rate as the opportunity cost of capital, where the investor is concerned with the "potential earning" being forgone if the capital was invested elsewhere.

In public investments, the discount rate is sometimes a reflection of the differential premium attached to spending at present and spending in the future. [Mwase 88] concluded that it is generally acceptable to base the discount rate on a combination of the social time preference rate (reflecting society's preference at the margin for present over future goods) and the social opportunity cost (reflecting the rates of return, including any capital gains, that would have been obtained if the relevant marginal alternative had been invested in the private sector). Unfortunately, none of these is easy to establish. In many road agencies, the rate used is more of a policy matter than a technical justification [Haas 94, Mwase 88].

In the sensitivity analysis, our concern is how does the discount rate impact upon the response function being analyzed? A direct implication (upon the NPV) is that high discount rates reduce the influence of treatments applied towards the end of the analysis period [Riley 94]. If for example, we are evaluating two strategies, A and B, where A consists of a cost stream concentrated towards the end of the analysis period, and B has cost stream loaded more at the beginning of the analysis period, using a high discount rate will tend to favor A (assuming A and B have similar and uniform benefit streams). The opposite ranking would arise if we were to use a low discount rate.

Given the diverse school of thoughts on appropriate value of discount rate, the present research selected a value more indicative of the current practice in pavement management. [Haas 94] reports values of between 4 and 10 percent as more common, while [Mwase 88] supports a similar range of 3.5 to 12% from a review of various studies in Tanzania. The *ceteris paribus* tests in this thesis generated NPV values at 5, 10 and 20% for comparison, but most of the sensitivity results are reported on the basis of the 10% discount rate.

4.4.4 The Procedure

The procedure for *ceteris paribus* sensitivity analysis proceeded by running the HDM-III model ten times with all the inputs factors fixed at their base values except that the factor to be investigated was changed for each run through predetermined increments about its base value. The increments used were, -80%, -50%, -20%, -10%, +10%, +20%, +50%, +100%, and +170% subject, of course, to the allowed range within the model. This range covered the practical range (discussed in Subsection 4.4.1) of most of the factors investigated at this stage. The fixed increments were preferred (over, for example, dividing the factor range into uniform increments) because they simplify the computation.

A group of six (6) links was used, representing typical conditions from the case study region [Mrawira 95a]. A batch program was set up that performs multiple HDM-III runs on the same link group. The batch program supplied for each run, similar input data, but with one input variable changed from its base value (either upward or downwards) by the increments given above. The HDM-III output report type 11 was found more useful for ranking alternatives on the basis of the net present values (NPV). The output from each run was compiled into one file for subsequent analysis.

The analysis was performed by extracting the NPV values from the HDM-III type 11 report into another file and computing the NPV elasticity for each link and discount rate separately through a series of spreadsheets.

4.5 The Concept of Elasticity of Factor Sensitivity

[Mrawira 96a] defines the elasticity of factor sensitivity of an input factor with respect to NPV as:

$$\varepsilon_{NPV} = \frac{\Delta NPV}{NPV_{base}} \div \frac{\Delta INPUT}{INPUT_{base}} \qquad \text{... (4.11)}$$

where,

ε_{NPV} = elasticity of factor sensitivity to the *NPV* prediction,

NPV = net present value of net benefits for a given strategy over the "do nothing" strategy,

ΔNPV = the change in *NPV* resulting when the input factor is changed by $\Delta INPUT$,

NPV_{base} = the *NPV* obtained with the base value of input factor, $INPUT_{base}$

INPUT = the HDM input factor being studied in the sensitivity analysis.

The equation defines the elasticity of factor sensitivity to the *NPV* as the relative change in the *NPV* per unit change of the input factor. The mathematical basis for this definition is given elsewhere [Doctor 89] and is revisited in the next chapter (section 5.7). This function was recommended as a better platform for comparing the impact of different input variables than the absolute change in *NPV* [Mrawira 96a].

The advantages of the elasticity concept approach include its potential as a common platform for comparing model factors with different factor ranges. The effect of an input factor upon a response function (*e.g.*, NPV) is twofold: (a) the change produced in the output by a unit change in the input, and (b) the effect of the magnitude of factor range in practice. The elasticity concept provides a compact form for combining both the significance of the factor upon the variability in the response function (*e.g.*, NPV) and the range of variability in the input factor itself. Therefore, the most important advantage of the elasticity approach (Equation 4.11) is that by definition, it normalizes the scaling effect of the absolute factor change used in the study. In other words, if for example, over a given factor range Δx_j of the factor x_j, the factor effect upon the response is linear, then the elasticity of sensitivity of the factor x_j will be constant irrespective of the size of Δx_j used.

4.6 Data Requirements and Design of the Field Study

4.6.1 Role of Data in the Research

In most research studies field data is required for direct use either to build an empirical model or to test hypotheses in the study. In this thesis field data has neither of the above direct uses. The primary requirements of data in this study are twofold. First is the need to provide "base case states," that is, the typical values for the HDM-III input variables. Alongside the mean values, which were needed in delimiting the input space for the sensitivity analyses (and also in determining values for default inputs), a second important need was to estimate the variability (the practical lower and upper boundary) of all the input factors observed in the case study region.

The observed (*i.e.*, the practical) range of input factors was important to both the *ceteris paribus* studies and the experimental design investigation (Chapter 5). In the *ceteris paribus* tests it was desired to simulate factor increments extending to the entire practical range. This objective was only partly achieved in the implementation of the *ceteris paribus* tests, but fully utilized in the experimental design investigation.

Rationalizing the factor sensitivities over the many different factor ranges can become a tedious procedure. Although batch processing of the HDM-III model runs for a *ceteris paribus* investigation can implemented, careful planning and effort has to be spent on coding a pre- and post-processor. This problem (of rationalizing the scale effects of different factor ranges) was the primary motivation for developing the concept of elasticity of factor sensitivity (Section 4.5). By definition, the elasticity of factor sensitivity is the percentage change in the NPV associated with one percent change in the factor. Under linear or approximately linear factor assumption, the elasticity is independent of the factor range used in the investigation. Figure 4.1 shows the role of different factor ranges, Δx on the elasticity of factor sensitivity, ε. As the relationship approaches linear, ε tends to a constant – independent of the magnitude of Δx.

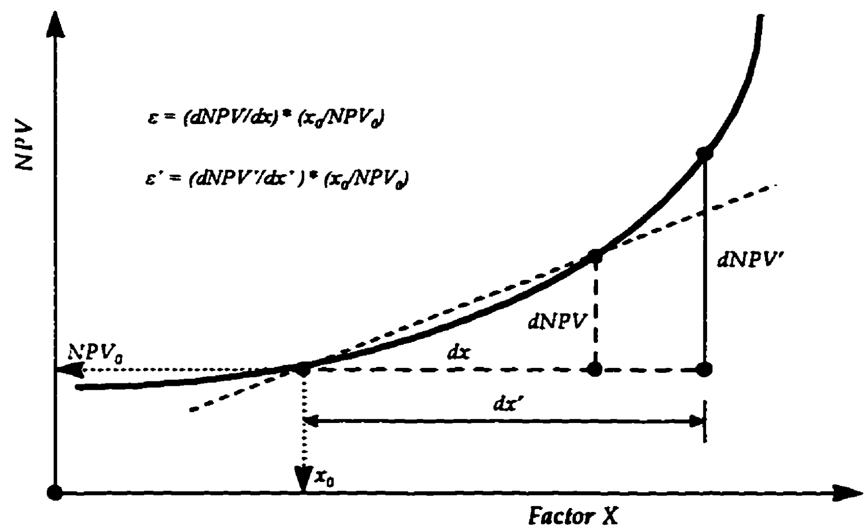

FIGURE 4.1 ***Elasticity of factor sensitivity versus the factor increment used***

The rationalizing property of the elasticity of factor sensitivity illustrated above justifies reporting the *ceteris paribus* factor sensitivities using any arbitrary factor ranges as long as the response is not highly non-linear.

Generally speaking, the data types required for this research are those data items normally used to run HDM-III. Figure 1.1 (Chapter 1) shows the major types of data required to apply HDM-III to a network level analysis while Table 4.4 gives more descriptive details of the model inputs.

As far as formulating rolling annual road rehabilitation and maintenance (R&M) programs is concerned, the inputs of interest are those falling under Series A, C, D, and E. The roles of the other data classes are: Series B defines new pavement construction; series F for defining non-standard inputs -- exogenous benefits and costs, whereas Series G, H, I, J, and K are for control input that define the analyses performed by the HDM-III code. Since the thesis study focused on model reduction for the purposes of prioritizing R&M programs at the network-level, the input variables relevant to the investigation are the four series: network characteristics (Series A), maintenance strategies and cost factors (Series C) vehicle characteristics and unit costs (Series D) and traffic loading data (Series E).

TABLE 4.4 The HDM-III Input Data Structure *[Watanatada 87b]*

Series	Series Name	Purpose of the Series
A	Existing Link Characteristics	Specify characteristics and conditions of road sections at the beginning of the analysis period
B	Construction Options and unit costs	Specify optional projects for improving road sections, including quantities and costs of construction inputs, and characteristics of the road after improvement
C	Road Maintenance standards and Unit costs	Specify alternative maintenance standards to be applied to different types of road surfaces and associated road maintenance costs
D	Vehicle fleet	Describe the physical and utilization characteristics and related unit costs of different vehicle type in the fleet
E	Traffic volumes and growth patterns	Input traffic flow volumes and time profiles for different vehicle types
F	Exogenous Costs or benefits	Permit the user to incorporate exogenously calculated benefits and costs other than construction, maintenance and savings in vehicle operating costs
G	Link - alternatives	Specify alternative sets of construction and maintenance policies for various links, with times or conditions for intervention (or trigger levels)
H	Group - alternatives	Define the grouping of the link - alternatives (in series G) for economic analysis and reporting purposes
I	Report Requests	Define the reports to be processed on financial costs, maintenance quantities and costs, traffic loads, vehicle operating costs; conditions for selected link and group alternatives
J	Comparison of alternatives	Specify the link and group alternatives to be included in economic analysis/ comparison
K	Run control information	Specify process control of input, analysis period, direct /delimit output. Specify VOC relations to be used; and miscellaneous information

4.6.2 Design and Implementation of the Field Research

A combination of methods was employed in a field work conducted in Tanzania in 1994 primarily to obtain the data used in the thesis research. Direct field observations, survey of existing records, as well as questionnaire survey were used in the field data collection. This combination of methods was inevitable given the fact that in most SSA countries documented systematic data are not readily available. Most of these low-income countries do not have formal pavement management systems and consequently very limited organized databases /information systems do exist, if any.

Appendix A provides a brief description of the case study area and outlines the key aspects of the field research implementation. The appendix focuses on: profile of the questionnaire respondents, data sources and summary statistics of the data relevant to this research. The purpose of the appendix is limited to giving a context to the study, and therefore it does not present a complete report on the field research. Such context could become useful in assessing the transferability of the study findings to other geographical /socio-economic contexts. Comprehensive reports on the field work are given elsewhere, see [Mrawira 95a and 95b] upon which Appendix A is based.

Questionnaire survey (by in person interviews) was the primary method employed to supplement documented data and direct measurements. The questionnaire form used in the field work is given in Appendix B. The target questionnaire respondents were the regional engineers[6] and senior personnel under REOs. Interviews were directed to senior engineers, in particular those directly in charge of regional and trunk road networks. A total of 11 regional engineer offices and two independently administered highway units were surveyed. The motivation was to capture the experience of the senior engineers in the road authority in estimating the relevant factors that reflect past and current practices in the case study region.

The questionnaire approach proved to be an important method in this case, particularly since documented data was mostly unavailable, and since some data items could not be measured directly within the scope of this study. Such data items were for example: pavement layer thickness, past

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[6] *The Ministry of Works, Communications and Transport is the agency responsible for the national road network in the Tanzania. Under the national authority each of the 25 administrative regions has a regional engineer's office which is in charge of the planning and implementation for the road network in the region.*

maintenance policies, design and rehabilitation practices, as built material records, R&M operations' unit costs, past pavement performance, *etc.*

4.6.3 Collection Protocols Specific to Data Types

Extensive effort was expended on direct measurement of road roughness for two reasons. Initial sensitivity tests indicated that roughness was the most significant factor influencing HDM-III life-cycle costs predictions. Since very little local experience existed (in Tanzania) on roughness measurements, the most plausible option for the study was to conduct direct measurements. The TRRL's in-vehicle mounted Bump Integrator was used measure roughness on a total of 2425 km of roads, of which 1345 km are paved. Details of equipment calibration, precision control factors and general lessons learned on low cost roughness measurements are given elsewhere [Mrawira 96b].

Appendix A provides a summary of the road roughness measurements from the field study (see Section A.4.3.2). It is noted from Tables A3 and A4 that the weighted average link roughness was about 4480 mm/km BI (5.7 m/km IRI). The average link roughness varied from 1340 to 4740 mm/km BI (1.9 – 6.0 m/km IRI). However, the 95% confidence range of the individual roughness observations were much wider (780 to over 7216 mm/km BI (1.2 – 8.7 m/km IRI)).

Link characterization data was collected mainly from inventory records available at regional engineers' offices and two independently administered highway units. As shown in Appendix A, link characterization data for paved roads were collected for a total of 66 links constituting a total of 2750 km. Examples of the data items under this category are: link length, geometric attributes (*e.g.*, width, shoulder width, curvature, gradient, number of lanes, *etc.*), structural attributes (*e.g.*, layer thickness, material types, gradation, compaction, base layer characteristics, *etc.*), *etc.* However, a few data items were estimated by interviewing the local engineers. Examples are condition data, horizontal curvature, rise plus fall, past performance, construction and R&M treatment history, *etc.*

Environmental attributes for the links were obtained from two separate sources. Ten to 50 years return period rainfall data for several meteorological stations was obtained from Directorate of Meteorology at the Ministry of Transportation. The latest 20 year monthly mean rainfall data were used for the study. Altitude data was estimated from the Tanzania National Atlas [GoT 76]. A better alternate source would be the 1:50,000 local maps, but the effort was beyond the scope of this study.

Chapter 5

LATIN HYPERCUBE EXPERIMENTAL DESIGN IN SENSITIVITY ANALYSIS OF HDM-III INPUT FACTORS

5.1 Introduction to the Chapter

The traditional approach to sensitivity analysis was reviewed in Chapter 2 (Subsection 2.5.2); situations in which it is favored over analytical approaches, limitations of the *ceteris paribus* technique, and hence the motivation for factorial designs. This chapter first reviews a number of relatively new methodologies from the field of statistics that are more efficient in the investigation of computer models, and then it presents the application of these techniques in the study to investigate the link characterization variables in the HDM-III model. The motivation is to highlight the advantages of the thesis approach to the investigation of factor interaction effects upon the HDM-III output variables of interest to rehabilitation and maintenance programming.

Section 5.2 revisits the formulation and analysis framework for traditional factorial designs that have been extensively applied in investigations of physical experiments. The special nature of computer experiments that negates the use of traditional factorial designs is highlighted in Section 5.3. Next, in Section 5.4, the principles of *Latin* squares and *hyper - Greco*[7] *- Latin* square designs are introduced as a background to the development of Latin hypercube designs, which are better suited to analysis of computer codes. In Section 5.5 the properties of the designed data used in the investigation of the link characterization variables in HDM-III are outlined. The post-experimental output data generation procedure is briefly introduced (in Section 5.6) by outlining the functions, and the development of a "preprocessor" code. Finally, in Section 5.7 the chapter concludes with an outline of the methods employed in the analysis of the post-experimental output data. A concept of interpretation of a special regression model form is introduced which lends well to comparing two approaches of estimating the factor effects – the stochastic modeling after [Sacks 89a and 89b] and the regression approach.

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[7] *Greaco and Greco are found in the literature as variant spellings for the same concept.*

5.2 General Design and Analysis of Factorial Experiments

The statistical science of experimental design, where the aim is to investigate the influence of more than one factor was formally introduced as early as the World War I [John 71]. Much of the stimulus to the development of modern statistical theory of experimental design came originally from agricultural research, where for example, the objective of an experiment could be to make comparisons between the effects of different *treatments* (fertilizer, pesticide, *etc.*), one of which is applied to one or more plots, upon crop yield, or any other response factor. Serious interest to apply experimental design to engineering research started in the late 1950s with various works, for example, Box and Hunter introduced response surface design to chemical engineers [John 71].

The design of an experiment consists of the following steps [Ogawa 74]:

- Selecting the input variables (treatments) to investigate,
- Specifying the factor levels to include in each experimental run,
- Deciding on rules by which the factor levels of one variable are combined with factor levels of other variables (to define the "conditions" for each experimental run), and
- Specifying the measurements to be made on each response variable.

The mathematical experimental design is mainly concerned with step 1 through step 3.

Factorial designs constitute a special class of experimental designs where multi-factor effects are investigated. While factorial designs have evolved to different forms, the basic approach to the analysis of results from experimental designs have remained much the same. In general, analysis of variance (ANOVA) is the common tool used to analyze the results of factorial experiments. The F-test provides a mechanism for ascertaining whether or not the factor effects (and interactions) are significant.

The F - statistic provides a measure of factor effect by a semblance of the ratio of within treatment (or within block) variability to the variability arising from the natural noise (residuals) in the yield.

One interesting approach to the representation of the factor effects, particularly, where it is desirable to rank/compare the significance of the different factors is the ANOVA percentage contribution. This approach is very useful, especially in computer experiments (like here) where the error term is zero. The ANOVA percentage contribution is defined as the relative amount of variability ascribable to the factor in relation to the total variability in the response variable:

$$AF^{(k)} = \frac{SST^{(k)}}{SSTot} \qquad \text{... (5.1)}$$

where, $AF^{(k)}$ = ANOVA relative contribution of factor k,
$SST^{(k)}$ = Sum of squares attributable to the factor k,
$SSTot$ = Total sum of squares in the response variable.

Conventional factorial designs are mainly useful in exploration of input variables measured with random errors. As discussed subsequently, in computer experiments where the input space (for the predictor variables) is planned *a priori*, the random error term is zero because computer outputs are deterministic. Further, higher levels (beyond 2^k) factorial designs are not computationally efficient particularly where a large number of predictor variables have to be investigated (like in the case at hand). While, the famous two-level factorial (2^k) designs offer the advantage of standard analysis algorithms, they suffer the inability to capture any non-linearity of factor effect between the low and high levels of the input variable. Therefore, a different approach to the investigation of computer models is desirable.

5.3 Computer vs. Physical Experiments

In many engineering and technological applications today, complex mathematical models are been implemented into computer codes. The codes take in a set of input values and produce the output value(s). These output values in turn are used in decision-making or as input to other processes. Computer models are popular in applications where large repetitive calculations are necessary. In some scenarios the model cannot be written in closed form and/or it requires an iterative solution. In other instances, the model form involves several complex algebraic equations with complex nesting that are near, if not impossible, to solve analytically. Yet in other instances, the model forms are recursive, in that outputs of one stage are fed to the next stage, and so forth in a serial fashion, so that the output(s) at any stage, n is also a function of the stage, n. The HDM-III model (the source code is over 22,000 FORTRAN-77 lines) has a little bit of each of the above three scenarios, and qualifies as a good example of a fairly complex computer model.

Given the input values, the computer code produces the outputs via complex mathematical manipulation. Investigation of such computer codes arise in many instances, for example, sensitivity analyses, in the optimization of the measurements of inputs, or when the computer model is expensive to run (time or otherwise) it would be desirable to build a predictor (*i.e.*, a reduced model) to act as a computationally less expensive surrogate for the full model, *etc.* In some cases, as it was hypothesized in this thesis, if only a few factors are important, it would be desirable to identify those active factors (screening) and, if possible, to determine the way in which they jointly affect the response of interest.

Computer models are distinct from physical experiments from the standpoint of statistical analysis in that they do not involve random error. A computer model fed with the same input values will always produce the same output. Due to lack of random error, traditional factorial designs are not very useful. For example, replication, a key technique used in conventional factorial experimental design to estimate experimental variance, leads to redundant information in computer experiments.

The question now arises of how such computer experiments can be carried out efficiently. Latin hypercube designs, a special class of randomized experimental designs, were introduced by [McKay 79] specifically to address this question.

5.4 The Latin Hypercube Design

Advances in computational power of the last three decades have motivated and made possible investigation of complex computer models used in many areas of science and technology. With the work of [McKay 79] the study of statistics has been pre-occupied with developing methodologies to efficiently analyze computer models. With moderate to large models (large number of input variables or excessive CPU time), a need to identify the most active factors (screening) becomes highly desirable. [Welch 92] reports previous approaches to screening that were mainly aimed at physical experiments with random error. [Welch 92] cites other works [Box 86, Morris 87, Srivastava 75 and Watson 61] which dealt with analyses to identify active factors on assumptions of factor sparsity (few active factors) and linearity and additivity of factor effects as well as presence of a random error.

An introduction to the theoretical construct of Latin hypercube experimental design is subsequently given. First, the *Latin* square designs, the *Greco-Latin* squares and the *hyper-Greco-Latin* squares are outlined. Then the generalized case of *Latin* squares – the *Latin hypercube* design is discussed.

5.4.1 The Latin Square Designs

The *Latin square* is an arrangement permitting two sets of block constraints, conveniently termed *rows* and *columns*, to be used simultaneously. By definition, a Latin square is a square of side p in which p *letters* are written p times in such a way that each letter appears exactly once in each *row* and each *column* [John 71]. Latin square designs are prominent in two contexts. They are often useful in studies where it is desired to ensure two-way blocking (two-way elimination of heterogeneity), with rows and columns representing the blocking and letters standing for the treatments.

The other context of Latin squares is to use them as fractional factorial designs. Supposing we have three factors each at p levels. To carry out a complete factorial would require p^3 runs. If we use a Latin square we can let the rows represent the levels of factor A, the columns the levels of factor B, and the letters the levels of factor C. Then we obtain a design in which each level of each factor occurs exactly once at each level of every other factor. From such a design it is possible to estimate the effects of all the three factors (assuming no interaction) with only p^2 runs, which represent a considerable saving. For $p = 5$ for example, the number of experimental runs required drop from 125 to only 25.

5.4.2 *Greco - Latin* and *Hyper - Greco - Latin* Squares

The Latin squares allow designs for three factors (by use of rows, columns and Latin letters). The *Greco − Latin* square designs evolved from the Latin squares to enable designs for four or more sources of variation. Given two Latin squares of the same degree, if one is superimposed on the other such that all combinations of letters – taking the order in account – occurs exactly once, then the two squares are said to be *orthogonal* to each other. A *Greco − Latin* square is obtained by superimposing such pairs of mutually orthogonal Latin squares. A *Greco − Latin* can be used to provide designs for four factors (rows, columns, Latin letters, Greek letters), each at p levels in p^2 runs. Similarly, adding a third mutually orthogonal square to a *Greco − Latin* square gives a *hyper − Greco − Latin square.*

In a *Greco − Latin* square the experimental units are grouped in four different ways – by rows, by columns, by Latin letters and by an additional classification usually designated by Greek letters. The orthogonal constraint ensures that the assignment of Greek letters is restricted such that each Greek letter occurs exactly once in each row and column. Treatments (designated by Latin letters) are now assigned to the experimental unit such that each treatment occurs once, and only once, in each row and column and with each Greek letter. Table 5.1 shows an example of *Greco − Latin* design for studying gasoline consumption for different types of gasoline, car makes, traffic patterns (day of week) and driver behavior.

The five factor *hyper — Greco — Latin* square designs could be extended to any higher dimension in the same analogy as we did the *Greco — Latin* square. For example, a sixth factor could be added by superimposing a fourth orthogonal square and designating the factor levels by lower case Latin letters. Similarly, a seventh factor can be added by superimposing another square and using Arabic numerals to denote the levels.

TABLE 5.1 An Example of Greco – Latin Square Design *[John 71]*

Car Number	Day of week				
	1	2	3	4	5
I	Aα	Bβ	Cγ	Dδ	Eε
II	Bγ	Cδ	Dε	Eα	Aβ
III	Cε	Dα	Eβ	Aγ	Bδ
IV	Dβ	Eγ	Aδ	Bε	Cα
V	Eδ	Aε	Bα	Cβ	Dγ

Key: Latin letters = type of gasoline; Greek letters = driver

Analysis of *Greco — Latin* square (and *hyper–Latin–Greco*) designs is again an ANOVA problem with added terms of source of variations (Latin letters, Greek letters, *etc.*).

5.4.3 The General Latin Hypercube Experimental Design

Latin hypercube sampling was first proposed by [Mckay 79] as a method to select values of input variables for performing sensitivity analyses on complex computer codes [Doctor 89, Welch 92, Gough 94]. The Latin hypercube design is a generalization of the *hyper - Greco - Latin* square design to k dimensions, where k is the number of variables in the model. The method is named after the *Latin* square [Kempthorne 52], introduced earlier, since it is the starting basis for the *hyper - Greco - Latin* square designs. Prior to [McKay 79]'s work the concept of *Latin* squares had been used as an efficient method of assigning treatments to experimental units that can be categorized by two independent schemes (*e.g.*, columns and rows), and also as a means of stratifying populations to increase the precision of factor effect estimates of interest [Doctor 89].

Each input variable is assumed to be a random variable with given probability density function, *pdf*. The simplest notion of Latin hypercube sampling is that of stratified sampling. The stratification is accomplished by dividing the range of the input variable into N intervals of equal probability $(1/N)$ as determined by the variable's *pdf*. For each input variable, one sample is drawn from each of the N intervals. The output of the sampling can be considered an $N \times k$ matrix, $\mathbf{D}$, where the columns represent variables and the rows contain the sample values for the appropriate interval. The values within each column are then randomly permuted, so that a row represents a random realization of the vector, $\mathbf{x}_j$ of the input variables.

For the sake of mathematical representation let the computer code been investigated have k input variables, then one set of input data (the jth set, for example) to the model can be represented by the row vector,

$$\mathbf{x}_j = (x_{1j}, x_{2j}, x_{3j}, \ldots, x_{kj}) \qquad \ldots (5.2)$$

where, $x_1, x_2, x_3, \ldots, x_k$ are the individual model input variables.

As a notational convention vectors are written in bold face, lower case letters and matrices in bold face capital case letters. The model factors, $x_1, x_2, \ldots, x_k$, can be assigned different values, the range of which is determined only by the constraints imposed by the computer model. In general, the input components are assumed continuous variables and independent of each other with only upper and lower limits imposed by the model. The computer model is then evaluated (run) at each of the N input sites with the values (or levels) of the input variables equal to the components of the N row vectors, $\mathbf{x}_j$, $(j = 1, 2, \ldots, N)$.

The corresponding model response (output) value for jth set of input variables is given by,

$$\mathbf{y}_j = f(\mathbf{x}_j) = f(x_{1j}, x_{2j}, \ldots, x_{kj}) \qquad \ldots (5.3)$$

The model outputs after the N runs consist of column vector(s), that can be conveniently designated by an $R \times N$ matrix, $\mathbf{Y}$, where, R is the number of output variables.

The number of possible combinations of factor levels, even for a model with few variables, is often infinitely large. The purpose of the experimental design is therefore to spread the input sites over the input space as efficiently as possible; the so called "space filling" requirement.

The primary use of the Latin hypercube design in our case is to select the N input sites (levels of the input vector $\mathbf{x}_j$, $(j = 1, \ldots, N)$ such that:

- Each input variable x_i fills the entire practical range (input space) of x_i as uniformly as possible.

- The order of the individual steps of an input variable x_i ($j = 1, 2, \ldots, N$) is completely randomized so that for any pair of input variables x_n and x_m are not correlated.
- The generated experimental data (called the design matrix **D** (of order $N \times k$)) and the corresponding response matrix **Y**, should enable efficient estimation of the main and interactions effects.

The advantages of Latin hypercube sampling are that it generates random variables more efficiently than unconstrained random sampling methods and requires fewer model runs for a given accuracy in the estimate of the *pdf* of the model response variables by efficiently sampling the entire range of each variable. [McKay 79] compared three candidate methods of selecting values of input to computer experiments: random sampling, stratified sampling and the *Latin* hypercube sampling. They showed that the *Latin* hypercube sampling has the advantage of a smaller variance estimate than the stratified sampling (this in always the case but holds under some conditions). More importantly, when the output matrix **Y** is dominated only by a few of the components x_i, ($i = 1, 2, \ldots, k$) of x the *Latin* hypercube sampling ensures that each of those components is represented in a fully stratified manner, no matter which components turn out to be important. Geometrically, a *Latin* hypercube of dimension k, can be collapsed into one of dimension p, ($p < k$), and still retain perfect fill over the p- dimensions.

Following the work of [McKay 79], Iman and Conover developed a computer code for generating Latin hypercube samples from a given variable *pdf* [Iman 82]. [Gough 94] and [Schonlau 96] also demonstrated the application of Latin hypercube design. In particular these later works dealt with efficient computational techniques of analyzing the response matrix, **Y**, once the design matrix, **D** has been fed through the model to generate the output. [Gough 94] perfected an approach by [Iman 82] of transforming a completely random Latin hypercube into one with better correlation properties and further applied a maximum likelihood estimation (MLE) technique after [Sacks 89a, Sacks 89b and Welch 92] to derive a simpler stochastic predictor which "explains" the effects of the multi-dimensional inputs $x_1, x_2, \ldots, x_k$. On the other hand [Schonlau 96] shows how to select a simpler predictor (non-linear parametric) from a prior non-parametric *Latin* hypercube design.

5.4.4 Modifying the Latin Hypercube for Factor Dependencies

The key assumptions for the Latin hypercube design is that the input variables are continuous over the input space and capable of varying independent of each other [McKay 79, Iman 82, Doctor 89]. However, situations may arise where the input variables do not meet these assumptions, (*e.g.*, in

HDM-III where some input factors are constrained upon the values of other factors). [Iman 82] developed a method for inducing pairwise dependencies among variables using rank correlation. Dependencies among random variables are usually described by a bivariate, or pairwise correlation coefficient, namely the Pearson product moment correlation coefficient defined by:

$$\rho_p = \frac{Cov(Y_i, Y_j)}{\left\{Var(Y_i)\, Var(Y_j)\right\}^{1/2}} \qquad \text{... (5.4)}$$

which is used a measure of the degree of dependence between the random variables Y_i and Y_j. However, it is appropriate only if the dependence is linear and the variates are Gaussian. [Iman 82] observed that most dependencies, even those that are highly nonlinear, are monotone over some range of values. The Spearman rank correlation coefficient:

$$\rho_s = \frac{Cov[R(Y_i), R(Y_j)]}{\left\{Var[R(Y_i)]\, Var[R(Y_j)]\right\}^{1/2}} \qquad \text{... (5.5)}$$

which is the Pearson product moment correlation coefficient computed on the ranks *R(Y)* of the data, measures the degree of monotonicity between random variables. [Iman 82] devised a method of using the Spearman bivariate rank correlations to induce the desired marginal distributions obtained from the original Latin hypercube design.

[Iman 82]'s method for inducing the dependencies among the variables is based on the decomposition of the desired rank correlation matrix to generate restricted pairings of the elements of the Latin hypercube design matrix, **D**. The values of the variables in **D** are not changed, but the values are paired in such a way to induce the desired dependencies between the variables.

The process of modifying the design matrix, **D** in order to induce the desired variable dependencies is as follows. Referring to the $N \times k$ design matrix, **D**, where k is number of input variables and N is the number of intervals per variable, the original Latin hypercube design **D**, theoretically has rank correlation matrix **I** (the identity matrix), that is, the k variables are independent. Let, **C** be the desired rank correlation matrix of a linear transformation of **D**. The correlation matrix, **C** is a necessarily positive and symmetric matrix; it can therefore be decomposed into the product of a lower triangular matrix with its transpose,

$$\mathbf{C} = \mathbf{VV^{\tau}} \qquad \text{... (5.6)}$$

where, $\mathbf{V}^{\tau}$ stands for "V transpose." It follows that the vector, $\mathbf{DV}^{\tau}$ should have the correlation matrix C. The equation (5.6) above is derived after Cholesky decomposition that was developed to provide an easy way of constructing Gaussian multivariate distribution from the vectors of independent unit Gaussian random variables, U ~ $N(0, 1)$. Suppose that it is desired to generate samples for a multivariate normal distribution, Z with mean μ and covariance V. Then the samples are generated from vectors μ of independent unit Gaussian by,

$$\mathbf{Z} = \mu + \mathbf{UQ} \qquad \text{... (5.7)}$$

where, Q is the lower triangular Cholesky decomposition of V, *i.e.*, $\mathbf{V} = \mathbf{QQ}^{\tau}$.

From equation (5.6) the "ideal" transformed Latin hypercube design matrix having the desired variable dependencies is $\mathbf{DV}^{\tau}$. Let R be the matrix of scores, $\{a_i\}$, resulting from the rankings of the columns of D. [Iman 82] used van der Waarden scores for the matrix R defined by [Conover 80] as:

$$a_i = \varphi^{-1} [i/(N+1)] \qquad \text{... (5.8)}$$

where, φ^{-1} is the inverse of the standard Gaussian *pdf*, and i is the rank of the element in the column. Let $\mathbf{R}^{*}$ be the matrix of scores after selective pairings of elements of the columns of R. The objective is to have the Spearman rank correlation matrix, $\mathbf{R}^{*}$ close to the desired rank correlation matrix C. If the rank correlation matrix U of every realization of R were exactly the identity I, then there would be no problem in using the Cholesky decomposition directly. However, since R is a random matrix, U will be approximate, but not equal to I for any realization D. Therefore, U must be pre and post multiplied by a matrix S so that:

$$\mathbf{SUS}^{\tau} = \mathbf{C} \qquad \text{... (5.9)}$$

In order to find S the Cholesky decomposition, $\mathbf{U} = \mathbf{QQ}^{\tau}$ is performed. U must be positive and definitive, so R must not contain identical columns. Substituting $\mathbf{U} = \mathbf{QQ}^{\tau}$ and equation (5.6) in equation (5.9) the result is:

$$\mathbf{SQQ}^{\tau}\mathbf{S}^{\tau} = \mathbf{VV}^{\tau} \qquad \text{... (5.10)}$$

from which it follows that,

$$\mathbf{S} = \mathbf{V}\mathbf{Q}^{-1} \qquad \text{... (5.11)}$$

and therefore,

$$\mathbf{R}^{*} = \mathbf{R}\mathbf{S}^{\tau} \qquad \text{... (5.12)}$$

The columns of the "original" Latin hypercube design matrix, **D** are then rearranged according to the ranking matrix $\mathbf{R}^{*}$ to produce a "modified" Latin hypercube design matrix, $\mathbf{D}^{*}$ which has a rank correlation matrix close to the desired **C**.

5.5 Designing the Experiment for Link Characterization in HDM-III Model

So far this chapter has dealt with the theoretical constructs of experimental design, in particular, the theory of Latin hypercube designs. This section presents the characteristics of the experimental design matrix obtained (by applying the principal thus far introduced) for a group of forty link characterization variables in the HDM-III model. The motivation is to discuss the statistical properties of the design matrix used in subsequent analyses in relation to attributes likely to impact upon the validity of the analysis of the model output(s) based on this design. In other words, the interest is in the sufficiency of the experimental design data before they are fed into the model being investigated. The last section of this chapter outlines the theoretical basis of the analysis technique applied to the post-processed results.

A complete model investigation process consists of three major stages:

- Input data generation (the experimental design process *per se*),
- Output generation (*i.e.*, preprocessing or running the design data through the model), and
- Analysis of the (post-processed) response variable(s).

A greater part of this Chapter deals with the first step, *i.e.*, the experimental design, naturally because of its central role in relation to justifying the validity of the results of the overall investigation. It is argued that if the experimental data can be shown to fully explore the input space (both in factor range and combination of scenarios) for the study region, then it can be inferred with a high degree of confidence that the results (of stage 3) are valid and justified. Subsection 5.5.1 details the characteristics of the "original" Latin hypercube design, emphasizing the statistical quality of a balanced sampling at any sample size.

5.5.1 The "Original" Design Matrix

The statistics of the original design matrix for the link characterization variables can better be understood by looking at the Latin hypercube design process for this group of variables. The range of values for the 41 link characterization input variables was shown in Table 4.1. As pointed out in Chapter 4 these factor ranges were determined mainly based on field data from Tanzania, the case study country. These ranges should be kept in mind when interpreting the results since sensitivity with respect to an input factor would tend to increase if a wider range is chosen. For the same reason, extensive care was taken in judging the practical range where direct field data was missing.

The study set out to conduct a total of 1000 experiments for this group of variables. The number of experiments was decided, as discussed later (Section 5.6), on the basis of several considerations including the CPU time requirements, high dimensionality of the problem (large number of variables) and sizes of factor ranges to be explored.

Out of the 41 total paved road link characterization variables, surface- and base-type are categorical variables with about 12 common pairings for the case study country. Unfortunately, not all of the surface-types can be paired independently to the base-types. To simplify the design process, the two categorical variables were removed from the design; allowing the use of the resulting design matrix with any chosen base-surface pair. The Latin hypercube experimental design was therefore implemented for the remaining 39 parameters.

In a straight Latin hypercube for N model runs, each factor's range is represented by an equally-spaced grid of N values, thus ensuring that the range is fully explored. In theory, for the 1000 model runs proposed above, the spacing in each variable would find by taking 1/999 of each parameter range. However, such fine subdivision of the factor range has not been found to be advantageous, and would only be desirable if all parameters had large factor ranges and it was suspected that the model output was highly nonlinear. The factor ranges in our case varied from as low as 0.8 – 2.0 to as large as 0 – 3000. A grid spacing of 1/25 of each parameter range was used, a value also used by [Gough 94] for parameter ranges from 0 – 1.8 to 0.5 – 20 units. For the rainfall (*MMP*) factor, for example, (range of 5 – 300 mm/month) the design will contain values of 5.0, 16.8, 28.6, ..., 300.0 mm/month but not in that order. Altitude (*A*) has a range of 0 – 3000 m, and it will take values 0, 120, 240, ..., 3000 m, and similarly for the other variables in the design. In a 1000 data points, each of the factor levels, (*e.g.*, 0, 120, 240, ..., 3000 for the factor *A*) will occur approximately 39 times (=1000/26).

For the completely random Latin hypercube, the factor levels would be in a random order, this ordering being statistically independent of the ordering for the other factors. The motivation is, combining, for example, the 1000 rainfall (*MMP*) values with the corresponding 1000 values for altitude (*A*) hopefully fills out the two-dimensional $MMP - A$ space, representing all combinations of these two input variables. [Gough 94] observes that, there is no guarantee that such random ordering will give good two- and higher dimensions properties. In particular, two input factors might be highly correlated with each other by chance, making it difficult to distinguish their effects. [Iman 82] describes an algorithm of improving the completely random Latin hypercube into one with better correlation properties, a method that was later enhanced by [Gough 94].

Table 5.2 shows a small part of the modified design matrix for link characterization variables. The spatial distribution of the Latin hypercube design is illustrated by Figures 5.1 and 5.2. Figure 5.1 shows a good "spread-out" of the design sites on two dimensional projection for the unconstrained factors. The probability density functions (*pdf*) for the variables in the modified design matrix are summarized by Table 5.3.

5.5.2 Constraints in the Model Factors and the "Modified" Design

HDM-III code imposes several constraints on some of the paved link characterization input parameters in such a way that the factors in these pairs (or groups) of variables cannot be varied completely independent of each other. As mentioned earlier, the original completely random Latin hypercube design matrix required special adjustment for these factor dependencies. The following paragraphs introduce the factor dependencies considered in the design.

There are five groups of factors that are dependent in one way or another under the paved link characterization input variables in HDM-III:

1. **Strength Parameters**: the specification of pavement strength in HDM-III can be done in three ways – Structural number (*SN*), Benkelman deflection (*DEF*) or both inputs together. The effect of using any of those options upon the output is not known; and therefore the *SN* and *DEF* values had to be designed as dependent on the option code.

TABLE 5.2 Part of the Modified Design Matrix

Case	*MMP*	*A*	*RF*	*c*	*W*	*SP*	*WS*	*ELAN*	*HSNEW*	*HSOLD*	*CMOD*	*HBASE*	*COMP*	*SNSG*	*SN*	*DEF*	*Kci*	*Kcp*
	mm/mo	m	m/km	deg/km	m	%	m		mm	mm	GPa	mm	%	%		mm		
1	134.8	0	43.2	476	6.3	4	2.16	1.84	111.2	264.6	21.74	323.4	93.4	30.80	4.02	3.04	3.696	0.90
2	276.4	2280	19.2	336	8.96	6.4	1.32	2.8	170.2	264.6	26.46	442.8	88	30.80	4.90	5.00	1.112	2.60
3	217.4	1320	38.4	420	4.02	2.8	0.6	1.24	40.4	146.6	2.86	323.4	94	11.60	1.38	0.69	3.544	1.70
4	229.2	2160	57.6	616	4.78	8	0	3.88	99.4	158.4	18.2	920.4	97.6	42.32	3.58	2.84	1.264	1.40
5	252.8	2760	86.4	616	5.92	0.4	0.84	3.04	276.4	40.4	11.12	164.2	98.2	9.68	2.04	2.06	2.024	1.70
6	99.4	1680	38.4	616	2.5	9.6	2.04	2.92	229.2	123	7.58	522.4	91	17.36	0.72	2.06	1.568	2.10
7	170.2	2640	43.2	196	3.64	3.6	0.24	1.6	64	170.2	26.46	84.6	95.8	15.44	2.48	0.10	3.848	1.00
8	241	2760	67.2	364	8.58	0.8	2.04	1.96	300	158.4	2.86	403	98.2	5.84	2.70	0.10	2.784	0.70
9	75.8	120	0	504	10.48	4.8	2.88	2.44	158.4	123	12.3	721.4	85	44.24	0.50	3.82	3.088	1.00
10	205.6	120	110.4	224	8.96	2.8	0	2.92	300	75.8	7.58	522.4	88.6	46.16	2.92	4.41	0.504	1.00
11	99.4	1920	43.2	588	6.68	2.8	2.4	2.32	146.6	217.4	7.58	562.2	98.8	25.04	3.58	0.49	1.568	1.70
12	241	1800	67.2	56	2.88	3.2	2.28	1.96	241	276.4	7.58	1000	92.8	25.04	5.56	2.84	1.872	0.50
13	158.4	2280	38.4	616	7.44	10	1.68	3.04	276.4	193.8	1.68	562.2	99.4	13.52	1.16	2.26	2.328	2.30
14	300	120	52.8	224	12	8.4	2.76	1	52.2	28.6	28.82	243.8	88	2.00	5.12	3.82	1.872	0.70
15	123	1080	9.6	252	3.26	5.2	2.52	3.52	123	5	21.74	243.8	93.4	42.32	5.12	0.49	0.656	1.00
16	182	1200	48	56	5.54	0	1.2	1.24	40.4	193.8	12.3	602	91	7.76	1.82	4.80	3.696	1.00
17	134.8	2040	9.6	364	2.5	2	2.76	3.52	264.6	52.2	7.58	840.8	95.8	7.76	4.68	0.69	0.504	2.10
18	134.8	480	72	672	7.06	7.2	2.76	3.04	40.4	170.2	0.5	283.6	91.6	3.92	6.00	1.67	0.960	2.80
19	87.6	1560	105.6	448	2.5	10	2.28	2.92	16.8	170.2	18.2	801	96.4	32.72	3.36	2.45	0.504	2.30
20	229.2	1200	33.6	560	5.92	4.8	2.16	1.6	264.6	40.4	1.68	124.4	92.2	42.32	4.02	1.86	2.024	0.60
21	182	2760	33.6	280	5.92	8.4	0.12	3.88	252.8	264.6	30	124.4	91.6	44.24	4.02	1.08	1.872	1.30
22	193.8	240	67.2	644	11.62	8.8	2.52	2.08	276.4	87.6	25.28	761.2	91.6	48.08	2.92	3.04	3.392	1.90
23	111.2	2880	62.4	504	5.92	6.8	0.72	3.76	16.8	276.4	21.74	363.2	85.6	50.00	2.92	4.22	1.112	2.50
24	64	0	76.8	252	2.88	0	0	2.32	64	241	19.38	1000	97	42.32	2.48	4.41	2.176	1.80
25	52.2	2520	76.8	28	7.06	2.8	0.84	1.72	170.2	146.6	13.48	442.8	98.8	30.80	6.00	3.82	0.504	3.00
26	111.2	240	120	196	7.82	6.4	2.28	3.4	5	300	21.74	44.8	94	23.12	5.56	0.30	0.808	1.10

Symbols according to the Glossary (see also Tables 4.1 and 5.3)

TABLE 5.2 Part of the Modified Design Matrix (continued)

Case	*Kvi*	*Kge*	*Kpp*	*Krp*	*Kgp*	*ACRA*	*ACRW*	*ARAV*	*APOT*	*RDM*	*RDS*	*QI*	*AGE1*	*AGE2*	*AGE3*	*CRP*	*RRF*	*ACRAb*	*ACRWb*
						%	%	%	%	mm	mm	m/km IRI	years	years	years	years	years	%	%
1	2.216	1.760	3.848	0.960	2.000	51.86	16.59	10.61	3.54	34	28	7.680	10	23	25	2.52	3.52	8.4	5.71
2	0.984	2.000	2.784	0.808	1.280	2.73	1.96	26.57	14.31	24	0	10.704	3	13	24	0.48	3.28	19.6	2.35
3	2.328	1.712	4.000	1.720	1.184	0.00	0.00	4.28	44.92	46	20	1.632	7	7	30	0.48	1.96	64.4	33.49
4	1.096	1.952	2.632	0.808	0.848	34.31	24.70	4.82	12.87	30	6	5.520	18	29	30	2.64	4.00	11.2	0.00
5	1.880	1.184	2.328	2.176	1.040	33.75	1.35	11.99	0.67	32	4	8.544	4	27	28	2.64	1.00	25.2	25.20
6	1.656	1.856	2.480	2.784	1.904	0.00	0.00	11.13	1.67	44	40	3.360	12	16	29	0.60	2.56	25.2	21.17
7	1.432	1.904	1.568	0.200	1.520	26.42	21.14	42.11	8.67	28	10	2.064	10	24	29	0.48	1.84	67.2	53.76
8	2.776	1.760	1.720	1.872	0.848	30.10	25.28	25.80	12.90	44	38	4.224	12	18	19	0.12	2.92	19.6	4.70
9	2.104	1.904	1.568	1.416	1.328	5.96	0.71	3.83	0.21	18	16	10.704	16	20	20	2.04	1.48	70.0	33.60
10	1.432	1.424	0.808	0.808	1.568	3.46	2.49	12.97	10.37	36	16	4.224	3	3	26	1.80	3.16	33.6	10.75
11	1.320	1.808	0.808	0.200	1.040	1.32	1.00	3.47	5.21	44	12	6.384	6	8	19	0.36	2.32	36.4	36.40
12	1.880	1.952	0.960	2.328	0.896	3.02	0.00	6.23	3.54	16	12	9.408	3	5	29	2.16	3.40	39.2	7.84
13	1.320	0.800	1.112	0.808	1.520	30.95	19.81	19.34	4.51	48	44	6.816	0	3	20	1.56	2.44	70.0	47.60
14	0.312	0.800	3.848	2.024	1.136	15.41	9.86	21.01	9.98	32	30	6.384	6	8	21	0.48	3.04	5.6	4.48
15	1.992	1.520	2.632	2.176	1.568	10.16	1.63	48.25	21.59	28	16	2.064	0	2	4	1.92	1.24	8.4	4.03
16	1.544	1.088	1.872	3.240	1.712	3.20	2.43	5.60	1.20	40	30	5.952	2	9	19	1.20	1.48	33.6	9.41
17	0.424	1.328	0.960	4.000	1.808	15.31	11.64	6.08	5.41	38	26	8.112	6	18	19	3.00	1.00	58.8	51.74
18	3.000	1.424	0.656	0.656	1.232	22.49	7.20	20.24	9.28	42	36	1.200	11	17	18	2.04	3.64	64.4	0.00
19	0.200	1.232	2.176	3.848	1.184	6.81	2.72	2.55	0.64	22	0	1.632	9	14	17	0.36	1.60	61.6	24.64
20	2.440	1.616	2.936	1.568	1.040	39.07	34.38	3.26	4.07	44	24	11.568	3	22	23	1.80	1.60	0.0	0.00
21	1.992	1.472	2.328	0.960	1.376	46.30	1.85	30.64	3.06	46	14	2.928	10	15	16	1.56	1.36	25.2	4.03
22	1.096	0.848	3.392	0.504	0.848	3.59	3.01	22.87	8.74	30	30	10.704	5	5	24	0.84	2.80	11.2	9.86
23	2.328	1.520	2.784	1.872	0.800	5.02	4.22	5.02	2.76	26	24	8.976	0	13	26	1.08	2.68	70.0	61.60
24	0.536	1.808	1.872	3.544	1.280	0.00	0.00	4.08	25.52	40	22	5.088	13	20	25	1.80	1.60	53.2	14.90
25	1.096	1.760	0.808	0.352	1.520	33.75	12.15	4.00	8.66	48	38	6.384	10	20	22	0.60	1.60	67.2	16.13
26	2.328	1.472	2.024	3.544	1.856	21.87	1.75	12.30	15.03	36	34	12.000	7	13	21	2.88	1.00	5.6	2.91

Symbols according to the Glossary (also see Tables 4.1 and 5.3)

2. **Surface Distress Parameters:** the areas of all cracks, wide cracks, raveled and potholes are constrained at two levels. First, total surface damage is assumed to consist of only cracks, raveling and potholes, and cannot exceed 100%, therefore the inequality, $ACRA + ARAV + APOT \leq 100$. Second, the area of wide cracks is only a portion of area of all cracks, thus: $ACRW \leq ACRA$.

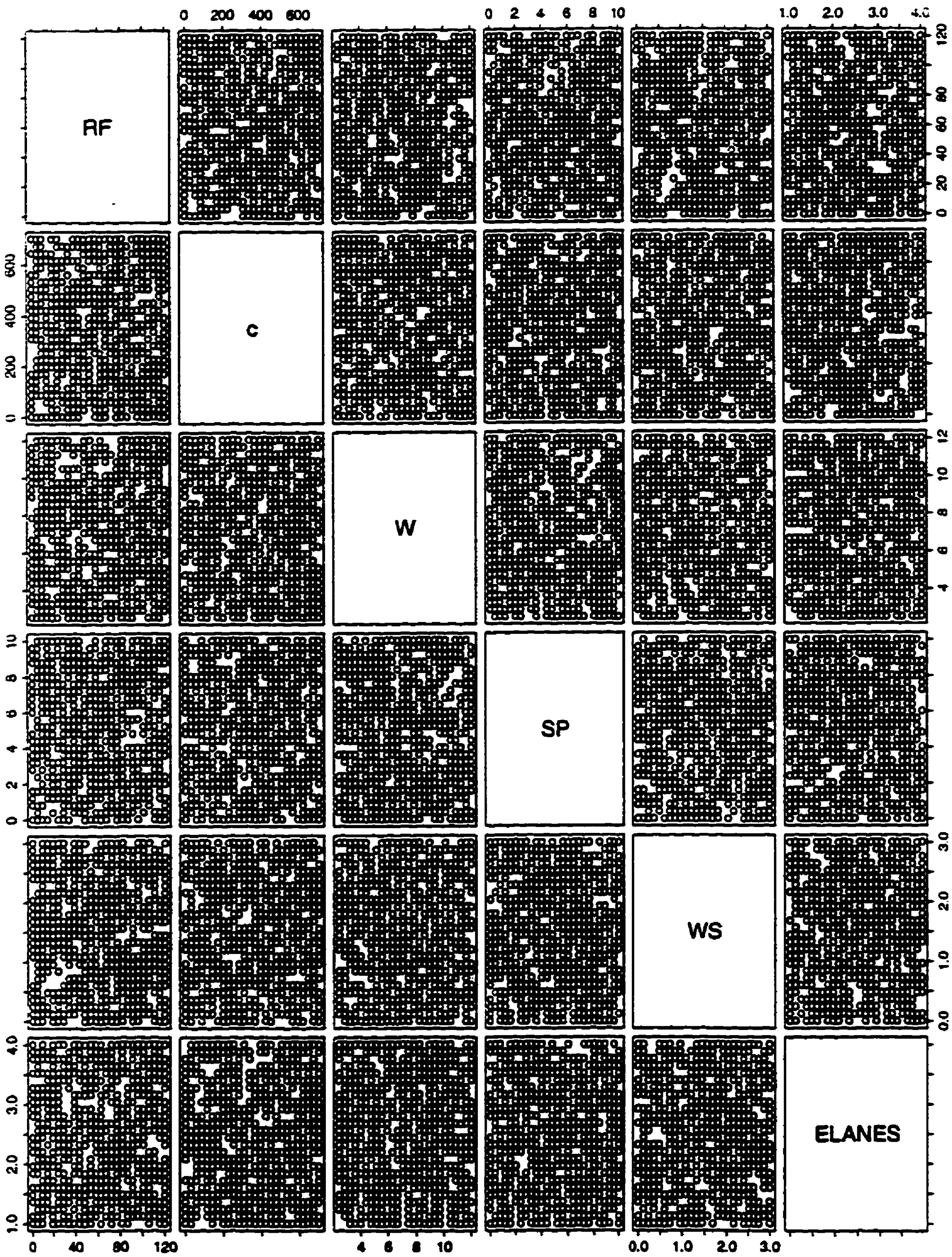
3. **Deformation Distress:** the variability in rutting in HDM-III is presently assumed not to exceed the mean value, thus the inequality: $RDS \leq RDM$, where RDM and RDS are the mean and standard deviation values of rut depth respectively.

4. **History of Pavement Treatments:** in HDM-III the age of the latest surface treatment cannot exceed the age of the last resurfacing, which in turn cannot exceed the age of the last re-construction, hence the relation: $AGE1 \leq AGE2 \leq AGE3$, where subscripts 1, 2 and 3 refers to preventive treatment, re-surfacing and re-construction respectively.

5. **Surface Distress History:** again the before (last treatment) areas of wide cracks and all cracks are related such that, wide cracks cannot exceed all cracks: $ACRAb \leq ACRWb$.

The design matrix was modified for the above dependencies first, by classifying the design variables into six groups, group zero includes all the input variables that can vary completely independently and groups one to five representing one of each of the above groups of dependent variables. The second stage of modification was to adjust the "design sites" such that the factor values for the variables in groups 1 to 5 meet the constraints given above. The details of the procedure was given earlier (Subsection 5.4.4).

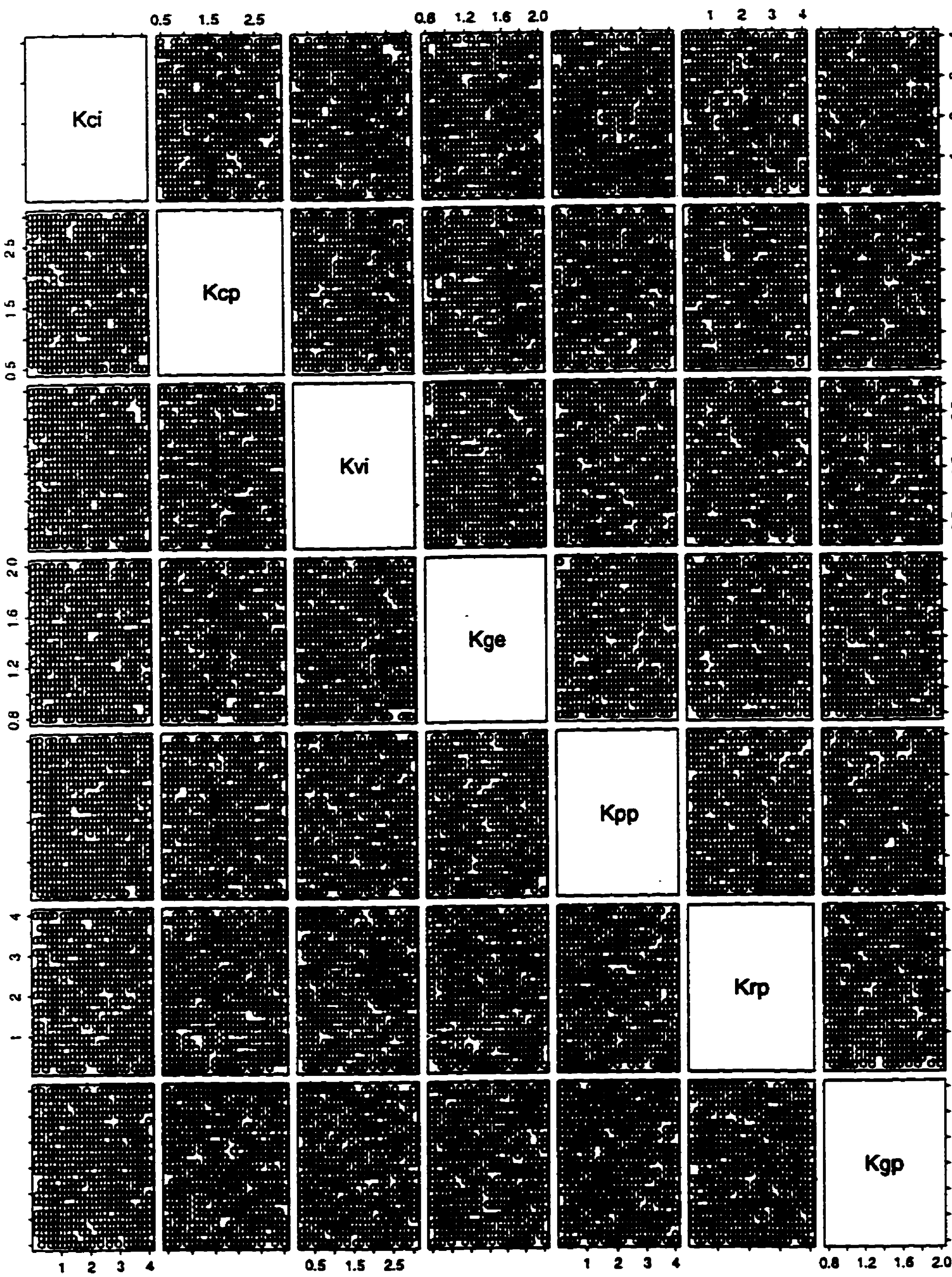
A major demerit of this adjustment is twofold. First, it results in a "distorted" exploration of the input space. That is, part of the effectiveness with which the original Latin hypercube design was filling (or distributing) the design sites over the input space is lost. Figure 5.2 shows the resulting coverage of design sites over the 2-dimensional space for the constrained variables. Looking at Figure 5.2 (a), the $ARAV - QI$ sub-space for example, has points mostly concentrated in the lower one-third of the ARAV range. Similarly, the design sites for $ARAV - RDM$, $ARAV - RDS$ or $APOT - RDM$, $APOT - RDS$, $APOT - QI$, *etc.*, effectively explore one-half or less of the ideal sub-space.



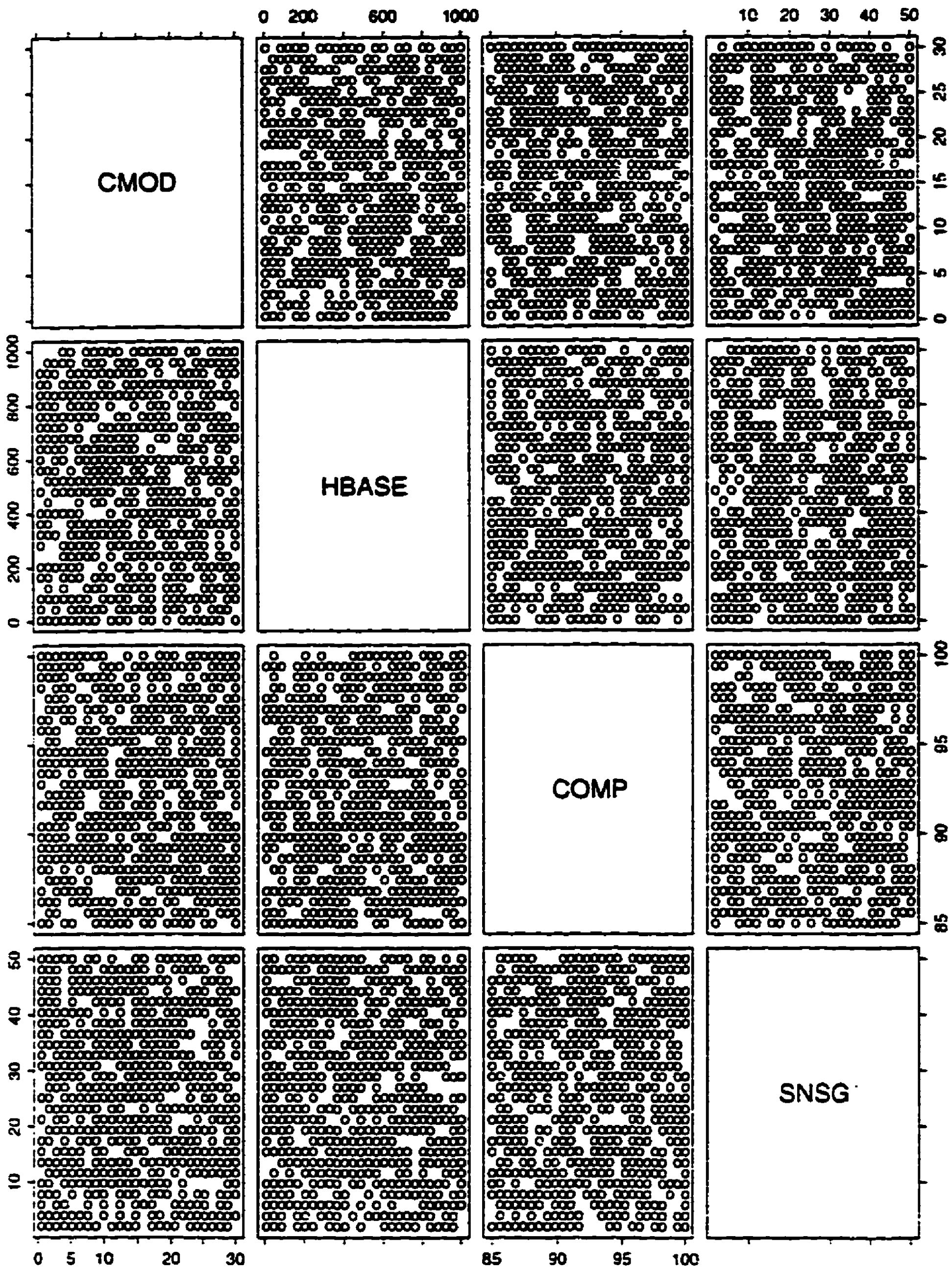
(a) Rise & fall, curvature, width, superelevation, shoulder width and effective number of lanes

FIGURE 5.1 Two dimensional projection of the "design sites" for the independent factors

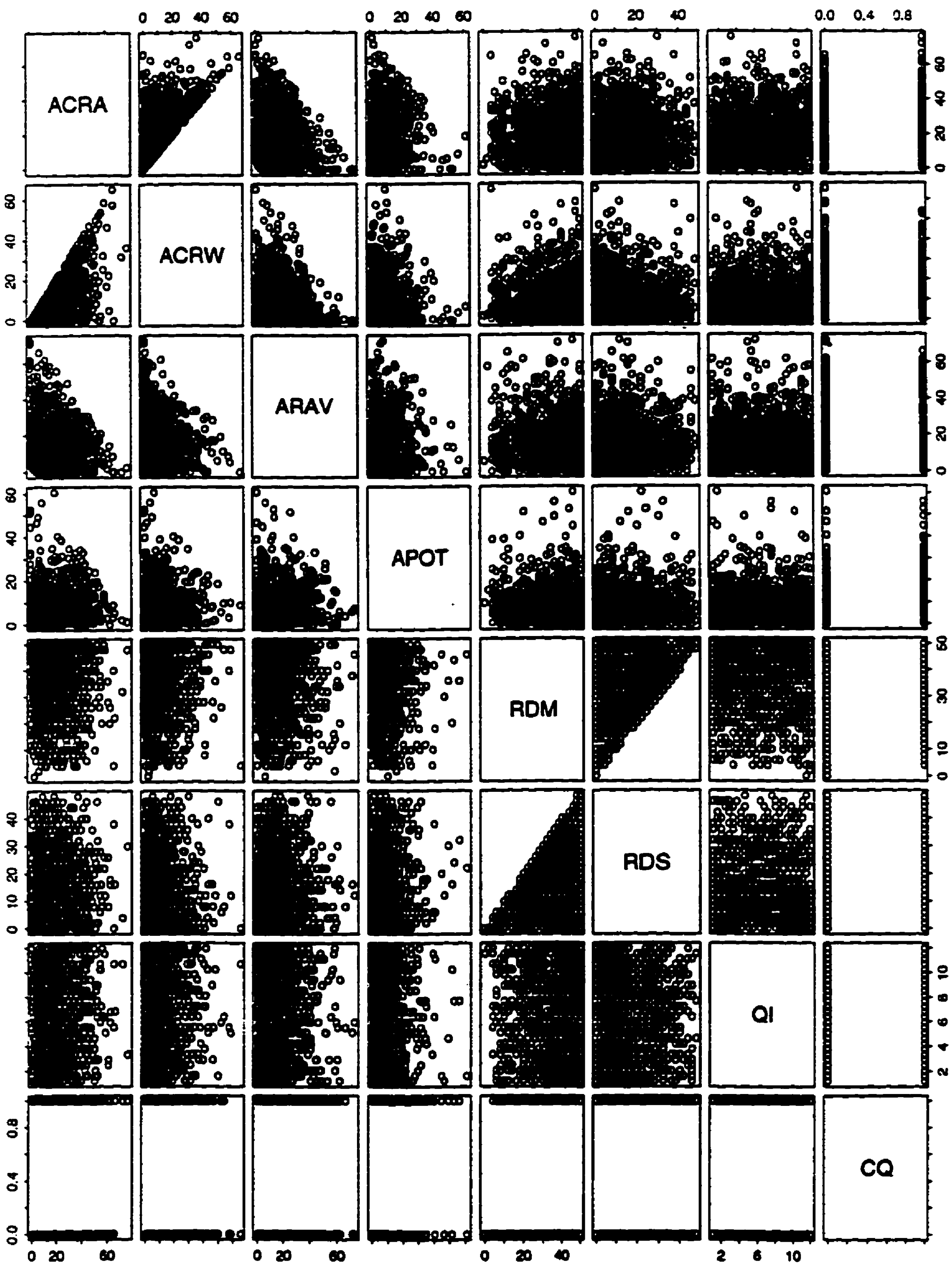
(Symbols according to the Glossary, see also Tables 4.1 and 5.3)



(b) Performance Calibration Factors



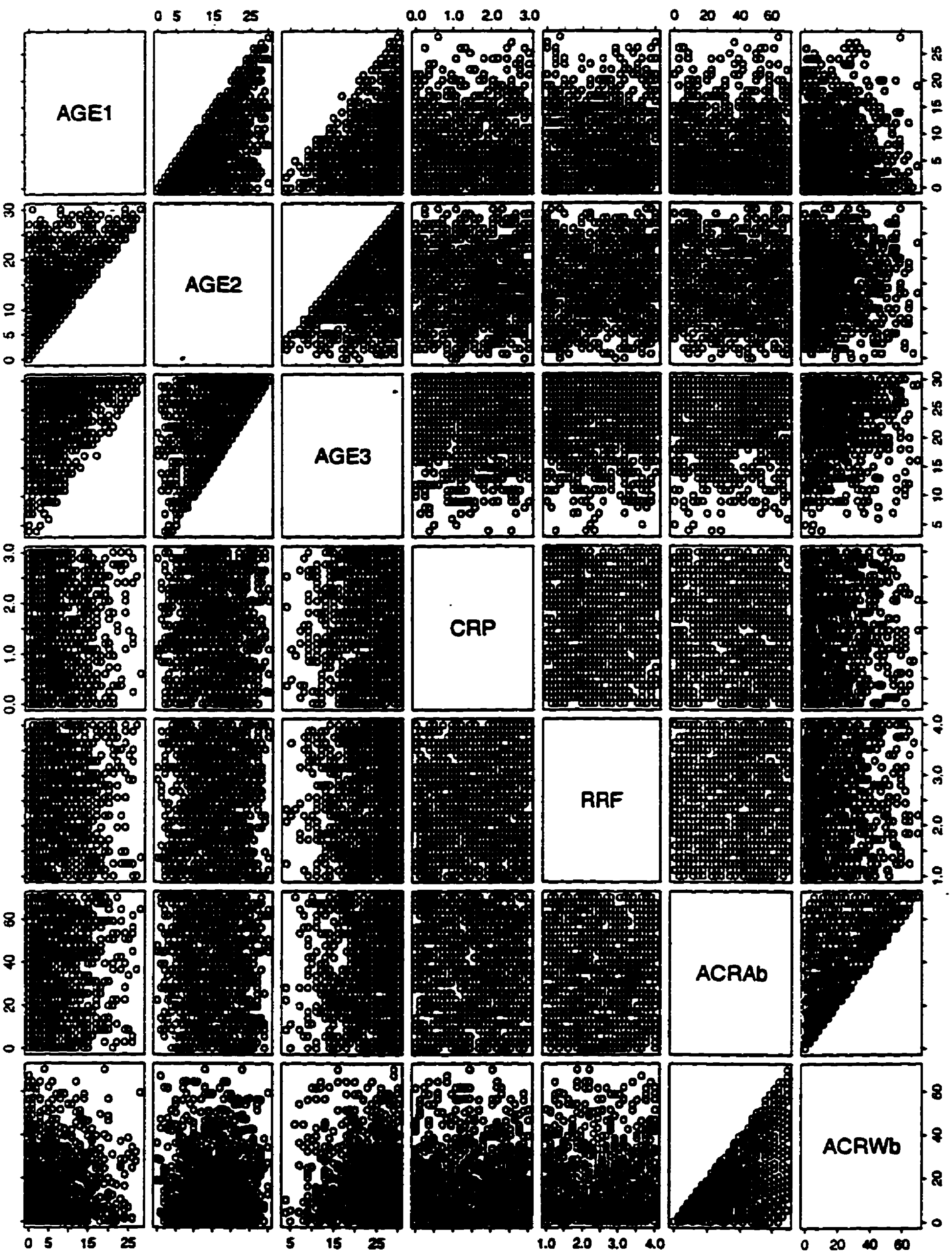
(c) *Soil Cement Res. Modulus, Base layer thickness, Compaction, and Subgrade CBR.*



(a) The Pavement Condition Parameters: all cracks, wide cracks, raveling, potholes, etc.

FIGURE 5.2 Two-dimensional projection of the design sites for the dependent factors

(Symbols according to the Glossary, see also Tables 4.1 and 5.3)



(b) Treatment history, distress retardation factors, and previous all - and wide cracks

TABLE 5.3 Modified Latin Hypercube Design Data Statistics

Variable (units)	Symbol	Minimum	Maximum	Mean	STDEV	Skewness	Median
Average monthly rainfall (mm)	*MMP*	5.0	300.0	152.5	88.5	0.0	152.5
Altitude [above mean sea level] (m)	*A*	0.0	3000.0	1500.0	900.2	0.0	1500.0
Rise plus fall (m/km)	*RF*	0.0	120.0	60.0	36.0	0.0	60.0
Horizontal curvature (deg./km)	*C*	0.0	700.0	350.0	210.1	0.0	350.0
Carriage-way width (m)	*W*	2.5	12.0	7.3	2.9	0.0	7.3
Super-elevation (%)	*SP*	0.0	10.0	5.0	3.0	0.0	5.0
Shoulder width (m)	*WS*	0.0	3.0	1.5	0.9	0.0	1.5
Effective Number of lanes	*ELAN*	1.0	4.0	2.5	0.9	0.0	2.5
Thickness of new surface layers (mm)	*HSNEW*	5.0	300.0	152.5	88.5	0.0	152.5
Thickness of old surface layers (mm)	*HSOLD*	5.0	300.0	152.5	88.5	0.0	152.5
Resilient Modulus of soil cement (GPa)	*CMOD*	0.5	30.0	15.3	8.9	0.0	15.3
Relative Compaction (%)	*COMP*	85.0	100.0	92.5	4.5	0.0	92.5
Subgrade CBR (%)	*SNSG*	2.0	50.0	26.0	14.4	0.0	26.0
Structural number	*SN*	0.5	6.0	3.3	1.7	0.0	3.3
Benkelman beam deflection (mm)	*DEF*	0.1	5.0	2.6	1.5	0.0	2.6
Cracking initiation calibration factor	*Kci*	0.2	4.0	2.1	1.1	0.0	2.1
Cracking progression calibration factor	*Kcp*	0.5	3.0	1.8	0.8	0.0	1.8
Raveling initiation calibration factor	*Kvi*	0.2	3.0	1.6	0.8	0.0	1.6
Roughness-age term calibration factor	*Kge*	0.8	2.0	1.4	0.4	0.0	1.4
Pothole progression calibration factor	*Kpp*	0.2	4.0	2.1	1.1	0.0	2.1
Rut depth progression calibration factor	*Krp*	0.2	4.0	2.1	1.1	0.0	2.1
Roughness progression calibration factor	*Kgp*	0.8	2.0	1.4	0.4	0.0	1.4
Area of all cracks (%)	*ACRA*	0.0	76.1	20.2	14.2	0.7	18.1
Area of wide cracks (%)	*ACRW*	0.0	65.5	10.0	10.3	1.6	6.7
Area raveled (%)	*ARAV*	0.0	72.7	16.1	12.9	1.2	13.0
Area of potholes (%)	*APOT*	0.0	40.0	8.7	8.1	2.0	6.4
Mean rut depth (mm)	*RDM*	0.0	50.0	33.6	12.4	-0.6	36.0
Standard deviation of rut depth (mm)	*RDS*	0.0	40.0	16.4	12.1	0.5	14.0
Roughness (IRI m/km)	*QI*	1.2	12.0	6.6	3.2	0.0	6.6
Construction faulty code [yes /no] (1/0)	*CQ*	0.0	1.0	0.5	0.5	0.0	0.5
Age of preventive treatment (years)	*AGE1*	0.0	28.0	7.3	6.1	1.0	6.0
Age of surfacing (years)	*AGE2*	0.0	30.0	14.9	6.9	0.0	15.0
Age from last re-construction (years)	*AGE3*	4.0	30.0	22.8	5.8	-0.8	24.0
Cracking retardation time (years)	*CRP*	0.0	3.0	1.5	0.9	0.0	1.5
Raveling retardation factor	*RRF*	1.0	4.0	2.5	0.9	0.0	2.5
Area of previous all cracks (%)	*ACRAb*	0.0	70.0	35.0	21.0	0.0	35.0
Area of previous wide cracks (%)	*ACRWb*	0.0	70.0	17.5	16.1	1.02	12.8

The second disadvantage of the adjustment is the inability to separate the individual factor effects within the groups of constrained variables. In other words, the stochastic model approach applied to the post-experimental output can only quantify the effect of the group as a unit and not the individual factors. Fortunately, as it will be seen later, none of the group factors turned out to be very active, and therefore no further detailed investigation of within group contributions became necessary.

Statistics of the modified Latin hypercube design are summarized by Table 5.3. The table shows that the "unconstrained" variables in the design are symmetrical about the mean values (the mean coincides with the median and zero skew). However, for the constrained variables, the design "sites" are not as balanced. Notice the shift of the median values from the mean for the constrained variables (as the *pdfs* changes from the original uniform distribution).

5.6 Processing the Design Data through the Model

To accomplish the investigation of factor sensitivities in this thesis three stages are involved:

(1) Input generation (the experimental design *per se*),

(2) Output generation (running/processing the design data through the model), and

(3) Analyzing the model response (post-experimental output) to qualify the factor effects.

The first stage was described in Section 5.5. The present section discusses the output generation stage. The approaches to analysis of the post- experimental output data will be introduced in Section 5.7.

After the involving task of designing and modifying the Latin hypercube design data the next stage in the investigation was to generate the model response data. The terms "experimental design data" or "design matrix" are used to refer to the results of the Latin hypercube design. The terms "post-experimental data" or "model response data" or simply, "output data" are used to refer to the output obtained after running the HDM-III model on the "experimental design data."

The preprocessing involved running the HDM-III model on the experimental data. For the purpose of demonstrating the methodology in this thesis, the experimental design was limited to the link characterization variables (Series A) for paved roads only. In other words, the design supplied input levels for Series A only; the other model inputs (Series C, D, and E) were kept constant at their typical values during the preprocessing. With the excessively large number of HDM-III input variables it was not considered feasible to implement an experimental design for all input variables at once.

The experimental design data resulting from the "modified" Latin hypercube design matrix consisted of 39 × 1000 order matrix. The large number of runs (1000) was decided by considering four factors:

(1) The high dimensionality involved (large number of variables to be investigated at once).

(2) Large disparity between factor ranges (*e.g.*, altitude: 0 – 3000m, roughness: 1.2 – 12 m/km IRI, *etc.*); effective exploration of the larger factor ranges required more data points.

(3) Presence of a large number of factor dependencies requiring adjusting the Latin hypercube design (Section 5.4.4). The distorted sampling of the input space improves with large N.

(4) The computer time required to generate the model response data was not excessive. (It took about 6½ to 7 hours on a "*80486/DX66*" desktop personal computer to pre-process the 1000 data points through the HDM-III model).

The HDM-III model investigated in this study is the personal (desktop) computer version based on disk operating system (*DOS*) platform. This version of HDM-III was coded in the *FORTRAN* programming language. The input data to the model is supplied through plain text (*ASCII*) disk-files. The code is very sensitive to the specific formatting of the input data file. The pre-processing involved four repetitive tasks (for each row of the design matrix): reading a row of the design matrix, creating the HDM Series A input file, running HDM-III on the input data, and writing an output file for post-experimental data analysis. This tedious task has to be repeated for all the 1000 rows of data in the design matrix. A pre-processor code was therefore developed to automate this disk intensive process.

The pre-processor code was designed and written in the *C++* programming language. The pre-processor flow chart is shown in Figure C.1 and the source code is given in Appendix C to the thesis.

5.7 Analysis of Post Experimental Response Data

Initially, the output generated from pre-processing the Latin hypercube design data (for Series A) through HDM-III consisted of NPV values for four R&M strategies. The NPV output matrix had eight columns representing two NPV values (at 10 and 20% discount rates) for each of the four strategies. The next stage of the study was to analyze the output so that the factor effects can be estimated. The analysis was carried out using two different techniques: (a) regression approach, and (b) a stochastic model approach. The two analysis techniques are subsequently discussed under subsection 5.7.1 and 5.7.2 respectively.

The results from the analysis of the initial output, the NPV (presented in the next chapter) indicated a some disparity between the regression approach results and those from the stochastic predictor. Further, regressing the NPV output to the linear-additive model (Equation 5.17) produced a fair to poor fit suggesting that the factor effects were highly nonlinear and/or multi-factor interactions were dominant. On the basis of this observation it was decided to investigate the life-cycle cost components to try and explain the behavior of the NPV output. Furthermore, the life-cycle VOCs were found to be several orders of magnitude larger than the agency R&M life-cycle costs. This ratio of VOCs to agency life-cycle costs from the case study ranged from 12 – 20 at 250 ADT to over 70 – 120 at 1500 ADT.

The pre-processing was, therefore, repeated, this time generating two streams of life-cycle costs – users' (VOC) and agency costs (R&M) for each rehabilitation and maintenance strategy.

5.7.1 A Regression Approach

5.7.1.1 Regression Coefficients as a Measure of Factor Sensitivity

In the early stages of the research the question was how can the sensitivity analysis be set up to address effects of factor interactions. At mid-stage, when it was decided to use the Latin hypercube design, the question became how could the results of the already substantial work based on the *ceteris paribus* approach [Mrawira 96a] be compared to the results from the experimental design approach. It was also desirable, at this stage, to develop a consistent, but simpler, methodology of analyzing the response data from the experimental design as an alternative to the rather computationally intensive stochastic approach that could only be demonstrated for a few response variables. A solution to the dilemma was found by re-examining the interpretation of parameters in a linear regression model. [Gunst 80] observes that,

> *"Assuming that a representative (output) data has been constructed for the purpose of investigation,... the estimated (regression) coefficients in a multiple-variable prediction*

equation are said to measure the change in the estimated response that is due to increasing one predictor variable by one unit while all other predictor variables are held constant."

Strictly speaking, this interpretation is not correct; it overlooks two important situations which complicate things: multi-collinearity of factors, and the effects of scale disparity between the predictor variables. These complications aside, the interpretation provides a basis for comparing factor sensitivity results. By carefully dropping factors with moderate pairwise correlations in the response data, and by "normalizing" or "standardizing" the estimated regression coefficients of a suitable model form an acceptable comparison platform can be achieved. As shown later, the "normalized" regression model coefficients are in fact measures of elasticity of factor sensitivity [Mrawira 96a] introduced in Chapter 4 (Section 4.5).

[Doctor 89] provides the mathematical basis for this interpretation and, hence, the justification for the concept of elasticity as an appropriate platform for comparing factor sensitivity.

In mathematical terms, the sensitivity of a response (output) variable with respect to a predictor (input) variable (the change in the response variable due to a small change in the predictor variable) is described by the partial derivative [Doctor 89]. If Y is a function f of n input variables, $X_1, \ldots, X_n$, say,

$$Y = f(X_1, \ldots, X_n) \qquad \ldots (5.13)$$

then the partial derivative,

$$\left.\frac{\partial Y}{\partial X_1}\right|_{x_1, \ldots, x_n} \qquad \ldots (5.14)$$

is a measure of the change in Y with respect to X_1 at the fixed point $(x_1, \ldots, x_n)$ in the input variable space. Since the units and numerical scale of Y and the X_i are often different, the partial derivatives are usually normalized (standardized) by dividing by the value at the fixed point so that the partial derivatives are on a more comparable basis. Therefore, the normalized sensitivity of Y with respect to X_1 at the fixed point $(x_1, \ldots, x_n)$, where the value of the response function is y is given by:

$$\left.\frac{\partial Y / y}{\partial X_1 / x_1}\right|_{x_1, \ldots, x_n} \qquad \ldots (5.15)$$

Note the resemblance of this expression to the definition of factor elasticity given by equation (4.12) in Chapter 4. Also the role of the "fixed point," $(x_1,\ldots, x_n)$ at which the derivatives are evaluated should be noted. For a highly nonlinear function Y, the partial derivative, and the function value y can be different for two adjacent points, $(x_1,\ldots, x_n)^p$ and $(x_1,\ldots, x_n)^q$, $q \neq p$. This highlights the dependence of sensitivity results upon the base case values used.

Determining the sensitivity of the response Y to each of the inputs $X_1,\ldots, X_n$, at the point $(x_1,\ldots, x_n)$ requires the calculation of n partial derivatives. The standardized partial derivatives can be ranked from the largest to smallest; the variable with the largest partial derivative has the largest effect on the output variable.

However, these partial derivatives can be misleading as a guide to the relative importance of the input variables [Doctor 89]. For example, two input variables may appear to be equally important because they are correlated. More importantly, for some complex models with nonlinear behavior in some or all the input variables, the magnitude of the factor effects may not be the same at all points in the input variable space. That is, the value of the normalized partial derivative (expressions 5.22) for a factor x_i may not be the same at two different points, $(x_1,\ldots, x_n)^p$ and $(x_1,\ldots, x_n)^q$, $q \neq p$ in the input space.

The traditional *ceteris paribus* sensitivity analysis (Subsection 2.5.2) method is based on a numerical estimate of the partial derivative of Y with respect to X_1 at the point $(x_1,\ldots, x_n)$ for example, as:

$$\frac{\Delta Y}{\Delta x_1} = \frac{f(x_1 + \Delta x_1, x_2, \ldots, x_n) - f(x_1, x_2, \ldots, x_n)}{\Delta x_1} \qquad \ldots (5.16)$$

where all variables but X_1 are held fixed.

Calculating the numerical estimate of the partial derivative of Y with respect to each of the variable X_i can be time consuming if the model has very many variables and if the model form is complex. This is one reason why the question of efficiency became a motivation to identify other techniques.

5.7.1.2 The Regression Model Form

A simple model form was required to which the post-experimental response data would be fitted permitting the use of the model parameters as sensitivity measures. The objective was not to find the best prediction equation, rather to determine a rational measure of comparing the factor effect of input variables upon the (post-experimental) response variable. With the derivative concept of sensitivity defined earlier [Doctor 89], the model had to be linear in the parameters and retain the same form irrespective of the degree of fit for the different response variables. The regression model selected is of the form:

$$Y = a_0 + a_1X_1 + a_2X_2 + \ldots + a_jX_j + \ldots + a_nX_n \qquad \ldots (5.17)$$

where, X_1, X_2, ..., X_n are the input variables in the design matrix, and Y is a response variable of interest (from the post-experimental output), *e.g.*, agency life-cycle cost on an overlay strategy, *etc.*

The model form adopted has the advantage that, the partial derivative with respect to a variable X_j is,

$$\frac{\partial Y}{\partial X_j} = \frac{\partial}{\partial X_j}\left(a_0 + a_1X_1 +,\ldots+ a_jX_j +,\ldots+ a_nX_n\right) = a_j \qquad \ldots (5.18)$$

or simply the factor coefficient. Once the variable X_j is found significant in the model, this allows the use of the coefficient a_j as a measure of factor effect in the response function, Y.

In keeping to our concept of elasticity of factor sensitivity [Mrawira 96a], which equals to the normalized partial derivative for the variable X_j, equation (5.15) becomes:

$$\varepsilon_j = \left.\frac{\partial Y/y}{\partial X_j/x_j}\right| x_1,\ldots,x_n = a\left(\frac{X_j}{y}\right) \qquad \ldots (5.19)$$

where, y and X_j represent appropriate measures of location of the response and input variable respectively.

In regression analysis the model coefficients, a_j are generally estimated by the least squares method where all data points are "averaged out" to determine the best estimator. It is, therefore, unrealistic to define a suitable fixed point, $(x_1,\ldots, x_n)$ at which to base the normalizing values y and X_j. For this reason, variable standardization techniques common in statistics are slightly different from equation (5.19) and are introduced later in Chapter 6.

5.7.1.3 Practical Considerations in the Regression approach

The complications to the interpretation of the regression coefficients require further expansion:

- Where covariation among predictor variables exists or some predictor variables are linearly dependent on other predictors interpretation of regression coefficients needs to be adjusted.
- The regression model has to predominantly account for the variation in the response variable before the regression parameters can be assigned any measure of factor effects.
- The coefficients (the fitted model parameters) alone cannot measure the factor effects if the factor ranges are not scaled similarly. The normalizing or standardizing approach is, therefore, an issue.

In other words, aside from the last point which refers to the need to normalize the results, our interpretation of the regression parameters of equation (5.17) as measures of factor effects is dependent on passing three critical tests. One, there is negligible covariation among the input variables in the design matrix; two, there are no dominant joint effects of one or more factors (factor interactions) in our computer code (HDM-III), and three the model fit is sufficiently good.

The first requirement is an experimental design problem; it is well taken care of by the "original" Latin hypercube design. Typically, the original design generated pair-wise factor correlations of below 0.004 (in theory zero). However, after adjusting the original design for the HDM-III variable dependencies (see section 5.4) the resulting modified design showed moderate pair-wise correlations as shown in Table 5.4. This problem (of possible distortion to the interpretation) was eliminated by re-examining the correlation matrix of the design data. For each pair of factors with moderate pair-wise correlation one of the factors was dropped from the model (equation 5.17). Model fitting was performed by keeping only the factors with pair-wise correlation of less than 0.10.

TABLE 5.4 Pair-wise Correlations in the Modified Latin Hypercube data

Factor	*ACRA*	*ACRW*	*ARAV*	*RDM*	*AGE1*	*AGE2*	*AGE3*	*ACRAB*	*ACRWB*
ACRA	1.000								
ACRW	0.678	1.000							
ARAV	-0.101	-0.066	1.000						
APOT	0.092	0.076	0.111						
RDM	0.021	0.003	0.009	1.000					
RDS	-0.028	-0.020	-0.023	0.496					
AGE1	0.016	0.023	0.023	-0.054	1.000				
AGE2	0.009	-0.017	0.002	-0.013	0.609	1.000			
AGE3	-0.012	-0.044	-0.014	0.018	0.367	0.549	1.000		
ACRAB	-0.002	-0.024	0.008	0.045	0.026	-0.008	-0.005	1.000	
ACRWB	-0.018	-0.039	0.010	0.027	-0.002	0.002	-0.025	0.653	1.000

Symbols according to the Glossary (see also Tables 4.1 and 5.3)

The linear-additive model (equation 5.17) is based on the initial assumption that there are negligible effects of factor interactions. This assumption would be confirmed by the degree of fit and later by the more rigorous stochastic predictor approach; the subject of the next section. The degree of model fit as measured by the Pearson correlation coefficient (R^2) for agency and users' life-cycle costs showed an excellent fit, typically R^2 of over 95% (Tables 5.5 and 5.6) suggesting that the role of any interaction term in the model are very insignificant. It was later confirmed by the stochastic approach results (reported in Chapter 6) that life-cycle costs are not sensitive to any interaction terms.

TABLE 5.5 R^2 for Users' (VOCs) Life Cycle

R&M Strategy	STP1		STP2		STP3		STP4	
Pavement Type	AC	SD	AC	SD	AC	SD	AC	SD
Traffic (ADT)								
ADT 264	0.949	0.947	0.947	0.945	0.958	0.957	0.958	0.957
ADT 500	0.954	0.953	0.950	0.950	0.959	0.958	0.959	0.958
ADT 1000	0.955	0.955	0.950	0.951	0.956	0.955	0.957	0.955
ADT 1500	0.957	0.957	0.951	0.952	0.955	0.954	0.956	0.954
ADT 2020	0.959	0.958	0.952	0.954	0.955	0.953	0.955	0.952

Key: SD = double surface treatment; AC = asphalt concrete

TABLE 5.6 R^2 for Agency (R&M) Life Cycle Costs

R&M Strategy	STP1		STP2		STP3		STP4	
Pavement Type	**AC**	**SD**	**AC**	**SD**	**AC**	**SD**	**AC**	**SD**
Traffic (ADT)								
ADT 264	0.046	0.041	0.141	0.92	0.189	0.119	0.245	0.151
ADT 500	0.179	0.166	0.965	0.964	0.995	0.995	0.978	0.979
ADT 1000	0.192	0.201	0.965	0.962	0.995	0.995	0.979	0.982
ADT 1500	0.214	0.240	0.965	0.962	0.995	0.995	0.980	0.982
ADT 2020	0.245	0.277	0.965	0.962	0.995	0.995	0.983	0.984

Key: SD = double surface treatment; AC = asphalt concrete

It is noted that degree of fit for agency life-cycle costs at the traffic of 264 ADT was poor. It would, therefore, be inappropriate to rely on the regression results to quantify the factor effects for this output. Similarly, the NPV outputs at this low traffic (of 264 ADT) gave a very poor fit to the model. This was supported by the stochastic approach results which (see Chapter 6) showed that the NPV was dominated by an interaction term of roughness (*QI*) and the initial surface distress (areas of cracking, raveling and potholes). The NPV for STP1 (10%) was also highly nonlinear with respect to main factor effect of roughness. As mentioned before, the regression model was thus considered inadequate in estimating the factor effects for the NPV output (at 264 ADT).

5.7.1.4 Criteria for Variable Significance

The model parameters of Equation (5.17) are estimated normally by use of maximum likelihood estimate (MLE). The general form of Equation (5.17) is: $\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}$, and the general MLE of the parameters is given by: $\boldsymbol{\beta}^{*} = (\mathbf{X}^{\tau}\,\mathbf{X})^{-1}\,\mathbf{X}^{\tau}\,\mathbf{Y}$. This solution works only if the matrix $(\mathbf{X}^{\tau}\,\mathbf{X})$ is nonsingular and has an inverse.

Under the assumptions that the fitted model is adequate and the error terms are Gaussian with mean zero and variance σ; mathematically written: $\varepsilon \sim N(\mathbf{0}, \mathbf{I}\sigma^2)$ then the estimate of variance of estimated model parameters, $\boldsymbol{\beta}^{*}$ is given by:

$$Var(\boldsymbol{\beta}^{*}) = (\mathbf{X}^{\tau}\,\mathbf{X})^{-1}\,\sigma^2 \qquad \text{... (5.20)}$$

The diagonal elements of the covariance matrix (Equation 5.20) are the variances of the individual model parameters. That is:

$$Var(\beta_j^*) = (\mathbf{X}^\tau \mathbf{X})_{jj}^{-1}\sigma^2 \qquad \text{... (5.21)}$$

The standard error, SE_β of the model parameter, β_j is the square root of its variance. The t-statistic is defined as the ratio of the estimated parameter, β^* to the estimated standard error of the parameter:

$$t = \frac{\hat{\beta}}{SE_{\hat{\beta}}} \qquad \text{... (5.22)}$$

Hypothetically, at constant β_j the smaller the SE_β the larger is the t-statistic (hence more significant is the model), and conversely. On the other hand, at constant SE_β, the larger the coefficient, β_j the larger is the t-statistic (and hence more significant) and conversely. Therefore, the t-statistic is an adequate measure of significance of a factor in the model. It reflects both the size of factor effect (the estimated coefficient) and the precision of estimate *i.e.*, how well the predictor explains the variability in the response variable.

The study performed sequential elimination of variables from the regression model; retaining variables with at least the critical t-statistic value of $|t_{cr}| \geq 1.96$. This value (of t-statistic) corresponds to the significance level of 0.05 (or a confidence level of 95%) that the variable contributes to the model.

5.7.2 A Stochastic Predictor Approach

The literature on the techniques of analyzing results of deterministic computer experiments is extensive. Details on various modeling and analysis techniques can be found, for example, in [Sacks 89a, 89b] while example applications in engineering are found in [Welch 92, Gough 94]. The outline of the estimation method given here is largely after [Sacks 89b, Welch 92 and Doctor 89].

Let the post-experimental output data be represented by a matrix $\mathbf{Y}$ consisting of one or more columns each representing a response variable vector, $\mathbf{y} = \{y(\mathbf{x}_1), y(\mathbf{x}_2)..., y(\mathbf{x}_n)\}^\tau$ where, $\mathbf{x}_1, \mathbf{x}_2,..., \mathbf{x}_n$ are the rows (also called "sites") in the experimental design input matrix, $\mathbf{D}$. Then the question at the analysis stage is how to model (or predict) the output $\mathbf{y}$.

One convenient way of modeling the output is to treat the deterministic response $y(\mathbf{x})$ as a realization of a stochastic (random) process,

$$Y(\mathbf{x}) = \beta + Z(\mathbf{x}) \qquad \text{... (5.23)}$$

where, β is an unknown constant (that can be replaced by a regression model in $\mathbf{x}$) and $Z(x)$ is a stochastic process. The random process $Z(\mathbf{x})$ is assumed to have mean zero and covariance between $Z(\mathbf{x})$ and $Z(\mathbf{x}')$ at two input sites, $\mathbf{x}$ and $\mathbf{x}'$ to depend only on their relative location $\mathbf{x} - \mathbf{x}'$, thus,

$$\mathrm{Cov}\,(Z(\mathbf{x}), Z(\mathbf{x}')) = \sigma^2 R(\mathbf{x}, \mathbf{x}') \qquad \text{... (5.24)}$$

where, σ^2 is the stochastic process variance and $R(\mathbf{x}, \mathbf{x}')$ is a correlation function that can be estimated from the design input data.

The rationale of this point of view, namely the representation of the deterministic response as a random function is that it respects the deterministic nature of a computer code since realization of stochastic process is deterministic, yet it provides a stochastic framework for assessing uncertainty. An alternative representation, the Bayesian approach, has been suggested elsewhere [Currin 91, Morris 93].

The correlation function $R(\mathbf{x}, \mathbf{x}')$ should be derivable from the input data; for computational convenience the function is normally chosen from a family of the so called *product correlation rule.* While there are many choices, a sufficiently flexible and common correlation family used is,

$$R(x, x') = \prod_{j=1}^{k} \exp\left(-\theta_j \left|x_j - x'_j\right|^{p_j}\right) \qquad \text{... (5.25)}$$

where, $\theta_j \geq 0$, $0 \leq p_j \leq 2$, and k is the number of variables in the computer code (the design matrix $\mathbf{D}$ has the order $N \times k$). The p_j can be interpreted as smoothing parameters – the response surface is smoother with respect to x_j as p_j increases – and the θ_j indicate how local the estimate is [Sacks 89b].

With the assumption that the stochastic process (equation 5.23) is Gaussian, the output data vector $\mathbf{y}$ can be modeled as multivariate normal with correlations given by equation (5.25). The deterministic nature of the code is preserved by noting that from equation (5.25), $R(\mathbf{x}, \mathbf{x}) = 1$, so replicate observations are identical.

The stochastic model (of Equation 5.23) provides a mechanism for estimating, through the likelihood, the factor sensitivity. To complete the solution, the maximum likelihood estimates (MLE's) of the unknown parameters: β in equation (5.23), σ^2 in (5.24) and $\theta = (\theta_1, \theta_2, \ldots, \theta_k)$ and $p = (p_1, p_2, \ldots, p_k)$ in (5.25) have to be determined. From the assumption that the stochastic process is Gaussian, the log-likelihood is,

$$l(\beta, \sigma^2, \theta, p) = -\frac{1}{2}\left[n \ln \sigma^2 + \ln \det \mathbf{R} + (\mathbf{y} - \mathbf{1}\beta)^{\tau}\, \mathbf{R}^{-1} (\mathbf{y} - \mathbf{1}\beta)/\sigma^2\right] \quad \ldots (5.26)$$

where, $\mathbf{1}$ is a vector of 1's because the regression component has only a constant term β, and $\mathbf{R}$ is the $n \times n$ matrix of correlations $R(\mathbf{x}_i, \mathbf{x}_j)$ for the design sites $(1 \leq i, j \leq n)$. Given the correlation parameters θ and p, the MLE of β is the generalized least square estimator given by,

$$\hat{\beta} = (\mathbf{1}^{\tau}\mathbf{R}^{-1}\mathbf{1})^{-1}\mathbf{R}^{-1}\mathbf{y} \quad \ldots (5.27)$$

and the MLE of σ^2 is:

$$\hat{\sigma}^2 = \frac{1}{n}(\mathbf{y} - \mathbf{1}\hat{\beta})^{\tau}\mathbf{R}^{-1}(\mathbf{y} - \mathbf{1}\hat{\beta}) \quad \ldots (5.28)$$

Substituting σ^2 and β back in the likelihood equation (5.26) the following equation is obtained:

$$l(\beta, \sigma^2, \theta, p) = -\frac{1}{2}\left[n \ln \sigma^2 + \ln \det \mathbf{R}\right] \quad \ldots (5.29)$$

To complete the solution it is required to numerically maximize the likelihood which is a function of only the correlation parameters from the design $\mathbf{D}$ and the output data. Full maximum likelihood estimation of the parameters in equation (5.28) is extremely computationally intensive, particularly where the dimension k of $\mathbf{X}$ is as large as in our case. Hence, algorithms have been developed, for example [Welch 92] that introduce the parameters sequentially as needed, and terminates at a reasonable level of precision. [Welch 92] gives details of developing such algorithms and some measures of reducing computing time.

Having determined the MLE's, the next step is to build the stochastic model for predicting $y(\mathbf{x})$. The best linear unbiased predictor (BLUP) at a new (untried) site $\mathbf{x}$ is:

$$\hat{y} = \hat{\beta} + \mathbf{r}^{\tau}(\mathbf{x})\,\mathbf{R}^{-1}(\mathbf{y} - \mathbf{1}\hat{\beta}) \quad \ldots (5.30)$$

where $\mathbf{r}(\mathbf{x}) = \{R(\mathbf{x}_1, \mathbf{x}), R(\mathbf{x}_2, \mathbf{x}), \ldots, R(\mathbf{x}_n, \mathbf{x})\}^{\tau}$ is the vector of correlations between the $Z(.)$'s at the design points and at the new site $\mathbf{x}$.

From this predictor, it is now feasible to quantify the relative effects of the inputs, assuming the predictor is good enough, a point which will shortly be addressed. The response can be decomposed into an average, main effects for each input factor, two-factor interactions and higher-order interactions. The overall standardized average of $\hat{y}(\mathbf{x})$ over the experimental region is estimated by:

$$\hat{\mu}_0 = \frac{\int \hat{y}(\mathbf{x}) \prod_{i=1}^{K} dx_i}{\prod_{i=1}^{K} \left(b_i - a_i\right)} \qquad \ldots (5.31)$$

where, (a_i, b_i) is the range of values for the predictor variable x_i, k is the number of input variables in the design matrix, $\mathbf{D}$ and $\prod_i$ denotes the product over all i. The main effects of an input factor x_i (averaged over the other factors) is given by:

$$\hat{\mu}_i(x_i) = \frac{\int \hat{y}(\mathbf{x}) \prod_{j \neq i} dx_j}{\prod_{j \neq i} \left(b_j - a_j\right)} - \mu_0 \qquad \ldots (5.32)$$

The interaction effect of x_i and x_j is estimated as,

$$\hat{\mu}_{ij}(x_i, x_j) = \frac{\int \hat{y}(\mathbf{x}) \prod_{h \neq i,j}^{K} dx_h}{\prod_{h \neq i,j}^{K} \left(b_h - a_h\right)} - \hat{\mu}_i(x_i) - \hat{\mu}_j(x_j) + \hat{\mu}_0 \qquad \ldots (5.33)$$

and similarly for higher-order interactions. Note that the effects are estimated by replacing the true $y(\mathbf{x})$ by the predictor of equation (5.30). These definitions are essentially similar to the familiar analysis of variance for multi-way tables (each integral corresponding to a sum of squares for a treatment, *etc.*).

It is normally desirable to plot the estimated effects to provide visualization of the relative magnitude of the effects, and to indicate nonlinearities and interactions, *etc.* Plotting $\hat{\mu}_i(x_i)$ against x_i for example, gives a visual indication of the estimated main effect of factor x_i.

The question raised earlier of whether the stochastic predictor of equation (5.30) is adequate is now revisited. [Sacks 89b] points out that properties of the MLE are not well understood, which would suggest that the validity of the best linear unbiased predictor (BLUP) of equation (5.30) calculated by substituting MLEs of the correlation parameters to be questionable. On the other hand experience has shown that even crude MLEs can lead to useful predictions [Sacks 89b]. The article cites some other works where it was shown that some cases of the BLUP exhibit consistent and asymptotically efficient estimators even when the correlation coefficient is wrongly specified, provided the mis-specification leads to approximate normal.

To assess the goodness of the stochastic predictor of equation (5.30) it is typical to perform a cross-validation. The cross-validation empirical root mean square error (*ERMSE'*) is defined as:

$$ERMSE' = \left\{ \frac{1}{n} \sum \left[\hat{y}_{-i}(x_i) - y(x_i) \right]^2 \right\}^{1/2} \qquad \text{... (5.34)}$$

where, $\hat{y}_{-i}$ (x_i) denote the BLUP estimated (equation (5.30)) based on all data sites except the observation $y(x_i)$. To minimize the computation, the MLE's of the correlation parameters are not re-computed for each prediction; they are still based on the complete set. Nonetheless, the cross-validation *ERMSE* has been shown to be a good measure of prediction precision.

Again for the purpose of visualization of cross-validations, two types of plots are typically used. The plot of $\hat{y}_{-i}$ (x_i) against $y(x_i)$ is called cross-validation plot. A good BLUP predictor should plot close to a straight line. The second type of plots are the cross-validation residual plots. These are obtained by plotting the residuals $\hat{y}_{-i}$ (x_i) - $y(x_i)$ against x_i.

As it is obviously apparent from the preceding paragraphs, computer implementation of the numerical algorithms required to generate the design, and to carry out the maximum likelihood estimation of the correlation parameters, followed by computing/plotting the main effects and interactions and finally to perform the cross-validations and residuals can be quite a formidable coding (computer programming) task. The work in this study made use of existing codes (*ALEX* for the design, and *GASP* for the analysis of the post experimental data) thanks to Dr. William J. Welch of the Department of Statistics and Actuarial Science, University of Waterloo.

Chapter 6

SENSITIVITY OF LIFE-CYCLE COSTS TO LINK CHARACTERIZATION VARIABLES IN HDM-III MODEL

6.1 Introduction to the Chapter

This chapter presents the results of the factor sensitivity analysis. Given the large number of HDM-III input factors (see Table 4.4), or more specifically, the factors which relate to maintenance and rehabilitation priority programming (Figure 1.1), the only viable approach was to demonstrate by a case study. The results reported here are based on a case study looking at the link characterization input factors for paved roads. The factor effects for this group of variables were investigated by keeping the remaining HDM-III input factors at base case values reflecting typical conditions from the case study region. As mentioned in Chapter 4, the base case values of the HDM-III input factors were determined from field data collected in Tanzania in 1994. The Tanzanian conditions are generally typical and reflective of conditions in many countries in tropical Sub-Saharan Africa.

The sensitivity results are presented under two categories. The *ceteris paribus* results for selected variables are first presented (Section 6.2) respecting the extensive work done at the early stages of this research. The main thrust of the results of the investigation from the experimental design approach is then introduced in Section 6.3. These later results are further subdivided into normalized derivatives (from a linear additive regression model) and results from the stochastic model approach.

The sensitivity results focus on the net present value (NPV) of the total life-cycle costs for a few typical R&M strategies. The argument for this focus derives from the thesis objective which was to investigate efficient application of the HDM-III model to the network level R&M priority programming. Typical model application at the network level is in economic evaluation of R&M treatments for existing alignments. The criterion commonly used in such applications is the NPV–comparing total life-cycle for a given R&M strategy to a "do minimum" or "do nothing" alternative.

Having said that, the behavior of the NPV predictions (from HDM-III) is not easily comprehensible since the model deals with a large number of factors, relating and interacting at various levels in a complex manner. In order to understand and explain some of the observed behavior of the NPV response, a look at the key components of the NPV may be necessary. For this reason, *i.e.*, for the purpose of explaining the findings on the NPV, the study went further to investigate factor sensitivities at the NPV components level. Consequently, the factor sensitivities reported throughout this chapter come at three levels: agency component, the users' cost component, and the NPV (total) of the life-cycle costs.

Section 6.4 discusses the key factor sensitivity findings, explaining some of the observed behavior and summarizing the factor sensitivity rankings. Section 6.5 concludes the chapter by addressing an immediate possible application of the sensitivity findings in the prioritization of data collection.

6.2 Results from the *Ceteris Paribus* Study

The framework of the *ceteris paribus* study was outlined in Section 4.4; this section presents the results from the study. The objective function used (the sum of the NPV values for the best three strategies) must be borne in mind while interpreting these results. The *ceteris paribus* investigation covered only a selected number of input factors, mostly under the link characterization class, and only a few from the vehicle characterization class. Two most common pavements surface types were investigated – asphalt concrete and surface treatments. The *ceteris paribus* results are subsequently presented, for convenience of the discussion, in four groups.

6.2.1 The Pavement Performance Calibration Factors

The *ceteris paribus* results for this group of factors have been discussed elsewhere [Mrawira 96a]. Table 6.1 summarizes the results over a ±20% change in the input calibration factor. As discussed in Chapter 4 (Section 4.5), the factor ranges investigated were much larger (-80% through +170% of the typical factor value). In most cases the practical range for the factors was ±20%, but in other cases the (-80% to +170%) interval was beyond either the factor practical range or the internal model limit for the factor. The use of the uniform fraction ±20% of the factor range for reporting the results is logical since one of the advantages of the elasticity approach (Equation 4.11) is the inherent standardization of scaling effect of the factor change used. This advantage of the elasticity concept was illustrated in Section 4.6.1. It was shown that, for responses that are not highly non linear, the elasticity of factor sensitivity is independent of the factor range used in the study.

Figure 6.1 plots the *ceteris paribus* results for the performance calibration factors.

TABLE 6.1 Sensitivity of NPV to Pavement Deterioration Factors *[Mrawira 96a]*

Calibration Factor	Symbol	Elasticity of NPV at Factor Change of -20%	-10%	+10%	+20%	Mean
Roughness Progression	*Kgp*	3.303	3.327	3.297	3.317	3.311
Roughness- Age/environment	*Kge*	0.785	0.791	0.796	0.836	0.802
Cracking Progression	*Kcp*	0.942	0.999	0.597	0.577	0.779
Pothole Progression	*Kpp*	0.668	0.667	0.638	0.650	0.656
Rutting Progression	*Krp*	0.164	0.190	0.201	0.219	0.194
Cracking Initiation	*Kci*	0.059	0.044	0.067	0.051	0.055
Ravelling Initiation	*Kvi*	-0.006	-0.005	-0.027	-0.015	-0.013

Symbols according to the Glossary

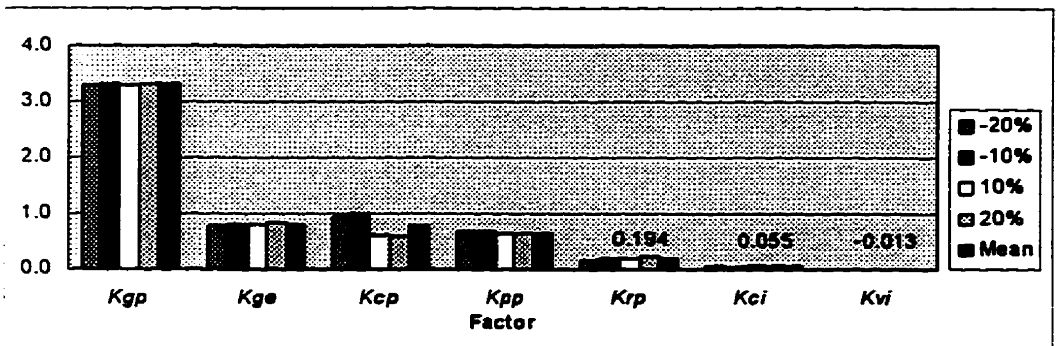


FIGURE 6.1 ***Elasticity of NPV with calibration factor change***

These results show that over the range of investigation, in overall the NPV criterion is most sensitive to the roughness calibration factors (*Kgp* and *Kge*). The results show that the next three calibration factors: the cracking progression factor (*Kcp*), the pothole progression factor (*Kpp*), and the rutting calibration (*Krp*) are comparatively of equal effect upon the NPV. Comparison of the ranking indicated by these results with the more comprehensive approach presented later suggests that the *ceteris paribus* results are only indicative, and should only be reserved for exploratory studies.

6.2.2 Environmental and Road Alignment Factors

In the HDM-III model the environmental variables are represented explicitly by input on average rainfall and altitude above mean sea level and implicitly by the *m*-index in the determination of the environmental-age roughness calibration factor, ***Kge***. The horizontal alignment attributes in the model are the carriageway width, shoulder width, superelevation and curvature, while the vertical alignment is characterized primarily by "rise plus fall" as a measure of gradient. The *ceteris paribus* study looked into rainfall, altitude, width and rise plus fall.

Table 6.2 shows a summary of the elasticity values for the environmental and road geometric alignment factors. Traffic factor is also shown as a scale of comparison of the effects. Figure 6.2 portrays the results on a bar chart.

TABLE 6.2 Sensitivity of NPV to Environmental and Alignment Factors

		Elasticity at Factor Change of				
Factor	**Symbol**	**-20%**	**-10%**	**+10%**	**+20%**	**Mean**
Width	*W*	-73.692	-0.582	-0.375	-0.336	-18.746
Traffic	*ADT*	5.028	5.271	5.509	5.714	5.380
Rainfall	*MMP*	0.438	1.083	-1.192	-0.629	-0.075
Rise plus Fall	*RF*	0.028	0.028	0.025	0.027	0.027
Altitude	*A*	0.016	0.027	0.004	0.004	0.013
Superelevation	*SP*	0.001	-0.0004	0.003	0.004	0.002

These results seem to suggest that rainfall, rise plus fall and altitude inputs have a negligible effect upon the NPV criterion. By comparison, the carriageway width dominates the NPV criterion with about three times as much impact as the traffic effect. It may be noted that the width effect is negative, implying that an increase in width results in lower NPV. This behavior is consistent with findings reported later from the stochastic model analysis of the Latin hypercube design data where it is shown that width dominates agency (R&M) life-cycle costs.

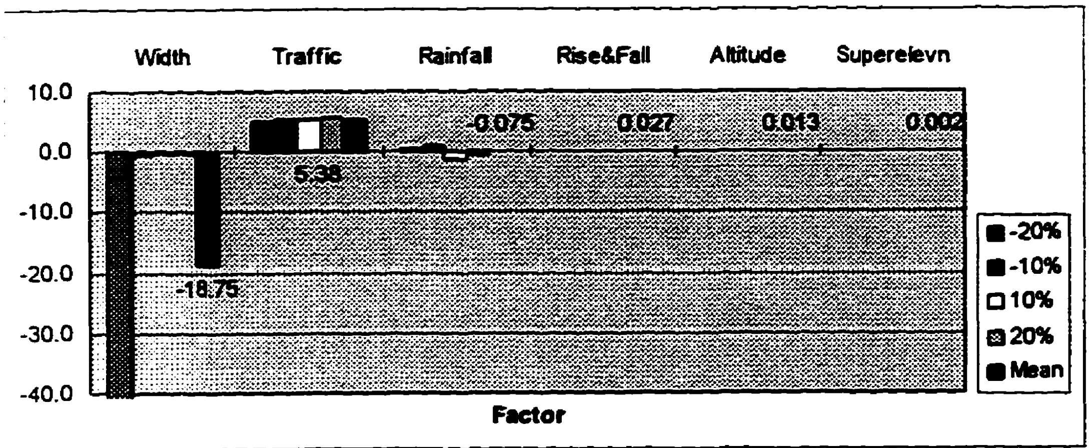


FIGURE 6.2 ***Elasticity of NPV with respect to environmental and alignment factors***

6.2.3 Vehicle Characterization Factors

The *ceteris paribus* experiments were also extended to investigate a few of the vehicle characterization variables in HDM-III. The input factors of interest here were the so called calibration factors for the vehicle operating cost relationships (normally grouped under Series D in the HDM vocabulary). Figure 6.3 shows the sensitivity results on some vehicle characterization factors while Figure 6.4 shows the sensitivity of the NPV to the VOC calibration factors. These later factors refer to the Parts Costs – Roughness (*PC – QI*) equation parameters and the Labor Hours – Parts Cost (*LH – PC*) equation parameters. Table 6.3 summarizes the results for the factors investigated under vehicle characterization variables.

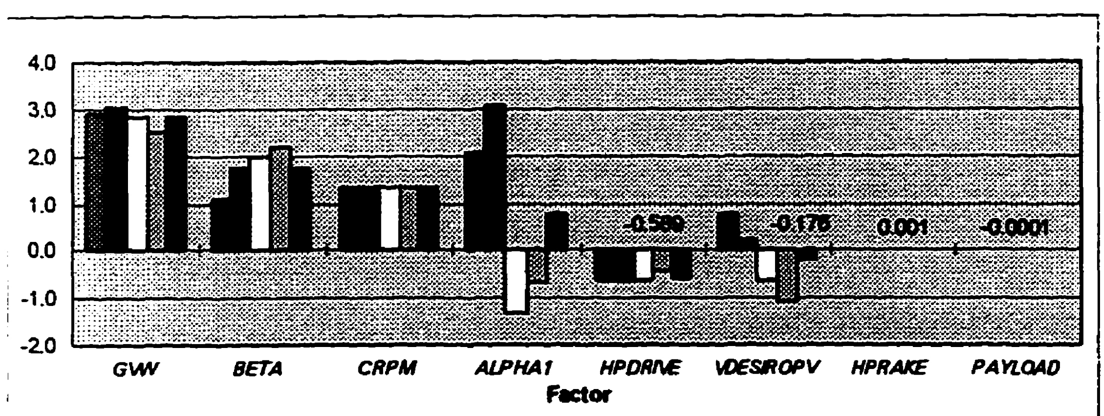


FIGURE 6.3 ***Elasticity of NPV with respect to some vehicle characterization factors***

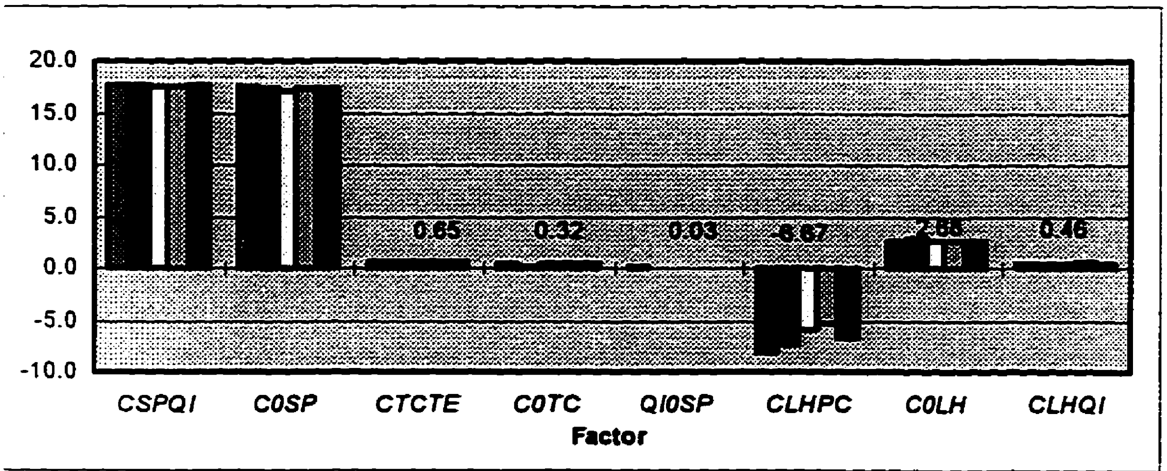


FIGURE 6.4 ***Elasticity of NPV with respect to VOC calibration factors***

TABLE 6.3 Sensitivity of NPV to Some Vehicle Characterization Factors

Factor	Symbol	Elasticity at Factor Change of -20%	-10%	+10%	+20%	Mean
Gross vehicle weight (metric tons)	*GVW*	2.919	3.025	2.815	2.495	2.814
Weibul shape parameter	*BETA*	1.114	1.757	1.976	2.191	1.759
Calibrated engine speed (rpm)	*CRPM*	1.327	1.328	1.326	1.326	1.327
Unit fuel efficiency factor	*ALPHA1*	2.073	3.081	-1.328	-0.664	0.790
Limiting desired speed (m/s)	*VDESIROPV*	-0.644	-0.640	-0.640	-0.432	-0.589
Usable driving power (HP)	*HPDRIVE*	0.772	0.230	-0.638	-1.070	-0.176
Usable braking power (HP)	*HPRAKE*	0.0006	0.0001	0.0009	0.0005	0.001
Payload (metric tons)	*PAYLOAD*	-0.0001	-0.0003	-0.00009	-0.00004	-0.0001
Roughness factor in $QI - PC$ exponent	*CSPQI*	17.794	17.792	17.582	17.477	17.661
Constant term in $QI - PC$ exponent	*COSP*	17.473	17.366	17.155	17.363	17.339
Tire wear coefficient	*CTCTE*	0.647	0.648	0.645	0.647	0.647
Constant term in tire wear equation	*COTC*	0.323	0.220	0.426	0.322	0.323
Limiting QI for linear $QI - PC$ equation	*QIOSP*	0.107	0.003	0.003	0.003	0.029
The PC exponent in LH - PC equation	*CLHPC*	-8.205	-7.342	-5.836	-5.295	-6.669
Constant term in the LH - PC equation	*COLH*	2.597	2.806	2.597	2.702	2.675
QI factor in LH - PC equation exponent	*CLHQI*	0.432	0.432	0.434	0.538	0.459

Symbols according to the Glossary; also see Table 3.5

The results point out some interesting roles of the input factors under vehicle characterization. It is seen that the Roughness – Parts (*QI - PC*) equation parameters dominate the NPV criterion, in particular, the Roughness coefficient and the constant term, both in the exponent of this equation. The next most important factors according to these *ceteris paribus* results are the Labor Hours – Parts Cost (*LH – PC*) equation parameters. Again in the exponent parameter of this equation, the coefficient of the parts costs and the constant term are the most significant factors.

As expected, the other significant variables under the vehicle characterization group are the gross vehicle weight (GVW), the vehicle fuel efficiency, Weibul shape parameter (respecting the role of air resistance at high speeds) and the engine speed (rpm).

6.3 Results from the Latin Hypercube Design Investigation

6.3.1 The Post Experimental Output Data

The post experimental data investigated consisted of two pavement types (*i.e.*, surface – base pairs):

- Asphalt Concrete on granular base (AC/GB), and
- Double Surface Dressing on cement stabilized soil base (SD/CB).

These surface – base pairs were selected among 13 common pairs since they represent the most popular pavement types in the case study region (see, for example, Table A.2, Appendix A).

As discussed in Section 2.1 the principal interest in the study was to investigate NPV of the total life-cycle "net benefits" since it is the HDM-III output mostly used criterion in R&M priority programming. In this subsection the sensitivity results based on the regression approach of the NPV output from running HDM-III on the Latin hypercube design data will be discussed. The findings suggest that the NPV criterion is highly non-linear with respect to the most sensitive input factors. Seeking to explain this nonlinear behavior of the NPV, and in order to develop a consistent platform for discussing the sensitivity results, the study went a step further to investigate the key cost components of the NPV – the agency and the users' life cycle costs.

The NPV output data investigated was generated at two stages. An exploratory data was based on 10% discount rate and an analysis period of 15 years for a low traffic volume of 265 ADT. The bulk of the NPV data from the Latin hypercube experimental design was based on 10% discount rate but an analysis period of 30 years. The study compared the regression approach results to the stochastic approach results for the traffic levels of 265, 500, 1000, 1500 and 2020 ADT. This traffic range was chosen since typical road links in the low income economies of Sub Saharan Africa (as exemplified by the case study country, Tanzania) carry traffic in the range of 200 to 1000 ADT.

The NPV stochastic predictor for the exploratory data (see Section 6.3.2) achieved relatively poor predictions and showed that the main effects of the most active factors are highly non-linear. Poor fit was also obtained for the regression approach. In an attempt to further explore the behavior of the NPV predictions from the HDM-III model, the study tried out different conditions. Further NPV values (and agency and users' costs) were generated from the experimental design data at 10% discount rate and 30 years analysis period for the traffic levels of 500, 1000, 1500 and 2020 ADT.

With respect to life-cycle costs, the output investigated was generated on the basis of 30 years analysis period with no discounting applied. The argument for this choice is given in Subsection 4.4.3. The regression approach to factor sensitivities subsequently presented covers traffic levels of 265, 500, 1000, 1500 and 2020 ADT. However, due to the computer time constraint, the stochastic approach was not feasible for all the response data. This latter analysis was performed on the response data for one pavement type and for two traffic levels of 500 and 1000 ADT.

For the two pavement types the output data investigated in the regression approach employed output from 1000 model runs — making use of all the data points in the Latin hypercube design matrix. Agency and users' life-cycle costs were tabulated for each of the five R&M strategies. A discussion of the pavement treatment strategies (coded STP0, ..., STP4) was given in Sections 3.7 and 4.3.

6.3.2 Factor Sensitivities from the Regression Approach

6.3.2.1 Regression Approach Sensitivity Results: the NPV Prediction

The net present value (NPV) output data described above were regressed on the linear additive model (*i.e.*, assuming low factor interactions) given by Equation (5.17). As discussed earlier (Subsection 5.7.1) this model specification was chosen to permit the direct use of the estimated model parameters (after normalizing) as measures of factor sensitivity. The question of adequacy of the model specification does not arise here since the sole use of the model is not prediction, but rather, "explanation." The degree of fit would indicate the validity of the assumptions of factor additivity, linearity and low factor interactions, and, therefore, to what extent the simple model form can be used to explain the factor sensitivities. In other words, the regression approach would not always work, particularly where the response variable is highly nonlinear, or exhibits moderate factor interactions.

Rewriting Equation (5.17) in compact form, the additive linear regression model adopted was:

$$Y = \alpha + \sum \beta_i x_i \qquad \text{... (6.1)}$$

where, the summation of x_i 's include all non-correlated variables from the design matrix.

Regressing the NPV output obtained from running HDM-III on the Latin hypercube design data at ADT 265 produced a fit ranging from quite poor to an acceptable level (Table 6.4). The table shows that the R&M strategy STP1 exhibit the poorest fit, while resealing and overlay strategies (STP3 and STP4) are better explained by the model (R^2 about 0.6 to 0.8). Given the large sample size (n=1000) and the deterministic nature of the computer experiment, this degree of lack of fit suggests that the NPV is subject to either strong non-linearities or/and significant factor interactions. The stochastic approach results presented later confirmed the presence of both phenomena.

TABLE 6.4 R^2 Values on Regressing NPV Output to the Additive Linear Model

Strategy	Discount Rate	Pavement Type	
		AC	SD
STP1	10	0.220	0.192
	20	0.244	0.206
STP2	10	0.495	0.469
	20	0.632	0.615
STP3	10	0.632	0.632
	20	0.783	0.779
STP4	10	0.663	0.666
	20	0.717	0.780

Table 6.5 shows an interesting pattern of the significant variables upon the NPV criterion. The most important observation is that the order of factor significance changes slightly with the R&M strategy and with the discount rate. We see from the table, for example, the four most significant factors for all the strategies are the rutting calibration factor (*Krp*), the pavement width (*W*), the roughness (*QI*) and the cracking calibration factor (*Kci*). Note that the discount rate has a definite role in the sensitivities. The order of the three most significant factors for strategies STP1, STP2, and STP4 at 10, 20 and 0% discount rates respectively changes to width (*W*), roughness (*QI*) and cracking initiation factor (*Kci*).

Comparing different strategies at different discount rates the table shows, for example, width (*W*), roughness (*QI*), cracking initiation factor (*Kci*) and rise plus fall (*RF*) remain significant in NPV prediction for all strategies at various discount rates. On the other hand, the factor sensitivities for the rutting calibration factor (*Krp*) and the initial area of potholes (*APOT*) seem to be strongly influenced by the discount rate.

TABLE 6.5 NPV Standardized Factor Coefficients Averaged Over ADT 250 – 1500

	STP1		STP2		STP3		STP4			mean
	Discount Rate (%)									
Factor	10	20	0	20	0	10	0	10	20	
Krp		-0.628	-0.671		-0.570	-0.555		-0.419	-0.511	0.559
W	-0.336	-0.329	-0.353	-0.469	-0.452	-0.531	-0.617	-0.637	-0.443	0.463
QI	-0.445	0.106	0.133	-0.410	0.208	0.219	-0.325	0.255	0.166	0.252
Kci	0.253	0.159	0.186	0.268	0.161	0.165	0.228	0.166	0.155	0.193
RF		0.145	0.186	0.108	0.127	0.168	0.121	0.152	0.186	0.149
APOT		-0.110	-0.120		-0.162	-0.151		-0.149	-0.199	0.148
Kge	-0.200	-0.150	-0.147	-0.164	-0.107	-0.100	-0.142			0.144
SNSG		0.124	0.149		0.128	0.142				0.136
SN	0.146	0.130	0.120				0.106		0.173	0.135
Kgp							0.100		0.167	0.134
HBASE				-0.137			-0.123			0.130
C	-0.143	-0.124		-0.120						0.129
HSOLD					0.127	0.111		0.143	0.129	0.127
DEF		-0.131	-0.112							0.122
RDS	-0.122	-0.135	-0.151	-0.117	-0.133	-0.132		-0.057		0.121
MMP				0.117			0.121			0.119
Kcp		-0.127			-0.110					0.119
HSNEW							0.063		0.152	0.108

Notes: Symbols according to the Glossary (see also Tables 4.1 and 5.3). R&M strategies as defined in Table 3.7. Analysis period was 30 years. Data size was 150.

6.3.2.2 Regression Approach Sensitivity Results: Agency and Users' Life-Cycle Costs

The high non-linearity and the presence of multi-factor interactions in the NPV predictions (suggested by the poor model fit and confirmed by stochastic predictor results reported later) motivated a search for other HDM-III outputs that could be used to explain the observed behavior of the NPV factor sensitivities. The life-cycle costs components (of the NPV) were logically the next level of investigation for this purpose. It is worth noting, as pointed out before, that a study of the NPV components is only useful in explaining the behavior of the NPV factor sensitivities. Given that most network level applications of the HDM-III model (the focus of this thesis) are in comparing

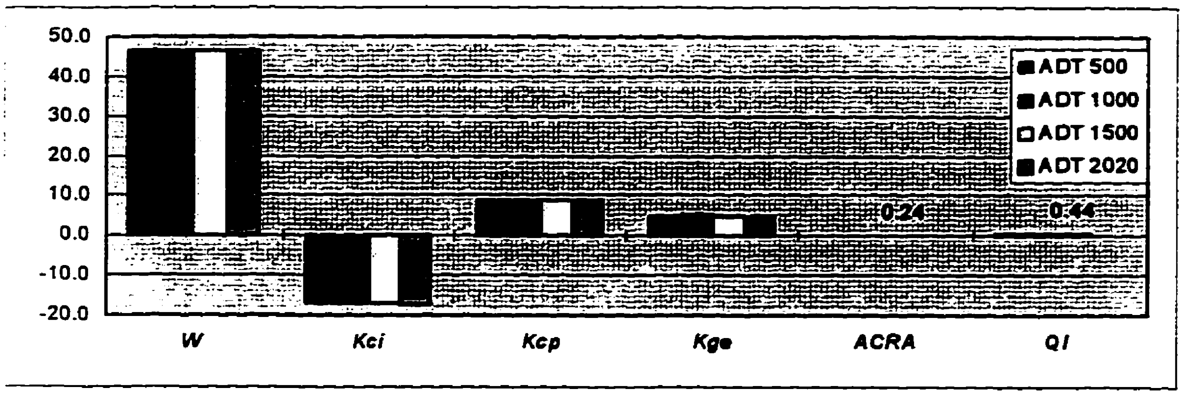
R&M strategies for existing alignments the NPV output remains the most useful criterion for analysis.

The life-cycle costs output generated from the Latin hypercube design data as described above was used in regression analysis employing as before the model form of Equation (6.1).

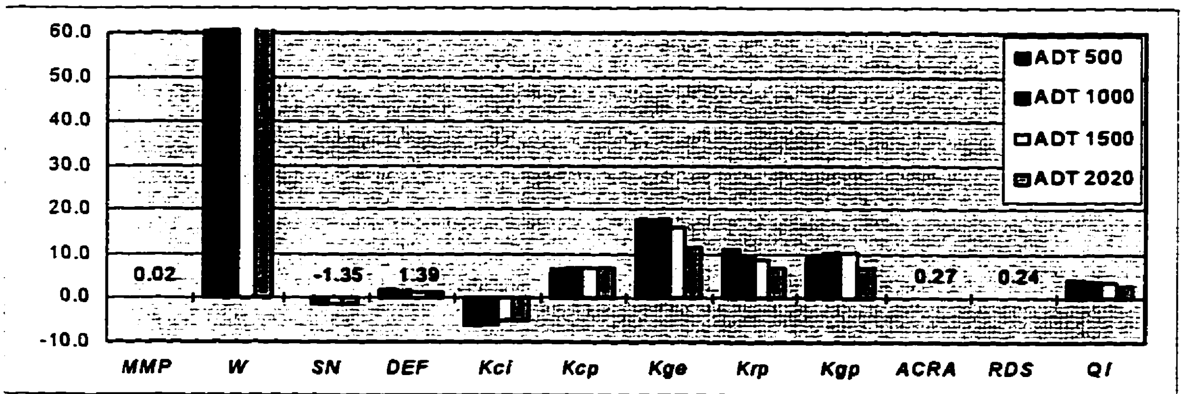
The users' life-cycle costs (LCC-VOC) show an excellent degree of fit for all strategies and at all traffic levels, typically R^2 of over 95% (see Table 5.6). The agency life-cycle costs are also extremely well explained by the simple model form (R^2 of 96% to over 99%) for all traffic levels (except 265 ADT) and for all strategies (except the patch only strategy: STP1). At the low traffic of 265 ADT the fit is very poor for all strategies while for the "patch only" strategy (STP1) the model fit is typically below R^2 of 20% for all traffic levels (Table 5.7).

These findings suggest that life-cycle costs components (agency and VOCs) for moderate traffic levels, unlike the NPV criterion, are mainly linear and additive with respect to the sensitive input factors. This phenomenon would be confirmed later by the results from the stochastic model approach.

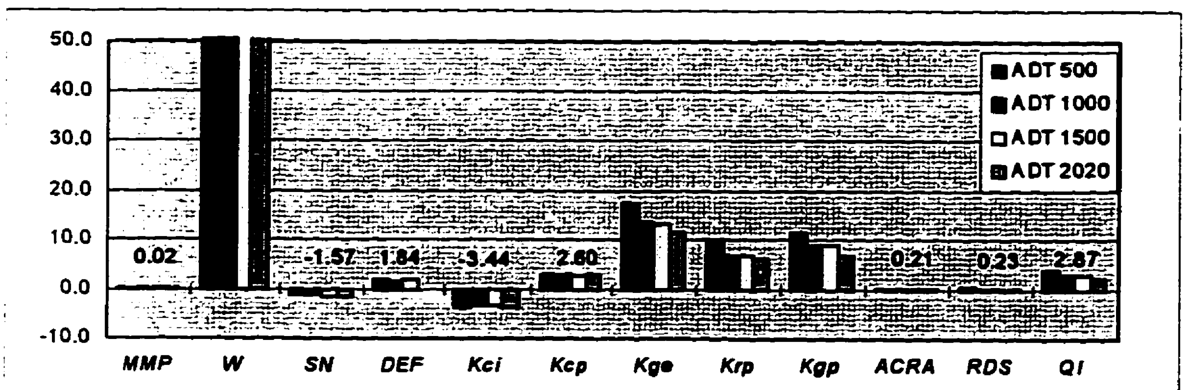
As expected, agency (R&M) and vehicle users' (VOC) life-cycle costs were found to be sensitive to different sets of input variables. While, for example, LCC-VOCs are consistently sensitive to altitude (*A*), rise plus fall (*RF*), and curvature (*C*), these variables are not significant in LCC-R&M. On the other hand, carriageway width (*W*) happens to be a very significant variable in R&M life-cycle costs but not in LCC-VOC. Figures 6.5 and 6.6 show the "raw" significant factor coefficients in the final regression models (at a significance level of 5 percent). These factor coefficients are "raw" in the sense that they are not *normalized* and, therefore, not direct measures of factor sensitivity. The next few paragraphs discuss the raw factor coefficients with the motivation of explaining the emerging patterns.



(a) *Patch all annual potholes and reseal every 6 years strategy on AC/GB pavement*

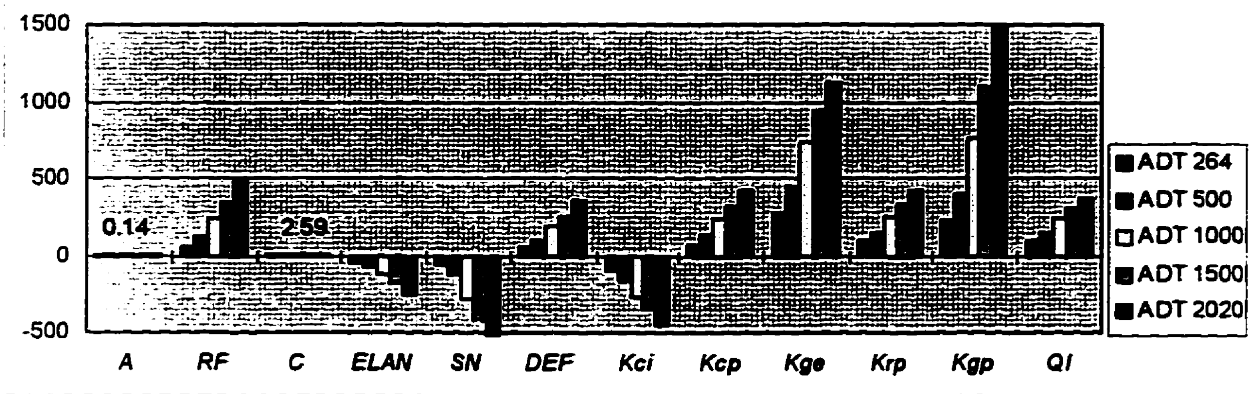


(b) *Patch all, reseal every 6 years and overlay at 5.5 mm/km IRI strategy on AC/GB*

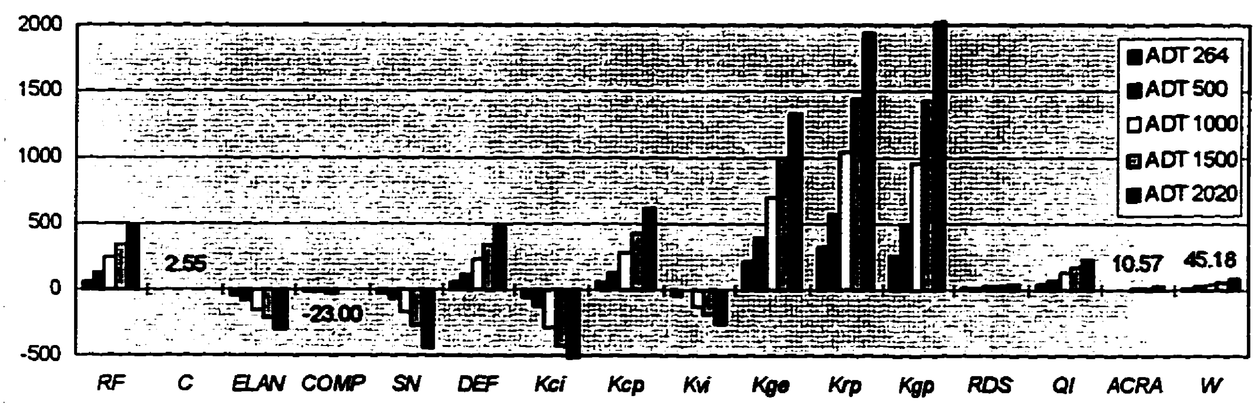


(c) *Patch all, reseal every 6 years and overlay at 5.5 IRI strategy on SD/CB pavement*

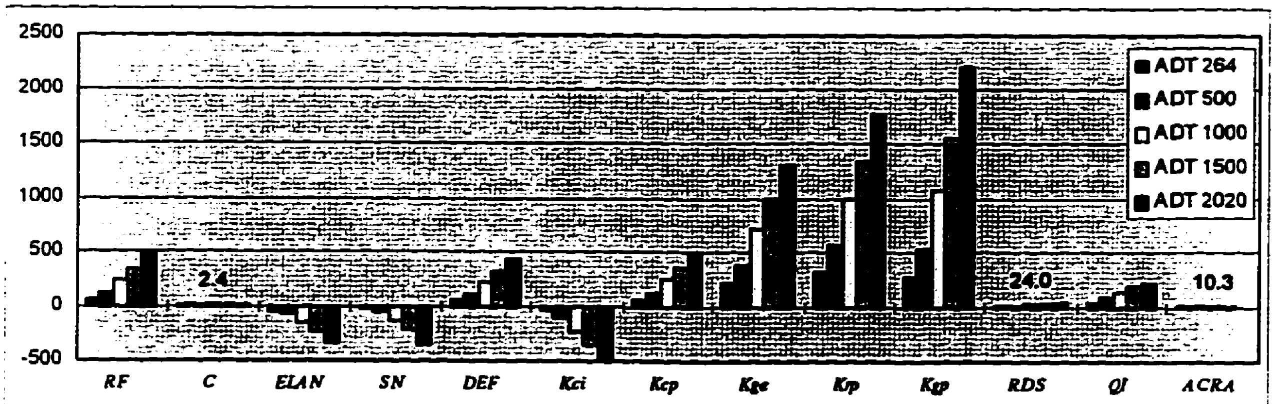
FIGURE 6.5 ***Life-cycle agency (R&M) costs output: raw factor coefficients (α = 0.05)***



(a) *Patch all potholes annually and reseal every 6 years strategy on AC/GB pavement*



(b) *Patch all reseal every 6 years and overlay at 5.5 IRI strategy on SD/CB pavement*



(c) *Patch all, reseal every 6 years and overlay at 5.5 IRI strategy on AC/GB pavement*

FIGURE 6.6 ***Life-cycle users' costs (VOC) output: raw factor coefficients (α = 0.05)***

With respect to the "raw" factor coefficients (Figures 6.5 and 6.6), several observations seem evident from looking at the regression approach results. Figure 6.5 (a) to (c) indicates that ranking of the active factors changes from one strategy to the next. However, since these are still the "raw" factor coefficients, realistic ranking of factor sensitivities is better discussed using normalized factor coefficients (next section). What is more interesting from Figure 6.5 (a) to (c) is that change in traffic level seems to have no effect upon the prediction of R&M (agency) life-cycle costs. The factor coefficients remain fairly constant as the traffic level changes from 500 to 2020 ADT.

Figure 6.6 plots the "raw" factor coefficients for road users' life-cycle costs. Notice in this case, traffic increase causes a consistent increase on the "raw" factor coefficients for road users' life-cycle costs, as might be expected. The traffic level effect seems to be a constant multiplier. In Figure 6.6(c), for example, the *Kgp* factor coefficients at 500 and 2020 ADT are approximately 500 and 2020 respectively. As for the agency life-cycle costs, the relative magnitude of the "raw" factor coefficients changes slightly from strategy to strategy.

To summarize, the "raw" factor coefficients from the regression analysis of the post-experimental data suggest the following:

- Traffic has no significant impact upon the factor effects for agency life-cycle costs
- The ranking of significant factors changes slightly from one R&M strategy to another
- The effect of traffic on the "raw" factor coefficients for road users' life-cycle costs appears to be a simple constant multiplier (a scaling effect which may be removed by normalizing).

6.3.2.3 Standardized Regression Coefficients

The concept of using the regression coefficients of a suitably selected model form as measures of factor sensitivity was introduced in Subsection 5.7.1. It was argued that to eliminate the different scaling effects of the factor ranges investigated (and units of measurement) it is necessary to normalize or standardize the partial derivatives or the "raw" factor coefficients.

In summary there are three concerns that underlie factor standardization in this study:

- Predictor variables have different units of measurement.
- The typical range (practical variability) of each predictor variable is different from the next.
- The HDM-III outputs/predictions employ user-defined quantities (currency, units, *etc.*).

The two common methods of variable standardization in statistics are: (a) standard normal deviate, and (b) unit length scaling. The normal deviate transforms the data points, x_{ij} into their standard scores, z_{ij} given by,

$$z_{ij} = \frac{x_{ij} - \bar{x}_j}{s_j} \qquad \text{... (6.2)}$$

where, z_{ij} is the standardized score of the ith value of factor x_j and s_j is the standard deviation of the factor x_j values in the design matrix.

The unit length scaling standardization is given by the equation,

$$w_{ij} = \frac{x_{ij} - \bar{x}_j}{d_x} \qquad \text{... (6.3)}$$

where, $d_x = \sqrt{\Sigma \left(x_{ij} - \bar{x}_j\right)^2} = s_x \sqrt{(n - 1)}$

The standard normal deviate technique was used in this study since it is available in many commercial statistical packages. Both the predictor variables and the model outputs were standardized using the normal deviate; hence the coefficients are also called the *beta weights*.

Tables 6.6 and 6.7 present the standardized regression coefficients obtained for the traffic levels of 500 and 1000 ADT respectively. The standardized factor coefficients shown in the tables are now more comparable across R&M strategies. As suspected from the "raw" factor coefficients, the sensitivities at ADT 500 (Table 6.6) and at ADT 1000 (Table 6.7) agree very closely, suggesting that traffic level is a simple scaling quantity in the VOC. This is indeed the case from the underlying methodology of the HDM-III model. In particular, it is noted that, the factor sensitivities for agency life-cycle costs (Tables 6.6 (a) and 6.7 (a)) are almost unchanged from ADT 500 and ADT 1000.

The close agreement between the factor sensitivities for road users' life-cycle costs supports the argument that as long as the appropriate standardization is employed, factor sensitivities based on the regression approach could be investigated at any arbitrary traffic level. On the other hand, since NPV criterion involves a tradeoff between the agency and the road users' life-cycle costs, factor sensitivities for the NPV criterion cannot be determined independent of the traffic level.

Tables 6.6 and 6.7 also show that the factor sensitivities are specific to the R&M strategy used. While the carriageway width (*W*) and the rise plus fall (*RF*) account for over 96% of the total variation upon the agency and the road users' life-cycle costs respectively for all strategies employed, the ranking of the next sensitive factors seems to vary slightly from strategy to strategy.

TABLE 6.6 Standardized Regression Coefficients for ADT 500

(A) Agency Life-Cycle Costs

Strategy STP2

Factor	Asphalt Concrete on Granular Base	Surface Dressing on Soil Cement
	R^2: 0.965	R^2: 0.963
W	0.969	0.973
Kci	-0.140	-0.089
Kcp	0.049	0.049
ACRA	0.026	0.049
DEF		0.026
ELAN		-0.018
Kge	0.013	

Strategy STP4

Factor	Asphalt Concrete on Granular Base	Surface Dressing on Soil Cement
	R^2: 0.978	R^2: 0.978
W	0.981	0.982
QI	0.061	0.057
Krp	0.056	0.051
Kge	0.029	0.028
Kci	-0.031	-0.018
Kcp	0.022	0.011
RDS	0.019	0.019
Kgp	0.015	0.019
ACRA	0.015	0.017
DEF	0.013	0.013
MMP		0.010

(B) Users' Life-Cycle Costs

Strategy STP2

Factor	Asphalt Concrete on Granular Base	Surface Dressing on Soil Cement
	R^2: 0.949	R^2: 0.949
RF	0.965	0.965
QI	0.097	0.095
C	0.060	0.060
SN	-0.044	-0.042
Kge	0.034	0.034
Kci	-0.038	-0.024
Krp	0.036	0.032
DEF	0.032	0.030
Kgp	0.030	0.030
Kcp	0.021	0.019
ELAN		-0.019
A	0.014	0.014

Strategy STP2

Factor	Asphalt Concrete on Granular Base	Surface Dressing on Soil Cement
	R^2: 0.958	R^2: 0.957
RF	0.964	0.965
Krp	0.139	0.134
C	0.057	0.056
QI	0.052	0.051
Kgp	0.037	0.038
DEF	0.034	0.035
RDS	0.035	0.033
Kge	0.030	0.029
Kci	-0.031	-0.016
SN	-0.025	-0.021
Kcp	0.021	0.020
ELAN	-0.016	-0.021
ACRA	0.017	0.019
W	0.013	0.013

Symbols according to the Glossary; see also Tables 4.1 and 5.3.

TABLE 6.7 Standardized Regression Coefficients for ADT 1000

(A) Agency Life-Cycle Costs

Strategy STP2

Factor	Asphalt Concrete on Granular Base	Surface Dressing on Soil Cement
	R^2: 0.964	R^2: 0.962
W	0.969	0.973
Kci	-0.141	-0.078
Kcp	0.049	0.051
ACRA	0.026	0.046
DEF		0.040
ELAN		-0.018
Kge	0.014	

Strategy STP4

Factor	Asphalt Concrete on Granular Base	Surface Dressing on Soil Cement
	R^2: 0.979	R^2: 0.981
W	0.983	0.986
QI	0.054	0.045
Krp	0.049	0.035
Kge	0.029	0.021
Kci	-0.029	-0.018
Kcp	0.024	0.010
Kgp	0.017	0.014
RDS		0.014
ACRA	0.017	0.013
DEF	0.012	0.011
MMP	0.010	0.009

(B) Users' Life-Cycle Costs

Strategy STP2

Factor	Asphalt Concrete on Granular Base	Surface Dressing on Soil Cement
	R^2: 0.949	R^2: 0.950
RF	0.966	0.968
QI	0.084	0.076
C	0.060	0.061
SN	-0.051	-0.046
DEF	0.031	0.033
Kgp	0.031	0.032
Krp	0.031	0.027
Kge	0.029	0.028
Kci	-0.033	-0.021
Kcp	0.019	0.017
ELAN	-0.012	-0.015
A	0.014	

Strategy STP4

Factor	Asphalt Concrete on Granular Base	Surface Dressing on Soil Cement
	R^2: 0.956	R^2: 0.955
RF	0.964	0.964
Krp	0.131	0.121
C	0.059	0.059
QI	0.046	0.043
DEF	0.038	0.044
Kgp	0.038	0.040
RDS	0.032	0.030
SN	-0.031	-0.028
Kge	0.028	0.027
Kci	-0.035	-0.015
Kcp	0.024	0.023
ACRA	0.016	0.022
ELAN	-0.016	-0.021
W	0.014	0.015

Symbols according to the Glossary; see also Tables 4.1 and 5.3.

6.3.3 Factor Sensitivities Results from the Stochastic Model Approach

6.3.3.1 Diagnosis of the Stochastic Predictor for the NPV Output

Using the method discussed in Section 5.7.2 a best linear unbiased stochastic predictor (BLUP) for a given HDM-III output variable was estimated from the post-experimental data by maximum likelihood method as given earlier by Equation (5.30):

$$\hat{y} = \hat{\beta} + \mathbf{r}^{t}(\mathbf{x})\,\mathbf{R}^{-1}(\mathbf{y} - \mathbf{1}\hat{\beta})$$

where the symbols are as defined earlier (see Section 5.7.2).

This predictor is more flexible than, say, a low-order polynomial fit, and has been found to yield more accurate predictions in various applications [Gough 94]. Before using this predictor to estimate the factor effects it is imperative to assess the performance of this predictor.

Figure 6.7 shows a scatter plot in which NPV values (for strategy STP1 at 10%) predicted using the stochastic predictor are plotted against the actual HDM-III model output. A method of prediction-accuracy assessment commonly used in statistics known as *cross validation* was employed. In this method, the ith value of the response, y_i is predicted using all data except y_i. It is also a good practice to look at the cross-validation residuals plotted against the input variables. Figure 6.8 shows cross validation residual plots for NPV (for strategy STP1 at 10%) upon the first six predictor variables. The rest of the residual plots for NPV are given in Figure D.1 in Appendix D.

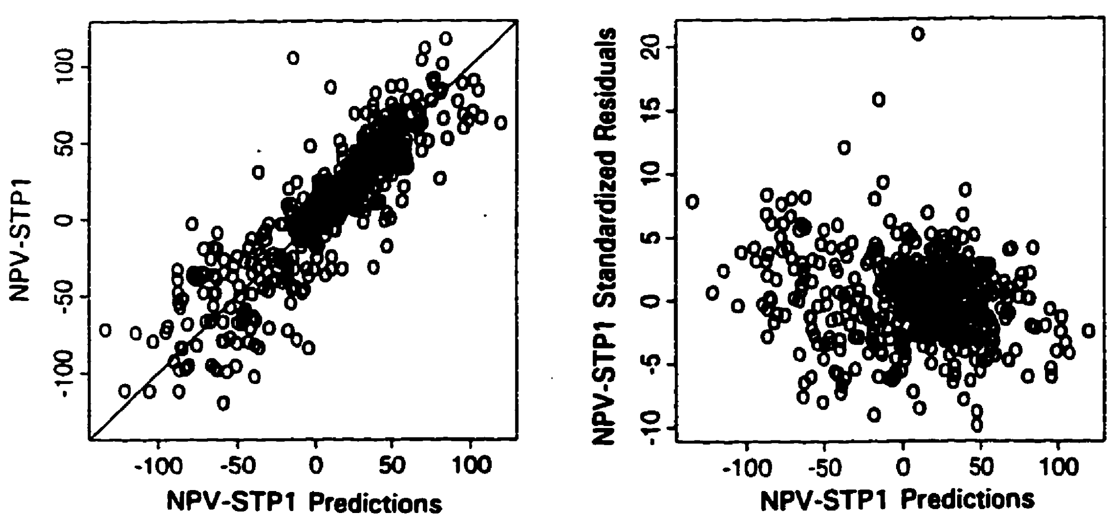


FIGURE 6.7 ***Cross validation predictions and residuals: NPV at 10% for STP1 (ADT 265)***

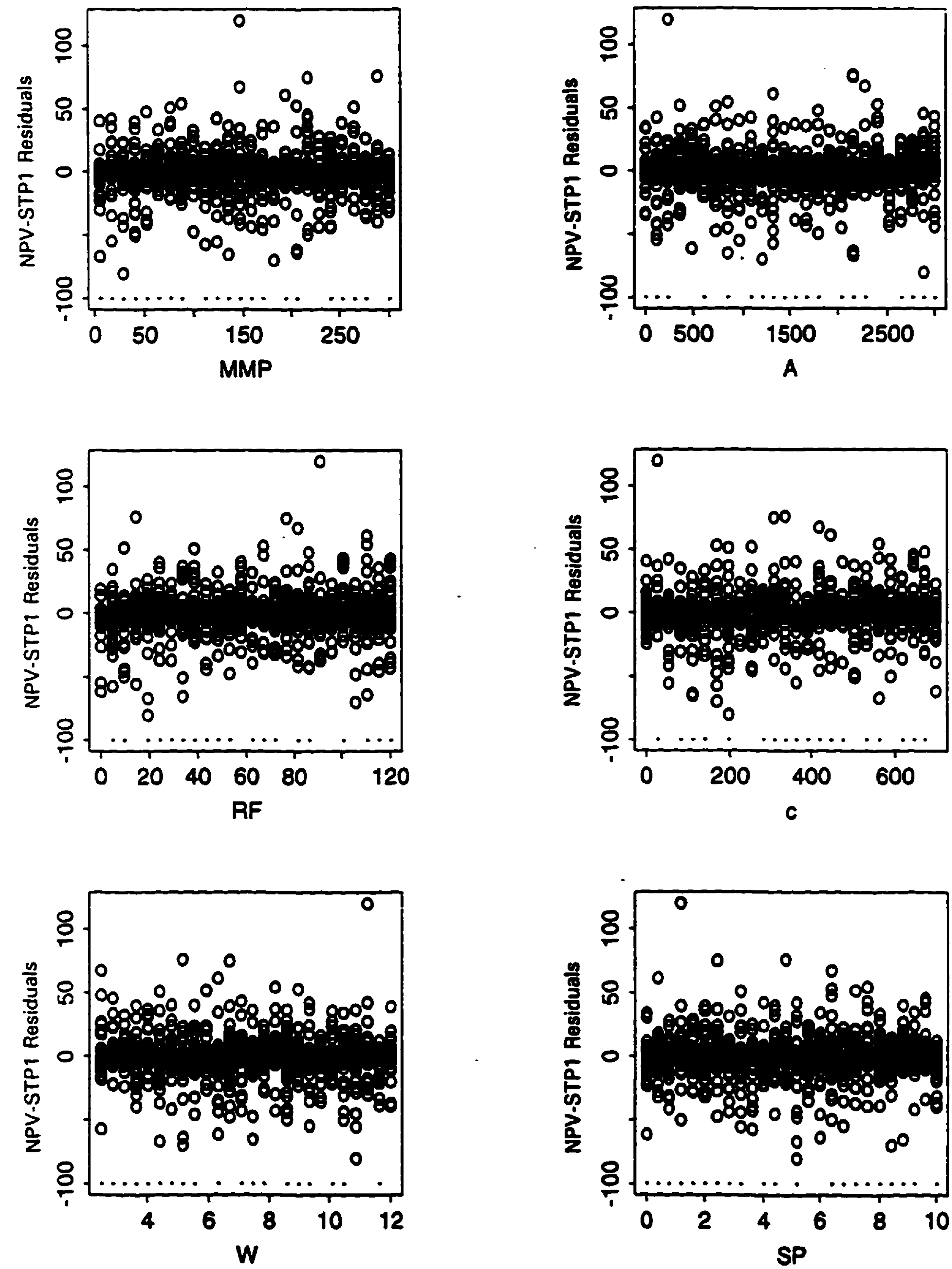


FIGURE 6.8 ***Cross validation residuals against predictor variables: NPV (10%, STP1, ADT 265)***
MMP= Rainfall, A= Altitude, RF= Rise plus fall; C= Curvature; W= Width, SP= Superelevation

As seen in Figure 6.7, the stochastic predictor is fairly acceptable, with more reliable prediction concentrated at the 0 to 60 range. The standardized residuals plot suggests that the predictor is less reliable at the low end of NPV values below zero. Furthermore, the cross validation residual plots against predictor variables (Figure 6.8 and D.1 (in Appendix D)) all suggest the stochastic predictor to be a well behaved model. It is noted that the trends that seem to be portrayed in the residual plots for the predictor variables *AGE1, AGE2, AGE3, ACRA, ACRW, etc.* are mainly a result of the distorted *pdfs* of the input variables (see Figure 5.2) rather than a mis-specification of the stochastic model.

In an attempt to further explore the non-linear behavior of the NPV the HDM-III output was investigated at different conditions. Two more streams of NPV values were generated at the higher traffic level of 1000 ADT. The stochastic predictors for these two NPV streams were estimated using the first 150 data points from the modified Latin hypercube design. Figure 6.9 shows the cross-validation predictions and residuals for the stochastic predictors of the NPV under strategies STP3 and STP4. As defined in Chapter 3 (Section 3.7.3), STP3 stands for medium R&M intervention level consisting of patching all potholes annually and overlaying the pavement once every 15 years. STP4 represents high intervention level consisting of patching, six yearly resealing and 50 mm AC overlaying when roughness exceeds 5.5 m/km IRI.

The performance of the stochastic predictor for NPV-STP3 is relatively better than NPV-STP4 (Figure 6.9). There seems to be a better agreement between the actual NPV values and those predicted by the stochastic model in this case than for the Figure 6.7. It is worth pointing out that the Figure 6.9 predictors are based on only 150 data points while the predictor of Figure 6.7 was based on 350 data points.

In overall, the NPV stochastic predictors are acceptable but relatively poorer than those presented later for the component life-cycle costs.

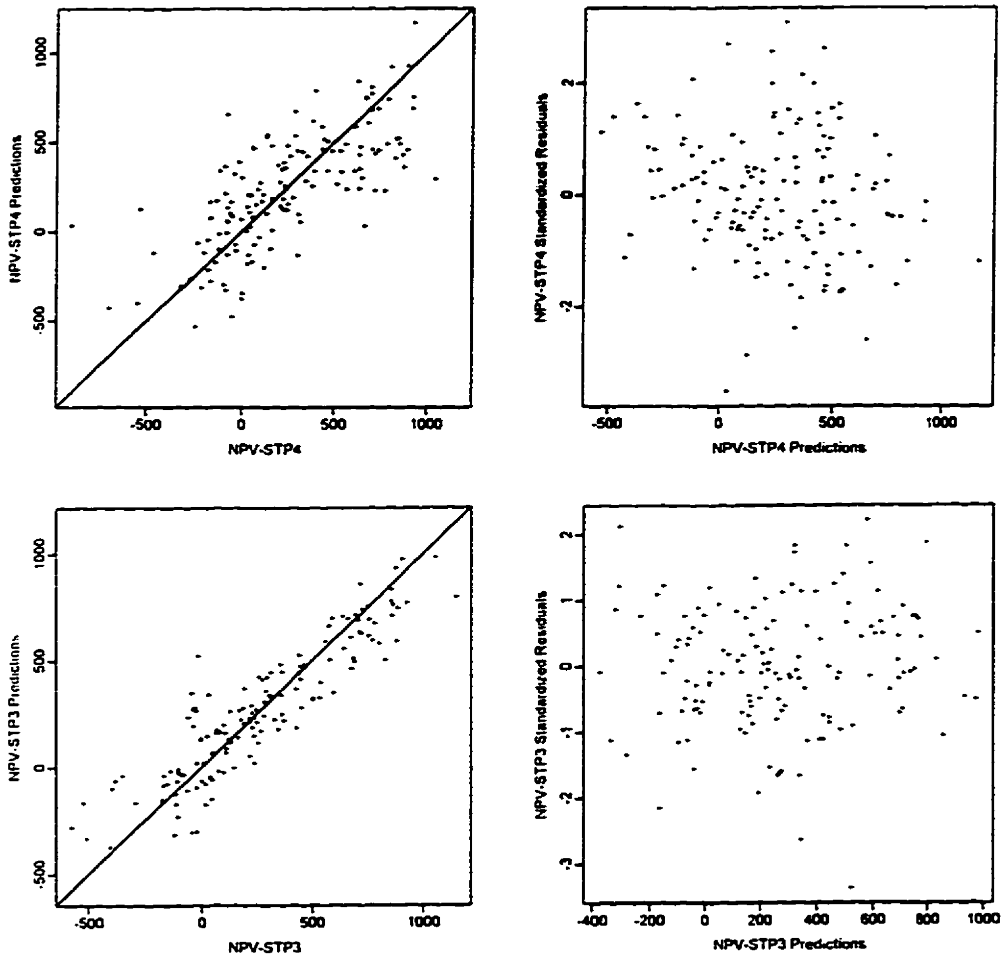


FIGURE 6.9 ***Cross validation predictions and residuals: NPV at 10%, ADT 1000***

6.3.3.2 Estimated Factor Effects on the NPV Output

Having assessed the fidelity of the statistical model, and demonstrating that the best linear unbiased stochastic predictor (BLUP) reasonably predicts the HDM-III output, the BLUP predictor can now be used to estimate the factor sensitivities. The computation method was discussed in detail in Subsection 5.7.2. The basic procedure is to "integrate out over all the other inputs" from the BLUP predictor as shown by Equations (5.39) and (5.40).

The analysis found that the NPV output for "patch only" strategy (STP1) is sensitive to two input factors: the road roughness (*QI*), and the pavement strength parameters (*DEF* and *SN* as a group). The main effect of roughness accounts for 24.7% of all the variability in the NPV output, while the strength parameters' main effects accounts for about 11%. The factor interaction between roughness and strength parameters dominate the NPV output with over 52% share of the variability.

To understand the behavior of the significant factors in the model output the main effects, $\mu_j(x_j)$ are plotted against, x_j for the predictor variables estimated to have important effects on the output. Figure 6.10 plots the main effects of roughness on the NPV criterion. The figure shows that the NPV output is highly nonlinear with respect to roughness input. Confining our view to only the 25% of the variability contributed by roughness, we see the effect of *QI* on NPV is very high at low levels of roughness up to about 5.5 m/km IRI beyond which a unit change in roughness has far less impact upon the NPV. It is interesting to note in Figure 6.10 that the roughness effect on NPV reaches a maximum at about 9 m/km IRI beyond which a further increase in roughness seems to lower the predicted NPV.

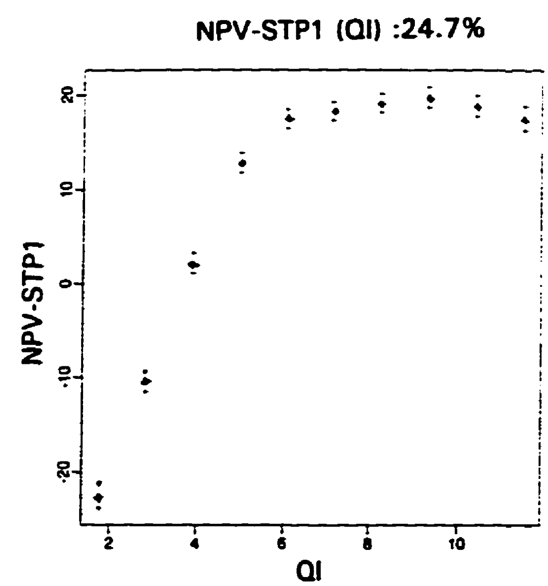


FIGURE 6.10 The main effects of the NPV at 10%, ADT 265 for the strategy STP1

It should be pointed out that visualization of both the main effects of the strength parameters and the interaction effect of strength parameters and roughness can not be computed from the same modified Latin hypercube design since the factor grouping (used to adjust the original design for factor dependencies) interferes with such computation. In other words, as far as the "constrained" factors are concerned, only the main effect for the group as a unit can be estimated. A separate design for the group factors would be required to determine the individual contribution of each factor in the group. In our case this applied to five groups of "constrained" factors in the Latin hypercube design for link characterization shown in Table 6.8. The term "constrained" is used to emphasize the fact that the factors could not be allowed to vary completely independent of each other in the experimental design.

TABLE 6.8 "Constrained" Factors in the Modified Latin Hypercube Design

Group Number	Group Reference	Variables in the Group	
1	Pavement strength parameters	*SN*	Structural number
		DEF	Benkelman deflection
2	Pavement distress parameters	*ACRA*	Area of all cracks (%)
		ACRW	Area of wide cracks (%)
		ARAV	Area raveled (%)
		APOT	Area of potholes (%)
3	Pavement deformation parameters	*RDM*	Mean rut depth (mm)
		RDS	Standard deviation of rut depth (mm)
4	Pavement history parameters	*AGE1*	Age of preventive treatment (years)
		AGE2	Age from last resurfacing (years)
		AGE3	Age from last pavement construction
5	Previous distress parameters	*ACRAb*	Previous area of all cracks (%)
		ACRWb	Previous area of wide cracks (%)

From the stochastic predictors for the two NPV streams at 1000 ADT the main effects were estimated as shown in Table 6.9. The table shows the ANOVA percentage contribution for the most active factors. It is seen from the table that the NPV for strategy STP3 is dominated by the rutting calibration factor, *Krp* (35%), the pavement strength parameters (*SN, DEF*) (14.5%), the carriageway width, *W* (7%), and the initial distress level (*ACRA, ACRW, APOT* and *ARAV*). These first four ranking significant factors account for close to two thirds of the total variability in the NPV for STP3.

The top four significant rankings in the NPV consist of the same factors for both strategies STP3 and SPT4. However, the magnitudes of the factor effects of these top active factors differ significantly from one strategy to the other. While the contribution of the *Krp* factor to the NPV is more than twice that of the group 1 factors (*SN* and *DEF*) for the strategy STP3, the effects are almost equal for the NPV under strategy STP4 (Table 6.9). Table 6.9 also shows that under STP4, the NPV is relatively sensitive to *Kge*, altitude (*A*), base layer thickness (*HBASE*) and shoulder width (*WS*). These factors are less active in the NPV under strategy STP3.

TABLE 6.9 ANOVA Contribution: Active Factors in NPV (10%, ADT 1000)

NPV-STP3		NPV-STP4	
Factor	**ANOVA %**	**Factor**	**ANOVA %**
Krp	34.822	*Group1* (SN, DEF)	16.861
Group1 (SN, DEF)	14.564	*Krp*	15.979
W	7.195	*Group2* (ACRA, ACRW, APOT, ARAV)	11.020
Group2 (ACRA, ACRW, APOT, ARAV)	6.448	*W*	10.758
Group3 (RDM, RDS)	5.419	*Kge*	7.995
Group4 (AGE1, AGE2, AGE3)	4.826	*A*	5.440
Group1 × Group5	2.755	*Group3* (RDM, RDS)	4.405
Group1 × Krp	2.176	*HBASE*	3.575
RF	2.127	*WS*	1.739
Kcp	1.928	*W × Kci*	1.680
Group1 × Kge	1.477	*Group1 × QI*	1.436
QI	1.291	*QI*	1.412
Group1 × QI	1.284	*Group1 × Kge*	1.356
Kci	1.176	*Kci*	1.271
W × Kci	0.936	*SNSG*	1.163
Kge	0.915	*Kci × QI*	1.097
Group1 × Group3	0.874	*Kci × Kge*	1.031
Kci × QI	0.583	*Kge × QI*	0.990
Total	*90.796*	*Total*	*89.208*

Notes: A × B stands for the interaction between factors A and B. Symbols according to the Glossary. Group factors see Table 6.8

Figure 6.11 shows the main effects of the active factors for the NPV under STP3. As mentioned before, the main effects of the "constrained" factors could not be plotted; they require an independent design to isolate them. It is interesting to note from Figure 6.11 that the most active factor – the rutting calibration factor (*Krp*) – has a negative main effect that seems to be linear over the range investigated. This phenomenon will be discussed further in Section 6.4. The main effect of the carriageway width upon the NPV for strategy STP3 is also negative, but non-linear. This is logical since the increased agency costs of R&M treatments resulting from widening a pavement may not be offset by the savings in VOCs arising from increased travel speeds.

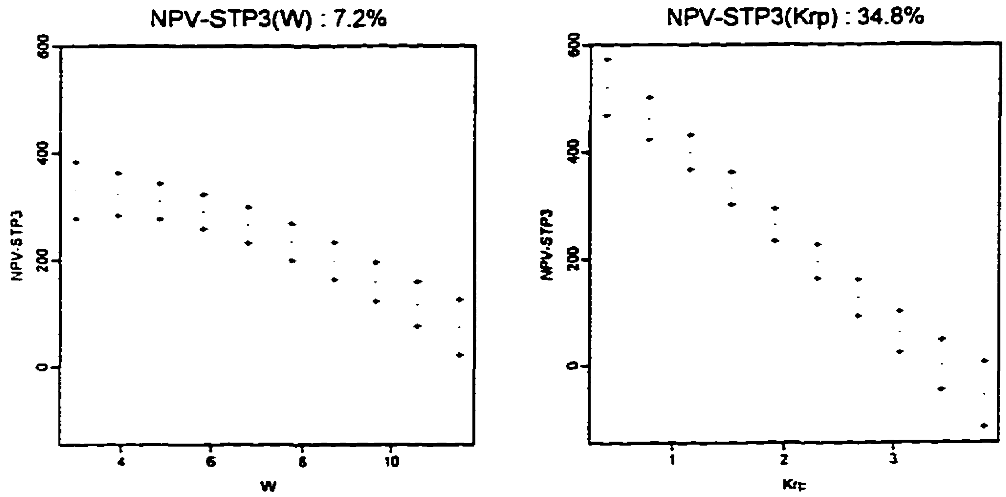


FIGURE 6.11 ***The main factor effects of NPV for strategy STP3 (ADT 1000)***

Figure 6.12 plots the main effects of the five "unconstrained" active factors for NPV under strategy STP4. The estimated factor effects of the NPV for strategy STP4 should be treated with caution given the low performance of the stochastic predictor in reproducing the HDM-III predictions. Notice the wide error margin in Figure 6.12.

An important general conclusion from analyzing the stochastic predictors for the NPV outputs is that the factor effects are highly non-linear. The magnitude of the individual factor effects as well as their shape seems to vary with the R&M treatment strategy used.

Comparing the factor effects at different traffic levels, it is noted that the strength parameters (*SN, DEF*) remain sensitive to the NPV predictions throughout the traffic levels. However, at the low traffic (ADT 265) the effect of the (*SN, DEF*) factors seems to be higher than at higher traffic. Also, it is interesting to note that at this low traffic the interaction of the strength factors (*SN, DEF*) and the roughness (*QI*) dominates the NPV (52%). Such interaction is insignificant at higher traffic.

6.3.3.3 Diagnosis of the Stochastic Predictor for Life-Cycle Costs

Figure 6.13 shows the cross validation predictions plotted against the actual HDM-III model outputs for the four response variables: agency and users' life-cycle costs for treatment strategies STP2 and STP4. The stochastic predictor and the actual HDM-III outputs for RM-STP2, VOC-STP2 and VOC-STP4 agree very closely. The prediction for RM-STP4 is not as good, but is very reasonable given the large sample size used employed (350 data points).

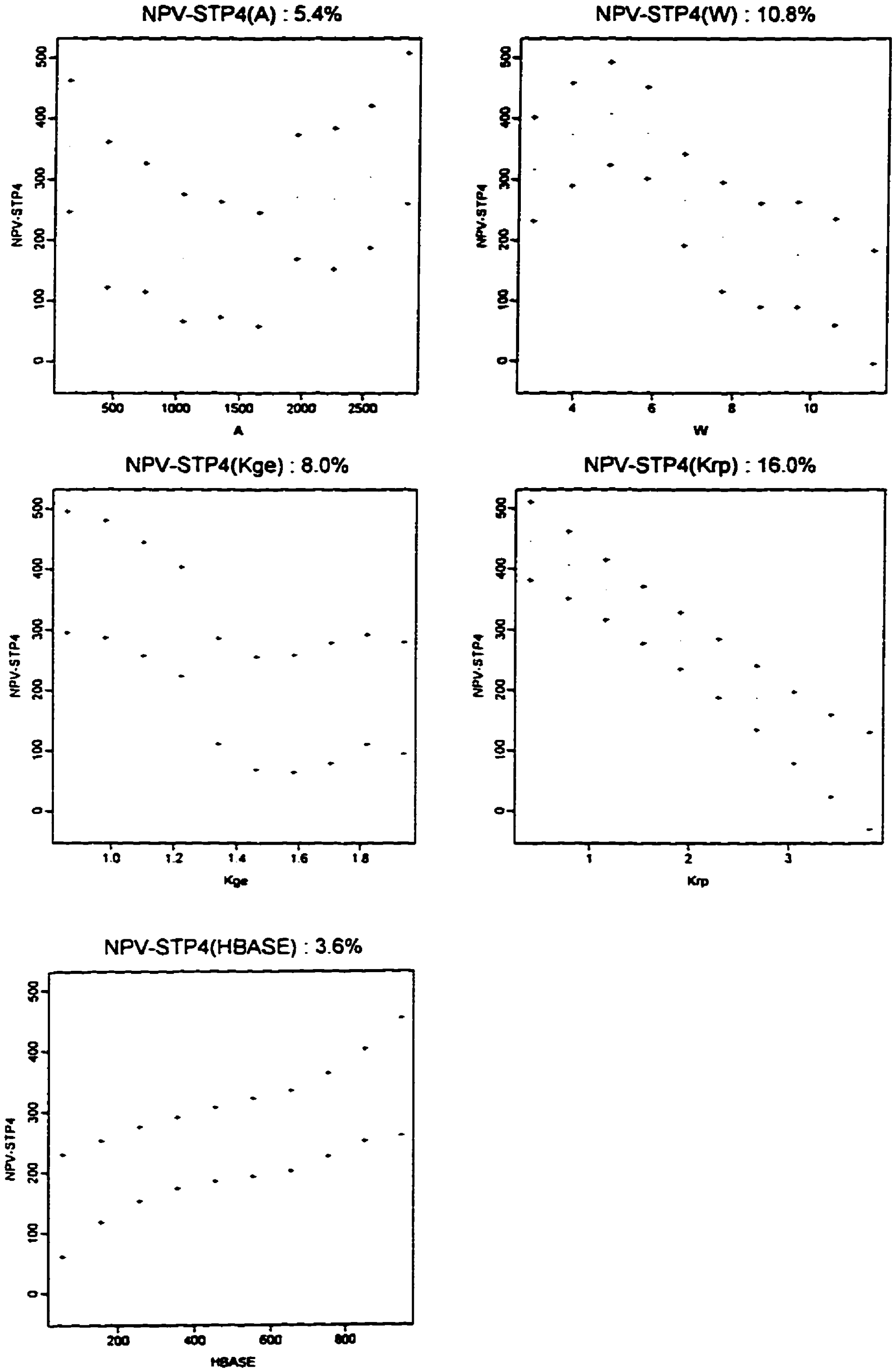
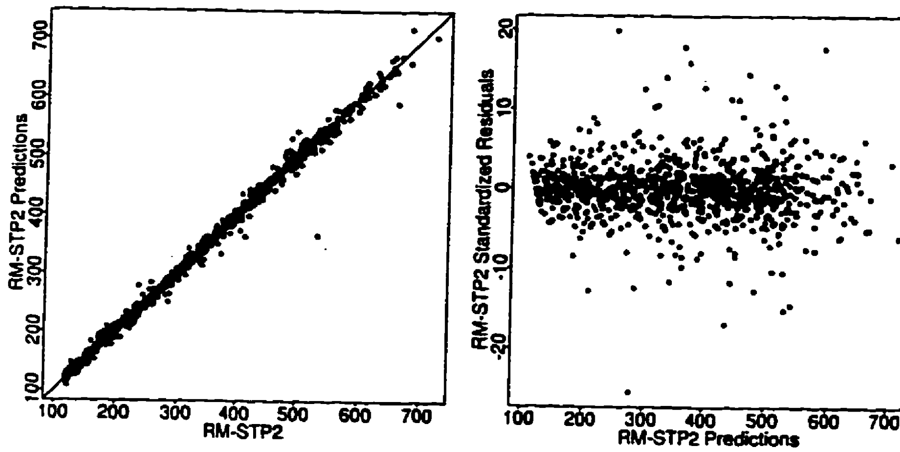
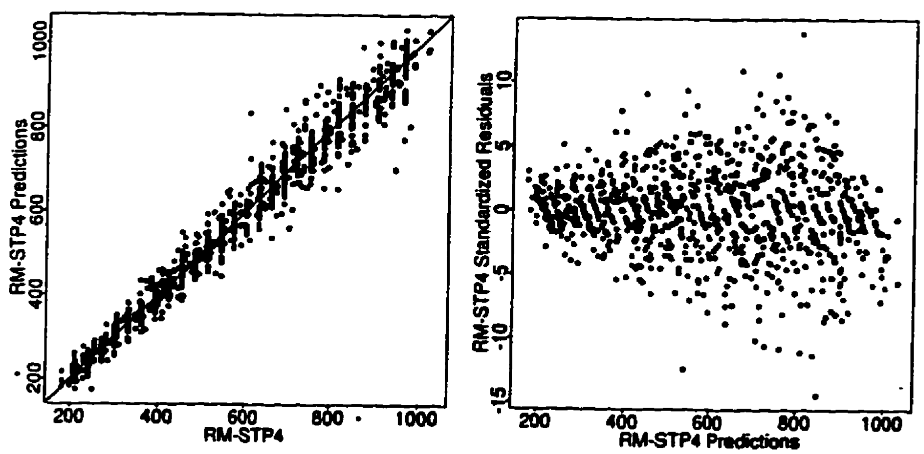


FIGURE 6.12 ***The main factor effects of NPV for strategy STP4 (ADT 1000)***

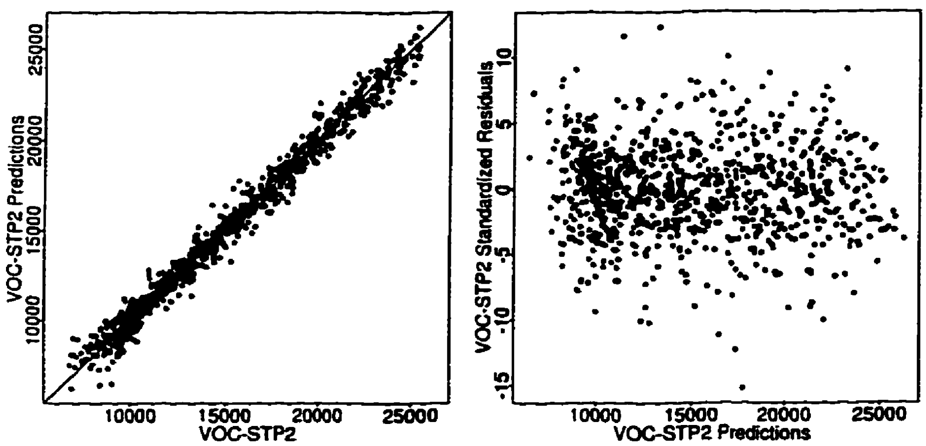


(a) Agency (R&M) life-cycle costs output for patch all, and reseal every 6 years strategy (STP2)

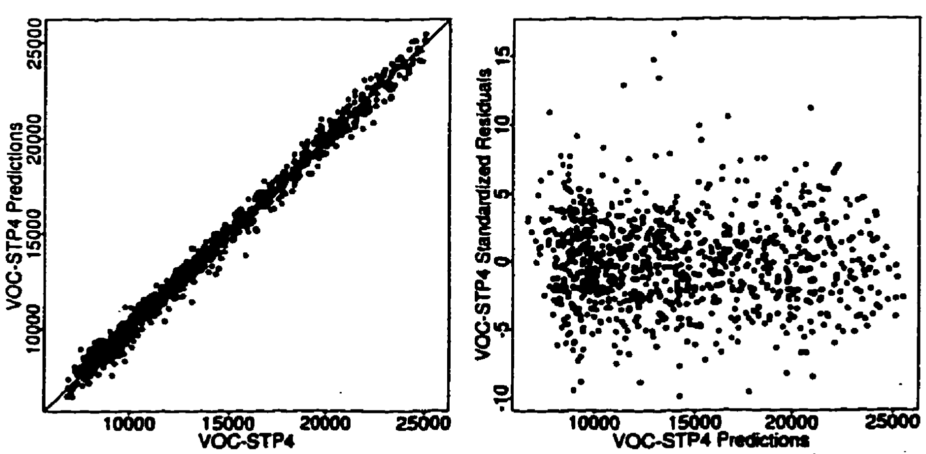


(b) Agency (R&M) life-cycle costs output for patch all, reseal every 6 years and overlay at 5.5 IRI strategy (STP4)

FIGURE 6.13 Cross validation predictions and residuals for life-cycle costs (ADT 500)



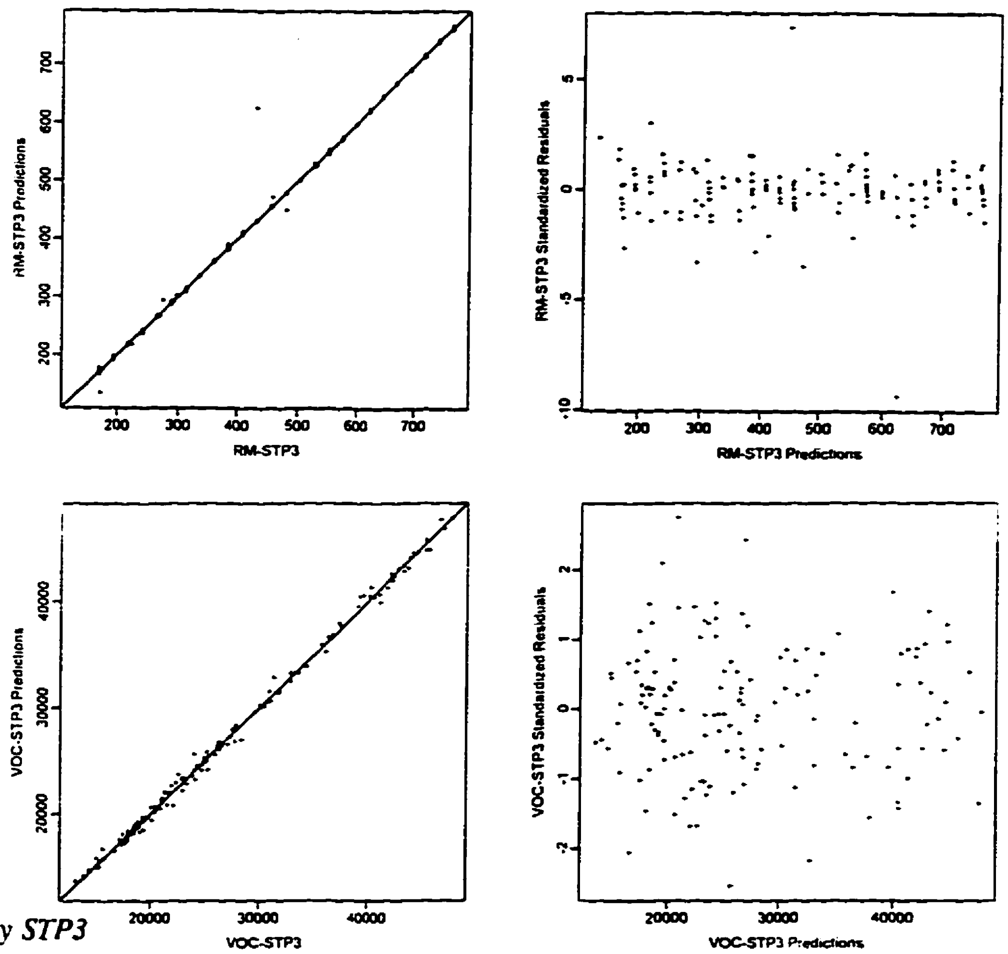
(c) Users' (VOC) life-cycle costs output for patch all and reseal every 6 years strategy (STP2)



(d) Users' (VOC) life-cycle costs output for patch all, reseal every 6 years and overlay at 5.5 IRI strategy (STP4)

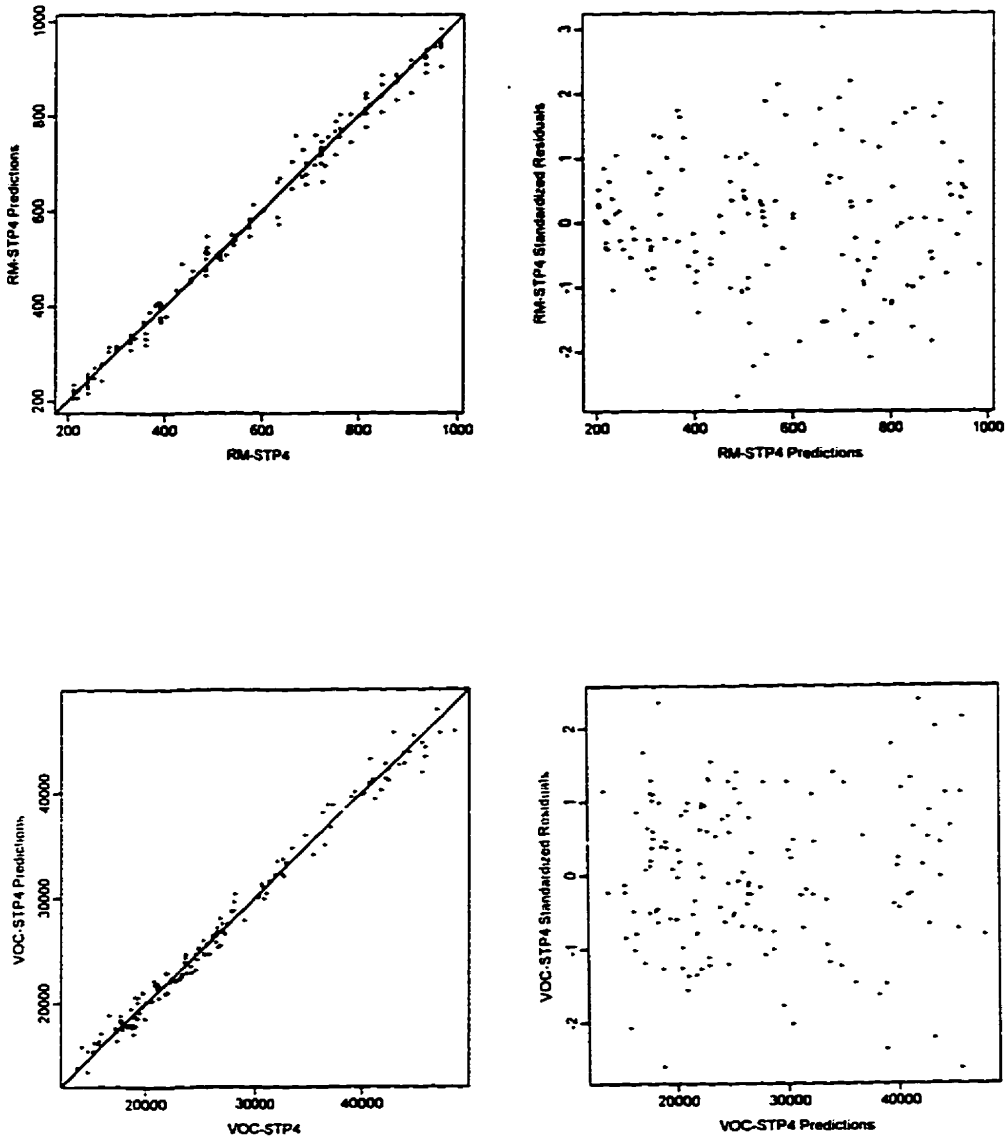
FIGURE 6.13 Cross validation predictions and residuals for life-cycle costs (ADT 500)

Four more response variables generated at ADT 1000 were modeled using the stochastic approach. The agency and users' life-cycle costs under the R&M strategies STP3 and STP4 were investigated. Due to computational effort constraint, the stochastic predictors for these latter response variables were built on 150 data points only. The diagnosis of the performance of the stochastic models is summarized by Figure 6.14. The figure shows plots of cross-validation predictions and residuals for component life-cycle costs under strategies STP3 and STP4 at the traffic of 1000 ADT. From the figure we see the stochastic models are almost perfect predictors of the HDM-III outputs. Consequently, the main effects estimated from these predictors should be much more reliable than those for NPV predictions. Figure D.2 in Appendix D shows cross-validation residuals plotted against the predictor (input) variables for the VOC life-cycle costs under strategy STP4 at ADT 1000. The residuals in this case are also well behaved. Again, the trends that seem to be evident in the residuals for the "constrained" variables is explained by the distorted plots of these variables in the design data (see Figure 5.2 and Section 5.5.2).



(a) Strategy STP3

FIGURE 6.14 Cross validation predictions and residuals for the life-cycle costs (ADT 1000)



(b) Strategy STP4

FIGURE 6.14 **Cross validation predictions and residuals for the life-cycle costs (ADT 1000)**

6.3.3.4 Life-Cycle Costs Sensitivity Results from the Stochastic Approach

Table 6.10 presents a summary of the factor effects upon the life-cycle costs output at ADT 500 as estimated from the stochastic approach. Several factors were found to be important in the predicted agency life-cycle costs. The carriageway width dominates the LCC-R&M predictions accounting for over 94% of the variability for both R&M strategies. For strategy STP4 the pavement roughness (*QI*) at the first year of analysis, rutting calibration factor (*Krp*), the pavement construction and treatment history (*AGE1*, *AGE2* and *AGE3*) and the roughness calibration factors (*Kge, Kgp*) play important roles in agency life-cycle prediction. On the other hand, the next most active factors in LCC-R&M for strategy STP2 are the cracking calibration factors (*Kci*, *Kcp*), and the pavement distress levels at the first year of analysis (*ACRA*, *ACRW*, *APOT*, *ARAV*).

TABLE 6.10 ANOVA Contributions: Active Factors in Life-Cycle Costs (ADT 500)

(A) Agency Life-Cycle Costs

Strategy STP2		Strategy STP4	
Factor	**ANOVA (%)**	**Factor**	**ANOVA (%)**
W	94.33	*W*	96.52
Kci	3.07	*QI*	0.64
Group2 (ACRA, ACRW, APOT, ARAV)	1.09	*Krp*	0.33
W× Kci	0.49	*Group4 (AGE1, AGE2, AGE3)*	0.20
Kci× Kcp	0.37	*W× Group4*	0.17
Kcp	0.20	*Krp× QI*	0.15
W× Group2	0.19	*Kge*	0.15
W× Kcp	0.03	*W× Kci*	0.15
HSOLD × Kci	0.02	*Kci*	0.10
Kci × CQ	0.02	*W× Group1 (SN, DEF)*	0.09
Kci × Group2	0.02	*W× Kgp*	0.08
Total	*99.83*	*Total*	*98.58*

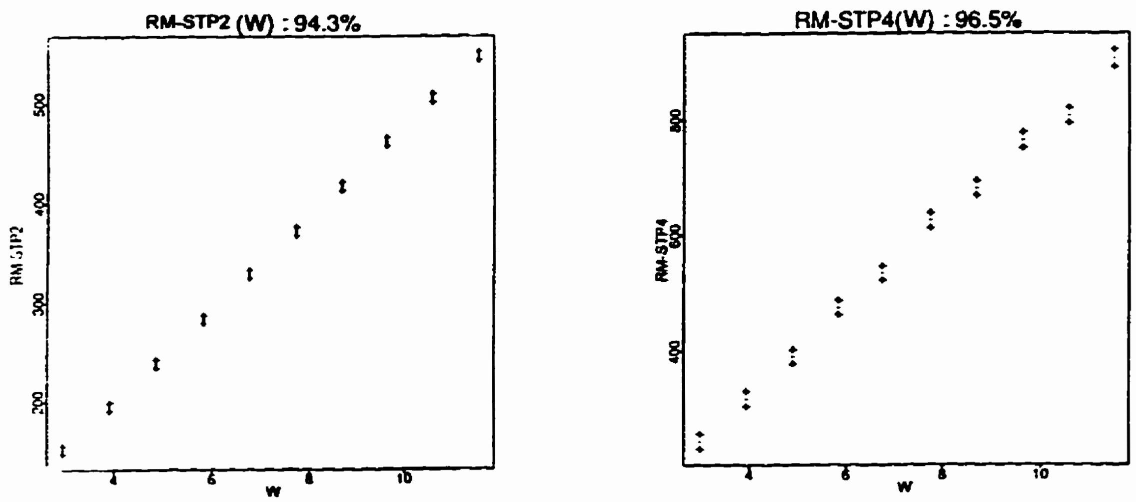
(B) Users' Life-Cycle Costs

Strategy STP2		Strategy STP4	
Factor	**ANOVA (%)**	**Factor**	**ANOVA (%)**
RF	95.73	*RF*	95.88
QI	1.40	*Krp*	1.98
Group1 (SN, DEF)	0.87	*Group1 (SN, DEF)*	0.45
Group1 × QI	0.30	*QI*	0.37
C	0.25	*Group3 (RDM, RDS)*	0.23
Group2 (ACRA, ACRW, APOT, ARAV)	0.17	*C*	0.20
Kci	0.15	*Kge*	0.19
Kci × QI	0.09	*Kci*	0.06
Krp	0.09	*Kcp*	0.05
Kge	0.08	*Group1 × Krp*	0.05
RF × C	0.06	*Krp × QI*	0.04
Total	99.19	*Total*	99.50

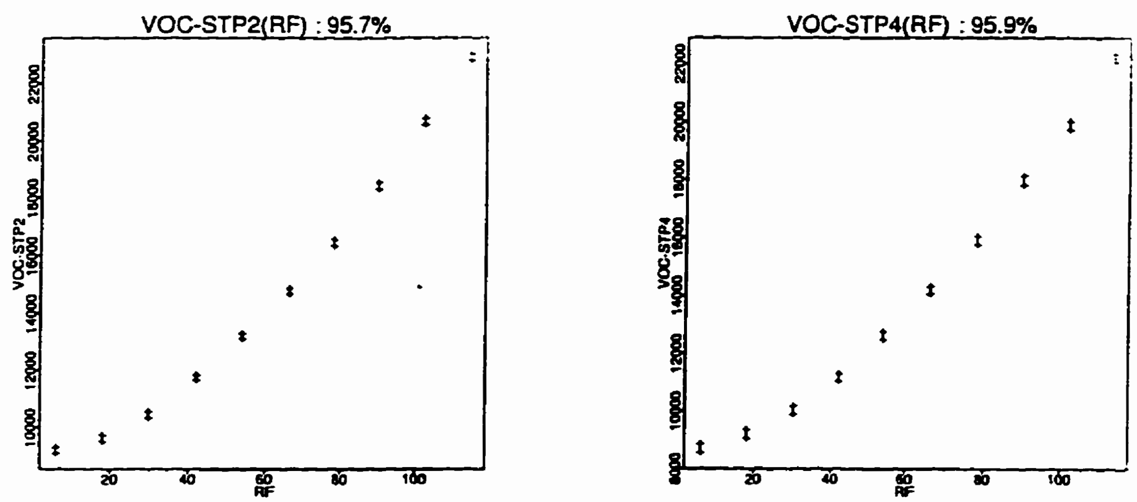
Notes: A × B stands for the interaction between factors A and B. Symbols according to the Glossary. Group factors see Table 6.8

Figure 6.15 shows the behavior of the main factor effects for life-cycle costs under two maintenance and rehabilitation strategies (STP2 and STP4). In Figure 15 (a), for example, the plot labeled RM-STP2(*W*) shows the estimated effect of carriageway width on the agency life-cycle costs for strategy STP2. The percentage assigned to each plot label is the ANOVA contribution of the factor in the overall variability of the response. Thus, Figure 15 (a) indicates that of the total variability in agency life-cycle costs (for strategy STP2) resulting from varying all the 39 link characterization inputs over the ranges investigated carriageway width accounts for 94.3%.

As seen in Figure 15 (a) the carriageway width effect is uniform over the entire range of investigation. The figure shows that the role of the rise plus fall factor (*RF*) in the life-cycle VOCs increases slightly at higher magnitudes of *RF*. This phenomenon is consistent with the underlying model construct; further elaboration is given in Section 6.4.



... Agency life-cycle costs strategy STP2 *(b) Agency life-cycle costs for strategy STP4*



(c) Users' life-cycle costs for strategy STP2 *(d) Users' life-cycle costs for strategy STP4*

FIGURE 6.15 Main factor effects for life-cycle costs (ADT 500)

Table 6.11 shows the factor sensitivities obtained from the analysis of the stochastic predictor for the life-cycle component costs at ADT 1000. Part (a) of the table presents the ANOVA contributions of the most active factors in the agency life-cycle costs under the two strategies STP3 and STP4. Part

(b) of the table shows the corresponding factor effects for users' life-cycle costs. The table shows that, similar to the life-cycle costs at ADT 500, the first four significant factor rankings account for close to 99% of the total variability in the life-cycle costs. Notice in this case the first five rankings of active factors for VOCs consist of exactly the same factors (*RF, Krp, SN, DEF, QI* and *C*) in the same order for both strategies STP3 and STP4. Further, unlike the case for ADT 500, the pavement construction and treatment history (*AGE1, AGE2, AGE3*) rank second in the agency life-cycle costs for ADT 1000.

TABLE 6.11 ANOVA Contributions: Active Factors in Life-Cycle Costs (ADT 1000)

A) Life-Cycle Agency Costs				*B) Life-Cycle Vehicle Operating Costs*			
RM-STP3		**RM-STP4**		**VOC-STP3**		**VOC-STP4**	
Factor	**ANOVA %**	**Factor**	**ANOVA %**	**Factor**	**ANOVA %**	**Factor**	**ANOVA %**
W	98.810	*W*	97.410	*RF*	95.736	*RF*	95.959
Group4	0.940	*Group4*	0.485	*Krp*	1.378	*Krp*	1.327
W × Group4	0.223	*W× SP*	0.239	*Group1*	1.114	*Group1*	0.720
Kvi× Group4	0.008	*Kge*	0.208	*QI*	0.336	*QI*	0.493
HBASE× Group4	0.006	*W× Group4*	0.179	*C*	0.220	*C*	0.429
Kvi	0.005	*Group1*	0.150	*Group1× Krp*	0.164	*Group3*	0.143
W.Kvi	0.002	*Kci*	0.150	*Group3*	0.097	*RF× Group5*	0.086
HBASE× Kvi	0.001	*Krp*	0.116	*RF× Group5*	0.096	*RF× Group1*	0.083
Group1	0.001	*SP*	0.105	*Kgp*	0.083	*Group2*	0.073
W × Group1	0.001	*Krp× QI*	0.088	*RF× Group1*	0.083	*Group5*	0.046
HBASE	0.001	*QI*	0.079	*RF× Krp*	0.069	*RF× C*	0.043
W × HBASE	0.001	*W× Kci*	0.076	*Kci*	0.069		
Total	99.999	Total	99.209	Total	99.445	Total	99.402

Notes: A × B stands for the interaction between factors A and B. Symbols according to the Glossary. Group factors see Table 6.8. Strategies as defined in Table 3.7.

Figure 6.16 plots the main effects of the most sensitive factor for the life-cycle components for the traffic level of 1000 ADT. Again, as for ADT 500, the figure shows that the effect of the carriageway width upon the agency life-cycle costs is approximately linear and positive in the range investigated. On the other hand the rise plus fall effect on the life-cycle VOCs is positive parabolic; the *RF* factor effect increases slightly at higher values of *RF*.

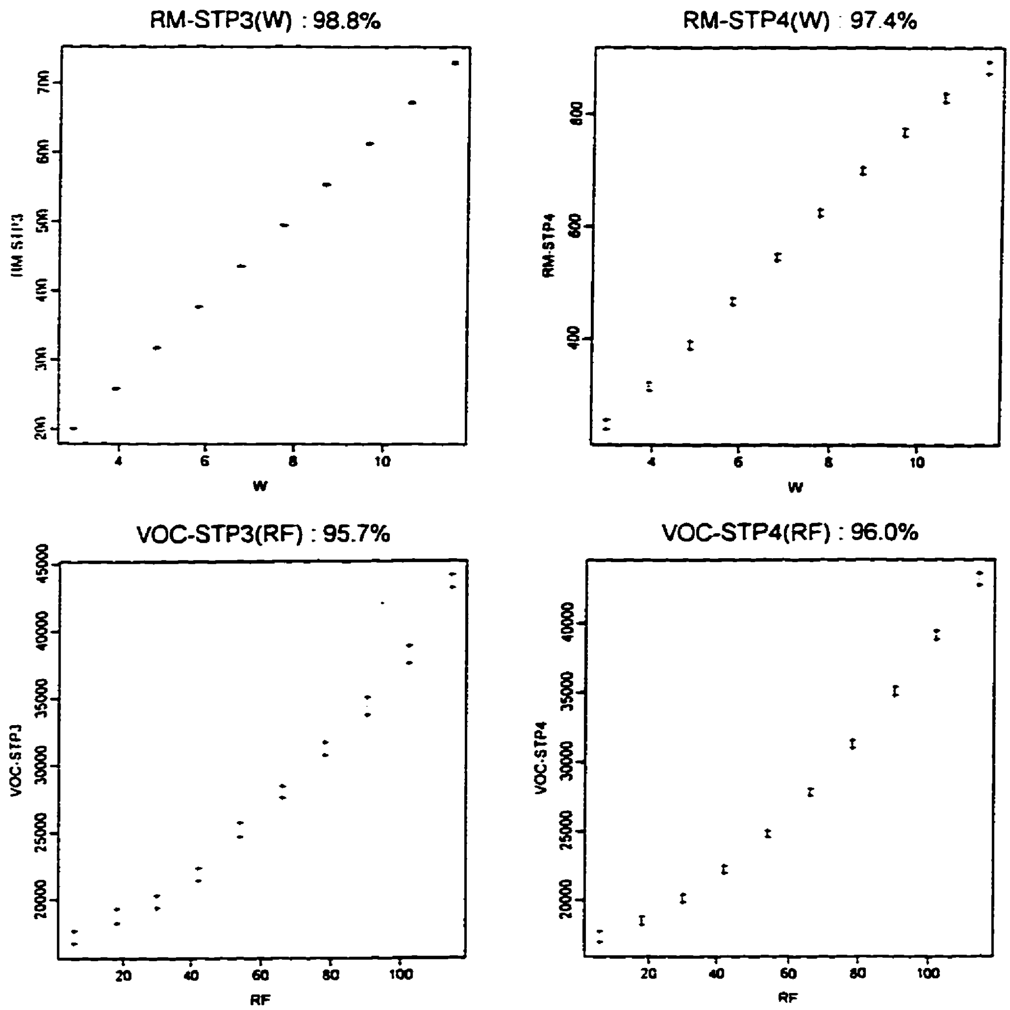


FIGURE 6.16 Main factor effects of life-cycle costs (ADT 1000)

6.4 Discussion of the Results

6.4.1 Behavior of the Agency and Users' Components of Total Life-Cycle Costs

The results presented in this chapter show that the NPV is highly non-linear with respect to sensitive input factors. The NPV prediction is also subject to high factor interactions. Further, it was shown that the rankings of sensitive factors changes slightly with the R&M strategy used.

The most interesting research finding with respect to the component life-cycle costs predicted by HDM-III is that both the agency and users' life-cycle components were shown to be dominated by relatively few factors, some of them not directly influenced by R&M treatments. The agency life-cycle costs component was found to be highly sensitive to the carriageway width. More than 96% of the total variability of the agency life-cycle costs over the input space investigated is explained by the width factor. This makes sense since the quantity of rehabilitation work is a product of the pavement width and the number of lane kilometers to be repaired. It follows, therefore, that unit costs of R&M operations would have the same sensitivity to the agency life-cycle costs. What was not obvious, before this study, is the relative weight of the sensitivity of the width (and unit costs) factor compared to other input factors.

Below this dominant factor in agency life-cycle costs (*i.e.*, of the remaining less than 6% variability) the next active factors vary according to the R&M strategy. For the common R&M treatments investigated, the agency life-cycle cost predictions are next most sensitive to the pavement construction and treatment history (*AGE1, AGE2, AGE3*), roughness and surface distress levels (*QI, ACRA, ACRW, APOT, ARAV*) at first year of analysis period, rutting calibration factor (*Krp*), the cracking calibration factors (*Kci, Kcp*) and the roughness calibration factors (*Kge, Kgp*).

The users' (VOC) life-cycle cost component was found to be dominated by the rise plus fall (*RF*) variable. This is expected given the significant role of road gradient (*RF*) in heavy vehicles fuel and tire costs (see Section 6.4.2). More than 95% of the total variability on VOC life-cycle costs is explained by the *RF* factor. Similar to the pattern in agency life-cycle costs, the remaining (less than 5%) variability is explained by different factors for different R&M strategies. In this case, the pool of active factors consist of mainly the same factors although the factor rankings were shown to vary from one R&M strategy to the next. The most active factors (after *RF*) for VOCs prediction were found to be the rutting calibration factor (*Krp*) the initial pavement strength (*SN, DEF*), the pavement roughness (*QI*) and the surface distress levels (*ACRA, ACRW, APOT, ARAV*) at the beginning year of analysis and the horizontal curvature (*C*). The mean and standard deviation of rut depth were also shown to be sensitive to both agency and users' components of the NPV.

The observed factor sensitivities for asphalt concrete on granular base were found relatively comparable to those obtained for surface dressing on soil cement pavements.

Having looked at the behavior of the key life-cycle cost components (agency and users') the question now is does this new understanding about the key components contribute to explaining the behavior of the total life-cycle costs savings – the NPV?

6.4.2 Behavior of the NPV Predictions from the HDM-III Model

The net present value (NPV) calculated by the HDM-III model was defined by Equations (4.8) and (4.9) in Chapter 4. The NPV represents the net saving of total life-cycle costs of a given strategy over a "do minimum" alternative. In simplified analyses where effects of generated traffic, travel time savings and exogenous costs and benefits are not considered Equation (4.8) simplifies to:

$$\Delta NB_{ky(m-n)} = \Delta VOC_{ky(m-n)} - \Delta RM_{ky(m-n)} \qquad \text{...(6.4)}$$

where, $\Delta NB_{ky(m-n)}$ = "net life-cycle cost savings" of strategy m relative to strategy n for link k.
$\Delta VOC_{ky(m-n)}$ = VOC savings of alternative m relative to alternative n in year y for link k.
$\Delta RM_{ky(m-n)}$ = agency cost difference of alternative m relative to n in year y for link k.

Notice the opposite signs for the users' costs and agency costs components. From Equation (6.4), an alternative associated with larger VOC savings will give a larger NPV. On the other hand, an alternative with large agency cost will generate a smaller NPV. This explains why the factor effect of pavement width (W) on the NPV is negative (Table 6.5, Figures 6.11 and 6.12). The high implied agency costs associated with the construction and life-cycle maintenance of a wider road are not offset by the reduction of VOCs resulting from the associated increase in travel speeds.

From the above definition of the NPV, one fundamental gap arises when interpreting the behavior of the life-cycle cost components (agency and users') for the purpose of explaining the observed behavior of the NPV. The life-cycle cost components represent the absolute cost values for the strategy in question, whereas, the NPV represents the life-cycle cost difference between a "do minimum" strategy and the strategy in question. In other words, economic evaluation of R&M programs is concerned more with cost differentials than the absolute life-cycle costs. Furthermore, in such analyses (where new constructions or capacity expansions are not being considered) the comparison "do minimum" versus the strategy in question is over the same existing alignment, therefore the alignment attributes, *e.g.*, rise plus fall (*RF*), curvature (*C*), *etc.*, remain unchanged.

Bearing in mind the above definition of the NPV, and the focus in a network level analysis on cost differentials rather than the absolute life-cycle costs, the observed behavior of factor effects on the NPV prediction can now be explained.

The ranking of factor effects on NPV found in the study (Tables 6.5 and 6.9) appears at a first glance to bear no relationship with the factor effects for the component agency and users' life-cycle costs. However, on a closer look, the factor sensitivity findings for the component agency and users' life-cycle costs (Tables 6.6, 6.7, 6.10 and 6.11) translate very well in explaining the observed behavior of factor sensitivities for the NPV. For example, the rutting calibration, *Krp*, turns out to be the most sensitive factor in the NPV – as expected since it is the second most active factor in VOCs after the rise plus fall. It is worth recalling that although the *RF* factor was most significant in the VOCs predictions, the costs tradeoff between a given strategy and the "do minimum" strategy is over the same alignment (fixed *RF*), hence the reduced sensitivity in the NPV predictions.

Another example is the ranking of the strength parameters (*SN, DEF*) in the predicted NPV. It is noted that these factors are highly sensitive to both the agency and users' life-cycle costs. Notice also how well the positions of the carriageway width (*W*), the initial pavement distress level (*ACRA, ACRW, APOT, ARAV*), the rutting factors (*RDM, RDS*) and the pavement construction and treatment history (*AGE1, AGE2, AGE3*) in the agency life-cycle costs translate to the rankings in the NPV.

6.4.3 Discussion of the Observed Interesting Factor Effects

The behavior of factor effects of some of the sensitive factors presented in this chapter were rather interesting; explanation of their observed effects in the NPV predictions was not obvious. Such factors include rutting calibration factor, *Krp*, (Figures 6.11 and 6.12), roughness, *QI*, (Figure 6.10), and roughness calibration factor, *Kge*, (Figure 6.12). This subsection looks further into some of these factors and explains the observed behavior.

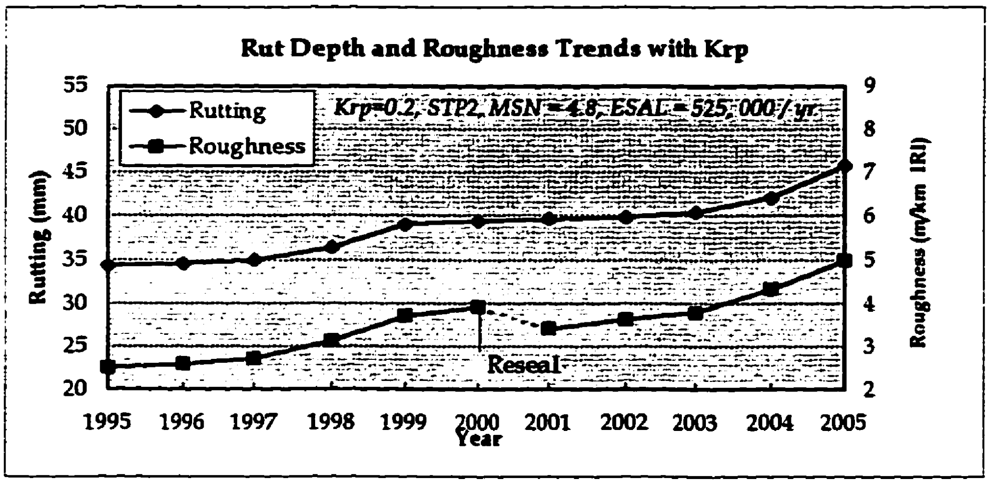
6.4.3.1 Variation of the Total Life-Cycle Costs NPV with the Rutting Calibration Factor

Figure 6.17 shows the effect of the rutting calibration factor (*Krp*) upon the rate of rutting and the resulting roughness progression for the typical road link used in the sensitivity study. At low *Krp* the rate of progression is low (Figure 6.17 (a)), changing only about 10 mm over 10 years. The age of the pavement at the start of analysis was 25 years; thus the initial rut depth of 35 mm. In Figure 6.17 (b) when *Krp* is at the high level of 3.8, the 25 years old pavement has reached a rut depth of 47 mm and progresses quickly to the maximum rut depth of 50 mm in less than a year. The effect of these deep ruts on roughness is seen as: (a) higher initial roughness, and (b) faster rate of progression (4.5 to 9 IRI in 10 years compared to 2.5 to 5 IRI in the same period).

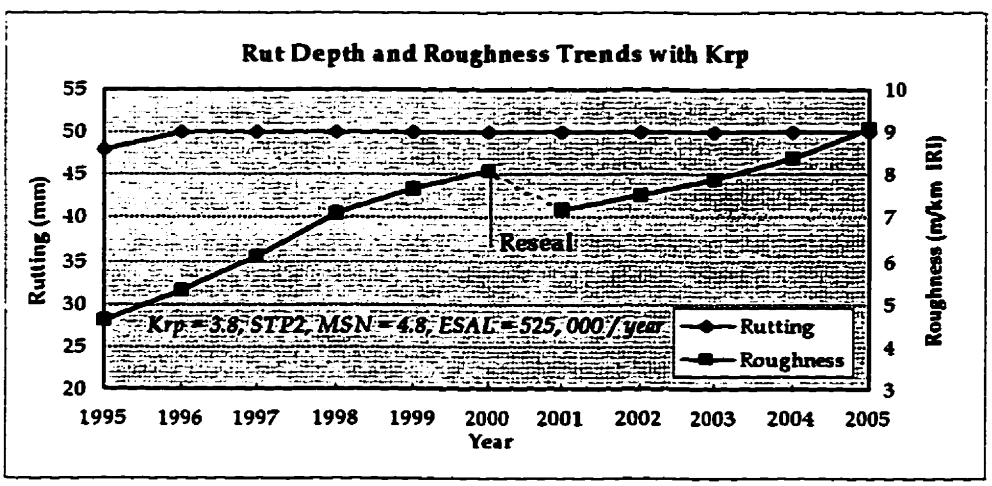
Figure 6.18 shows the implication of the performance discussed above upon the VOCs and the predicted NPV. Figure 6.18 (a) shows that the effectiveness of the high standard R&M strategies

(STP3, STP4) in reducing VOCs is lost at higher levels of *Krp* (implying higher mean roughness). VOCs for all strategies converge at *Krp* beyond 2 – 3. At low *Krp*, however, the high standard strategies are more effective in lowering VOCs than the low standard strategies (STP0, STP1).

The above phenomenon translates into the NPV behavior shown in Figure 6.18 (b). NPV, which here reflects only the VOC savings (agency costs were unchanged with *Krp*) is low at higher *Krp* since, as shown earlier VOCs for STP4 and STP0, for example, are much closer at higher roughness levels than they are at low roughness.

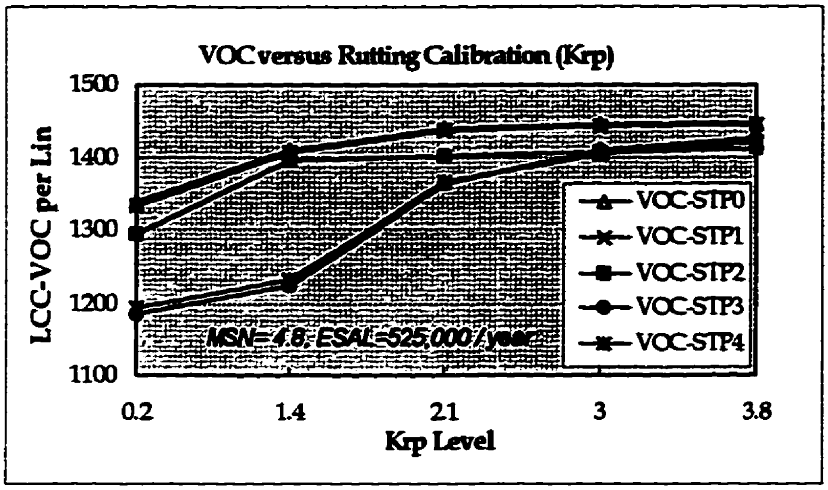


(a) *Krp = 0.2*

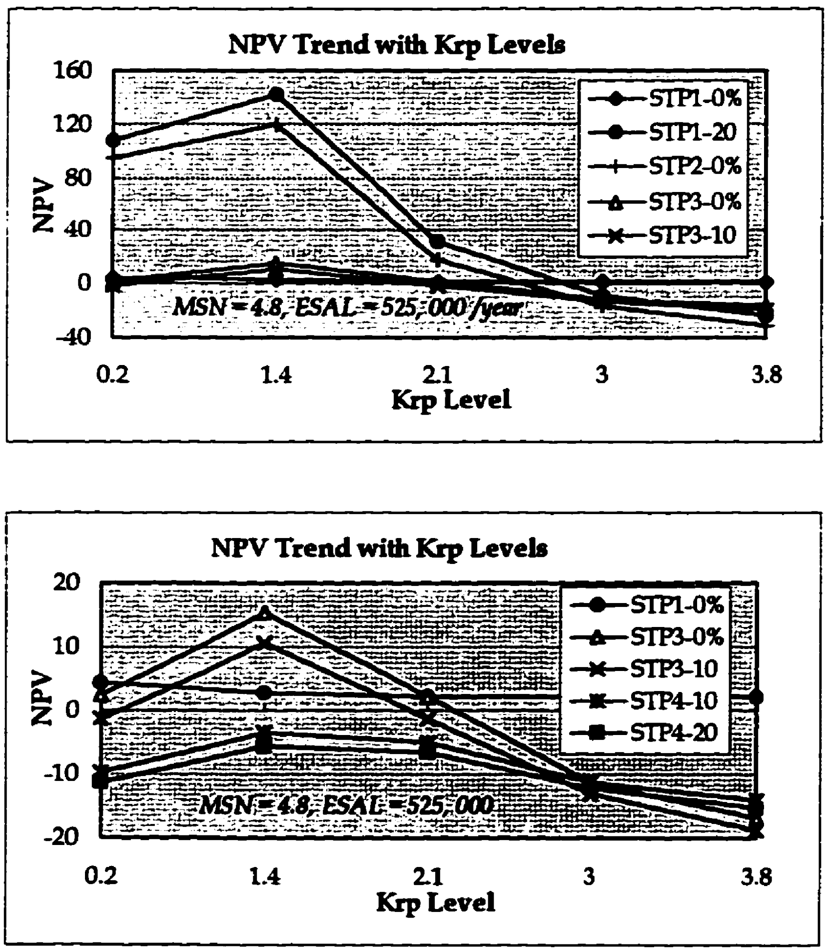


(b) *Krp=3.8*

FIGURE 6.17 Rutting and roughness performance at different Krp levels



(a) Life-cycle vehicle operating costs versus the rutting calibration factor (Krp)



(b) NPV of total life-cycle costs versus the rutting calibration factor (Krp)

FIGURE 6.18 Variation of the NPV with the rutting calibration factor (Krp)

6.4.3.2 *The Effect of Rise Plus Fall on the NPV*

The rise plus fall (*RF*) factor ranks only about 8th in the NPV predictions, however, it was found to be extremely significant in the prediction of absolute users' life-cycle costs. The behavior of this factor with respect to the VOCs predictions (Figures 6.15 and 6.16) was rather interesting and merits further discussion. Figure 6.19 shows the behavior of the key vehicle operation costs components consumption with respect to the rise plus fall factor for the typical road link used in the sensitivity study. Typically, the three resources: fuel costs, vehicle repair parts costs, and tire costs represent 55 to 65% and 75 to 80% of the total vehicle running costs at 10 and 120 m/km rise plus fall respectively for buses and trucks for a typical road link in the case study region. Again, typically trucks and buses account for up to 95% of the total VOCs for a road link with a typical traffic mix.

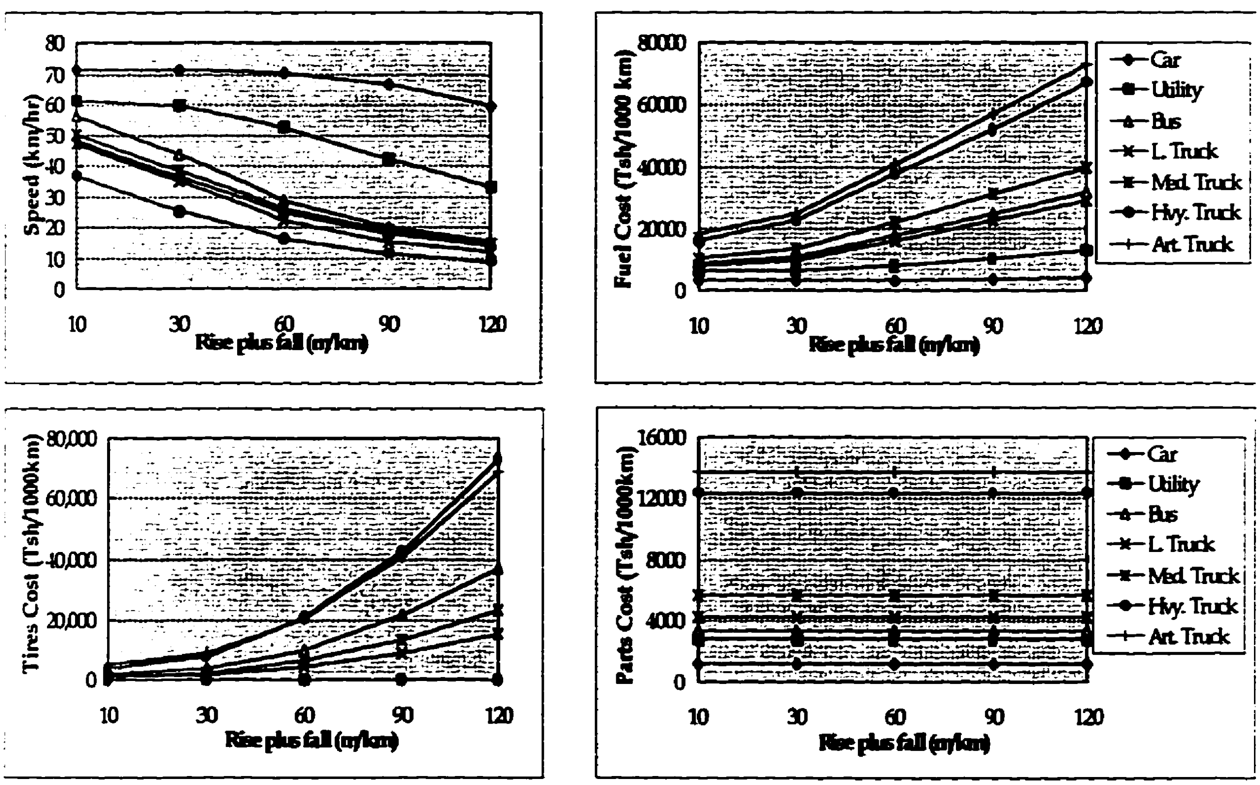
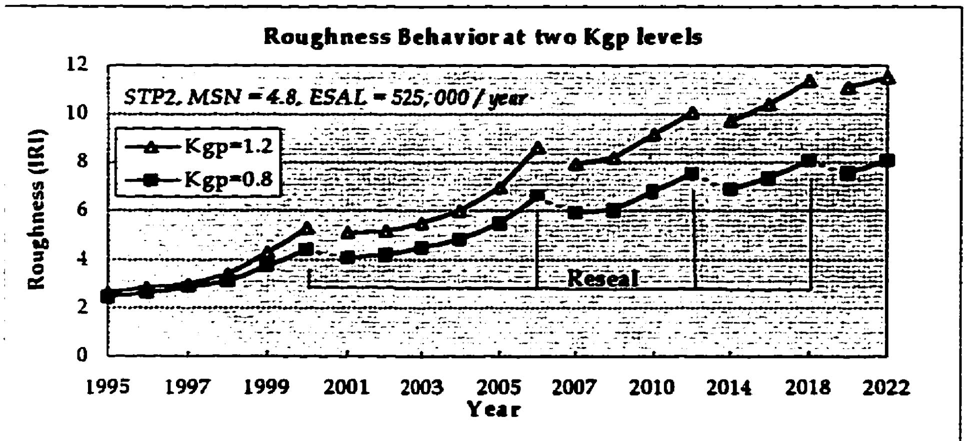


FIGURE 6.19 VOC key components versus rise plus fall (RF)

As shown in the figure, the rise plus fall (*RF*) has a general negative effect on travel speed; the effect is particularly noticeable for buses and trucks. The reduction in travel speed translates into very rapid increase in both fuel and tire consumption. Notice again the effect is most detrimental to the heavy vehicle classes. Interestingly, the parts costs seem to be unaffected by the rise plus fall factor.

6.4.3.3 *Effect of the Initial Roughness Level and the Roughness Calibration on the NPV*

Another interesting behavior is the significant role of the interaction between roughness and the strength parameters "*QI× (SN, DEF)*" at low traffic. The results show that the NPV for strategy STP1 at 265 ADT is dominated by the "*QI× (SN, DEF)*" interaction (52%). The main effects of roughness and those of the strength parameters separately account for only 35% of the ANOVA contribution. At ADT 1000 the interaction "*QI× (SN, DEF)*" has an almost insignificant effect on the NPV for strategies STP3 and STP4 (Table 6.9). This is a phenomenon worth investigating. Figures 6.20 through 6.22 show the role of the calibration factors on the predicted roughness, the life-cycle costs and the NPV.



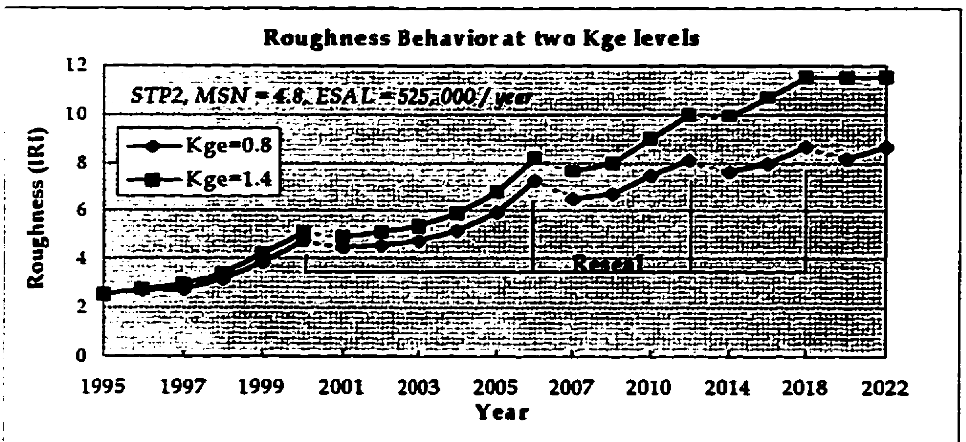


FIGURE 6.20 Roughness progression at two levels of the calibration factors (Kgp, Kge)

From Figure 6.20 it is noted that the roughness profile change associated with the *Kgp* change (0.8 - 1.2) is slightly higher but close to the change resulting from the *Kge* change of (0.8 - 1.4). Figure 6.21 shows the effect of the roughness profile change upon the predicted users' life-cycle costs. It is interesting to note that though generally the VOCs are close, in overall the *Kge* change is associated with slightly higher absolute users costs than the *Kpg* changes for the low strategies (STP0 and STP1). Consequently, the difference between the VOCs for the higher strategies (STP4 and STP3) and the VOCs for the null strategy, STP0 are higher for *Kge* than *Kgp* over the same interval. This behavior is reflected in the NPV changes shown in Figure 6.22. Note the interesting decrease in NPV as *Kge* and *Kgp* increase for low strategies (STP1, STP2), whereas for the higher strategies (STP3, STP4) an increase in either *Kge* or *Kgp* results in an increase in the NPV.

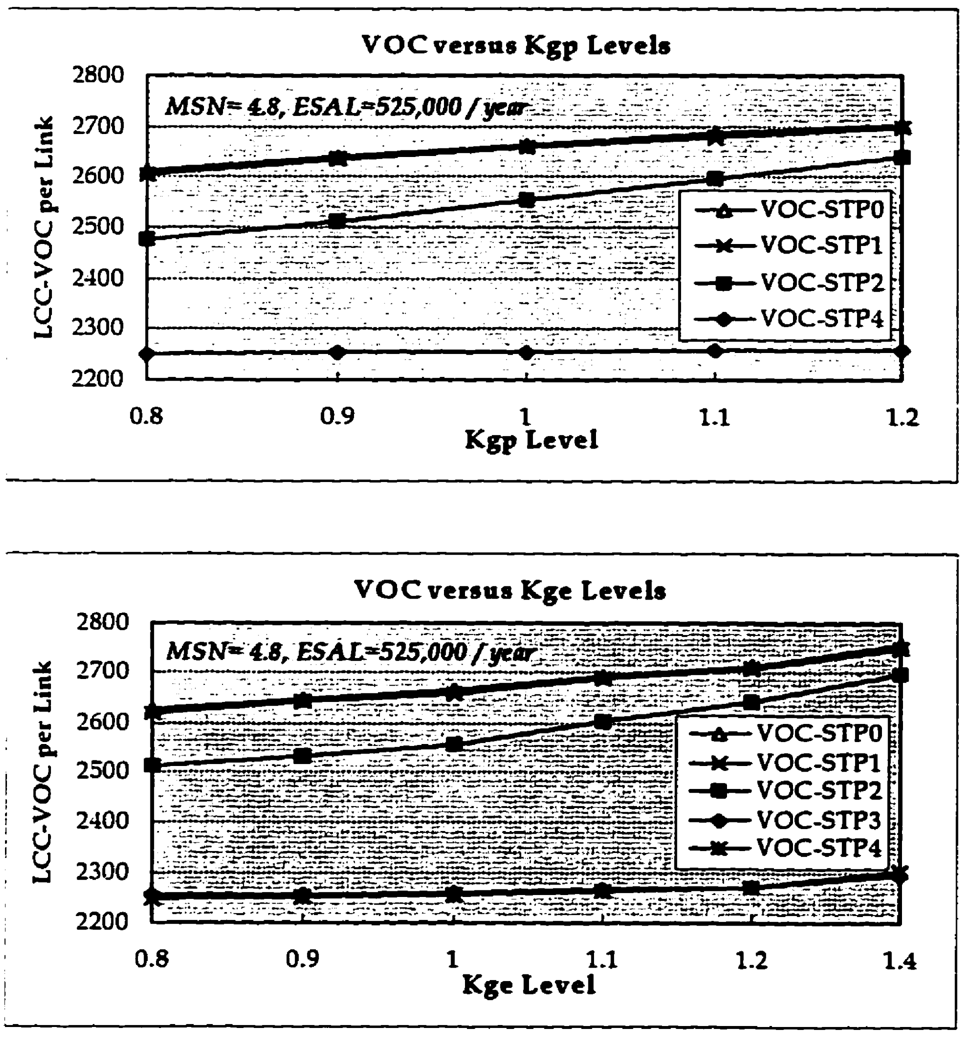
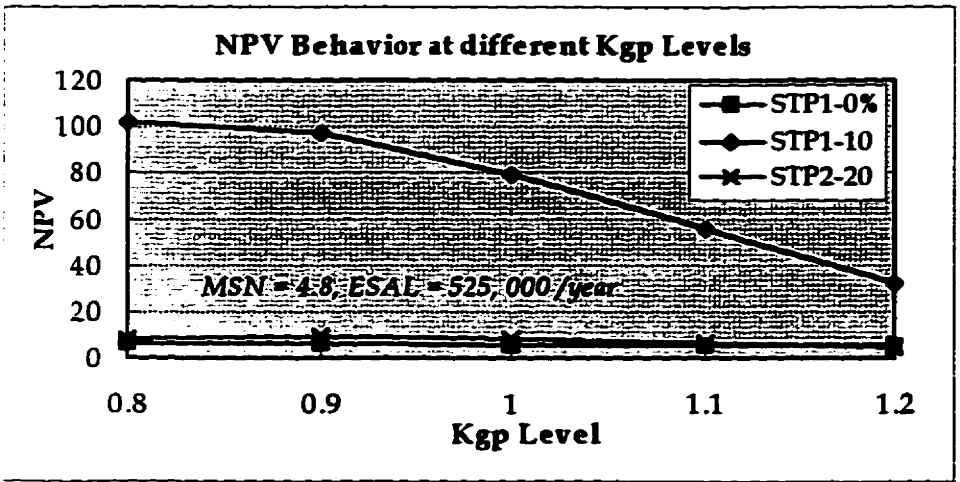


FIGURE 6.21 Effect of the roughness calibration factors (Kgp and Kge) on VOCs



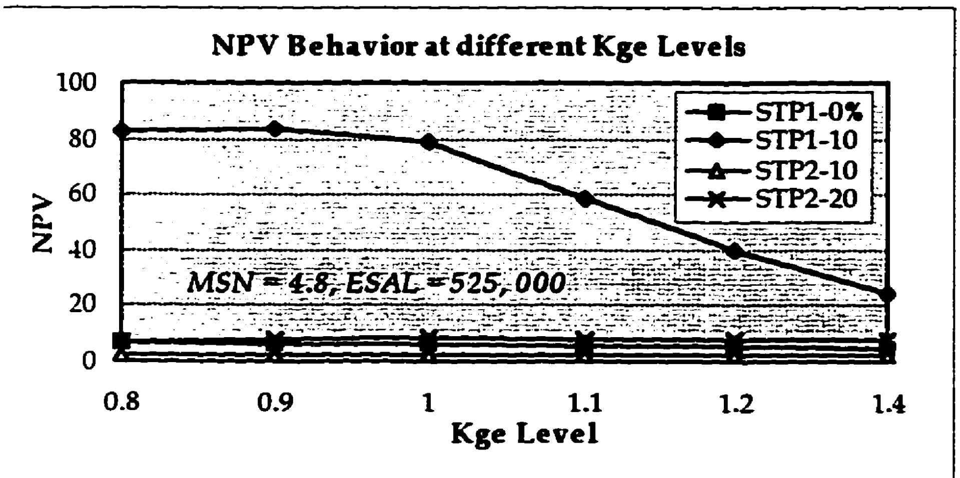
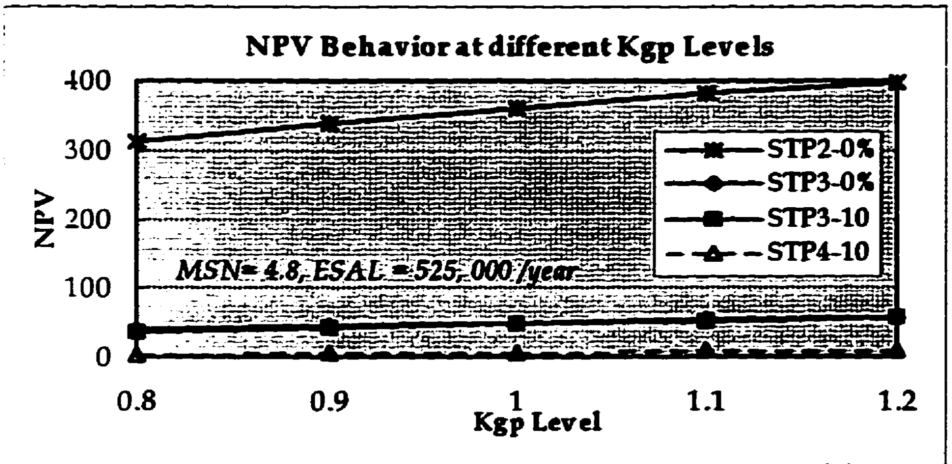


FIGURE 6.22 (a) Effect of the roughness calibration factors (Kgp and Kge) on NPV



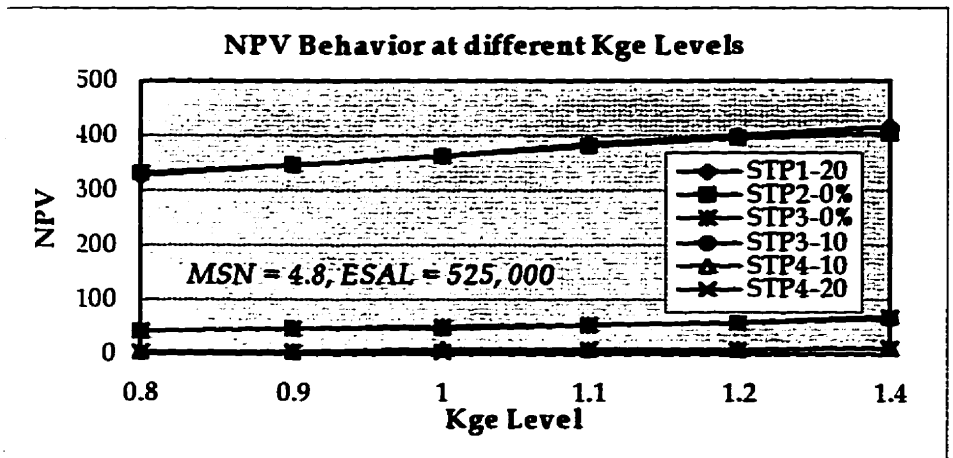


FIGURE 6.22 (b) Effect of the roughness calibration factors (Kgp and Kge) on NPV

6.4.4 Summary Ranking of Sensitive Input Factors

Table 6.12 shows a summary of the factor sensitivities. The factors have been ranked according to their sensitivity to the NPV predictions. The table also provides, for comparison purpose, the factor sensitivities to the component agency and users' life-cycle costs. It is worth pointing out that the NPV sensitivities (ANOVA%) were adjusted to account for factor interactions and averaged over the two strategies (STP3, STP4) and two traffic levels. The ANOVA percentages for agency and users' life-cycle costs are given only for comparison; they were adjusted for factor interactions but not averaged over traffic. Notice the effect of traffic level on factor rankings for component life-cycle costs.

Table 6.13 compares the final rankings based on factor sensitivities to the NPV and the corresponding rankings for the component agency and users' life-cycle costs for the individual strategies. The table highlights the important fact that the factor sensitivities are, as expected, dependent on the strategies being investigated.

Tables 6.12 and 6.13 show that the most significant factors in the NPV prediction are the rutting calibration factor (*Krp*), the pavement strength parameters (*SN, DEF*), the carriageway width (*W*), and the initial pavement distress level (*ACRA, ACRW, APOT* and *ARAV*). These first four ranking significant factors account for close to 64% of the total variability in the NPV.

The next most sensitive factors in the NPV are, the roughness–environmental calibration (*Kge*), the level of rutting and its variability (*RDM, RDS*), the altitude (*A*), and the pavement construction and treatment history (*AGE1, AGE2,* and *AGE3*). Road roughness (*QI*), cracking calibration factors (*Kci, Kcp*) and the base layer thickness (*HBASE*) were also found to be active in the NPV.

TABLE 6.12 Summary of Factor Sensitivities in ANOVA% Contributions

NPV		Agency Life-Cycle Costs				Users' Life-Cycle Costs			
Factor	**ANOVA***	**ADT 500**		**ADT 1000**		**ADT 500**		**ADT 1000**	
Krp	25.47	*W*	95.808	*W*	98.349	*RF*	95.873	*RF*	96.035
SN		*Kci*	1.875	*AGE1*		*Krp*	1.071	*Krp*	1.430
DEF	18.65	*ACRA*		*AGE2*		*QI*	0.992	*SN*	
W	10.19	*ACRW*		*AGE3*	0.856	*SN*		*DEF*	1.064
ACRA		*APOT*		*Krp*	0.139	*DEF*	0.815	*QI*	0.448
ACRW		*ARAV*	0.604	*Kci*	0.133	*C*	0.276	*C*	0.350
ARAV		*QI*	0.447	*SP*	0.130	*Kge*	0.160	*RDM*	
APOT	9.24	*Krp*	0.229	*Kge*	0.118	*RDM*		*RDS*	0.137
Kge	6.28	*Kcp*	0.207	*SN*		*RDS*	0.145	*AGE1*	
RDS		*AGE1*		*DEF*	0.099	*Kci*	0.115	*AGE2*	
RDM	5.80	*AGE2*		*QI*	0.073	*ACRA*		*AGE3*	0.059
A	3.60	*AGE3*	0.179	*Kpp*	0.027	*ACRW*		*ACRA*	
AGE1		*SN*		*HBASE*	0.026	*APOT*		*ACRW*	
AGE2		*DEF*	0.098	*RDM*		*ARAV*	0.105	*APOT*	
AGE3	3.33	*Kgp*	0.093	*RDS*	0.025			*ARAV*	0.057
QI	3.28	*Kge*	0.088					*Kci*	0.044
Kci	3.19							*Kgp*	0.042
HBASE	2.07							*Kge*	0.030
TOTAL %	91.10		99.628		99.975		99.552		99.734

* *ANOVA% for NPV were adjusted for factor interactions and averaged over two strategies and two traffic levels — ADT 500 and 1000. Symbols according to the Glossary.*

TABLE 6.13 Factor Ranking According to Sensitivity to the NPV

NPV		Agency Life-Cycle Costs				Users' Life-Cycle Costs			
Factor	**Rank**	**ADT 500**		**ADT 1000**		**ADT 500**		**ADT 1000**	
Krp	(1)	*Krp*	(5)	*Krp*	(3)	*Krp*	(2)	*Krp*	(2)
SN	(2)	*SN*	(8)	*SN*	(7)	*SN*	(4)	*SN*	(3)
DEF	(2)	*DEF*	(8)	*DEF*	(7)	*DEF*	(4)	*DEF*	(3)
W	(3)	*W*	(1)	*W*	(1)			*W*	(13)
ACRA	(4)	*ACRA*	(3)			*ACRA*	(9)	*ACRA*	(8)
ACRW	(4)	*ACRW*	(3)			*ACRW*	(9)	*ACRW*	(8)
ARAV	(4)	*ARAV*	(3)			*ARAV*	(9)	*ARAV*	(8)
APOT	(4)	*APOT*	(3)			*APOT*	(9)	*APOT*	(8)
Kge	(5)	*Kge*	(10)	*Kge*	(6)	*Kge*	(6)	*Kge*	(11)
RDS	(6)			*RDS*	(11)	*RDS*	(7)	*RDM*	(6)
RDM	(6)			*RDM*	(11)	*RDM*	(7)	*RDS*	(6)
A	(7)								
AGE1	(8)	*AGE1*	(7)	*AGE1*	(2)				
AGE2	(8)	*AGE2*	(7)	*AGE2*	(2)	*C*	(4)	*C*	(5)
AGE3	(8)	*AGE3*	(7)	*AGE3*	(2)				
QI	(9)	*QI*	(4)	*QI*	(8)	*QI*	(3)	*QI*	(4)
Kci	(10)	*Kci*	(2)	*Kci*	(4)	*Kci*	(8)	*Kci*	(9)
HBASE	(11)			*HBASE*	(10)				

Symbols according to the Glossary.

6.4.5 Comparison of the Sensitivity Findings with the Literature

As mentioned earlier in Chapter 2 the few isolated sensitivity studies on HDM-III found in the literature are of considerably limited scope and almost each of them is based on a different objective function. The brief section on sensitivity analysis in [Queiroz 91], for example, reports a *ceteris paribus* test of the effects of a 10% reduction in traffic level and 10% increase in R&M unit costs upon the predicted internal rate of return (IRR). [Queiroz 91] found that 10% lower traffic and 10% higher unit costs resulted in 4 to 8% lower IRR. These results agree with those reported by [Kerali 91]. The latter work was aimed at investigating the break-even traffic at which to upgrade a gravel road to paved standards, and was based on the NPV and IRR predictions as the analysis criteria. The results from [Kerali 91] show that for high rainfall in mountainous areas, an increase in traffic by 10 vehicles per day yields about 0.8% increase in the IRR (of the upgrading strategy).

Interpreting the NPV sensitivities given in [Kerali 91] (Table 3 pp. 36) as elasticity of the NPV with respect to traffic, values between 2.8 and 3.5 for discount rates of 5 and 10% respectively are obtained at the base traffic of 400 up to 700. These numbers compare well with *ceteris paribus* results from this thesis (Table 6.2). However, it is again emphasized that it is not appropriate to compare results that are based on the *ceteris paribus* investigation. It was shown earlier in this chapter that the *ceteris paribus* results are not conclusive. Besides, even when the elasticity approach is employed (to normalize /standardize the results for input /output factor ranges), consistent results are only achieved where the assumptions of linearity and additivity of factor effects are plausible. It was noted that for a response that is highly non-linear or subject to significant factor interactions the standardized *ceteris paribus* (and the linear regression) estimation of factor sensitivities fails.

The earlier works in 1987 and 1988 by [Bhandari 87 and Bank 88] investigated, again using the *ceteris paribus* technique, break-even traffic volumes at which it becomes economical to pave a gravel road. A more interesting contribution from [Bhandari 87 and Bank 88] is that dealing with the sensitivity of the NPV with respect to the pavement strength (*SN*). Based on studies carried out in Costa Rica and Mali, the two articles present interesting details of the interaction of the traffic level and the modified structural number (*SN'*) upon the predicted NPV over a large number of R&M strategies. The behavior of the NPV with respect to the traffic level (ADT) as reported in these earlier studies is comparable to that in [Kerali 91 and Queiroz 91].

6.5 A Factor Sensitivity-Based Framework for Prioritizing Data Collection

The findings from this research indicate that, for the typical link in the cross-section of paved roads in the case study region (15 - 20 years old, resurfaced 6 - 15 years ago, initial strength of 3.5 - 4.0 modified structural number, and 0.5 - 1.0 million *ESALs* per lane per year traffic loading), the estimation of the rutting calibration (*Krp*), pavement strength, pavement width, and initial level of pavement distresses is very important in determining the precision of the predicted NPV. Other factors that were shown to be significant in the NPV prediction include the initial rutting level and its variability, roughness level and its calibration and pavement construction and treatment history.

One important implication of the research findings is in the area of priority of local calibration of the pavement performance relationships in HDM-III. The sensitivity results indicate that the highest calibration priority should be given to the rutting progression calibration factor (*Krp*). The next most important calibration factors are the roughness-environmental-age factor (*Kge*) and the cracking calibration factors (*Kci, Kcp*). According to the findings, the ravelling calibration (*Kvi*) and the potholes calibration (*Kpp*) should be given the least priority in local re-calibration.

The role of roughness, and the calibration of its progression was shown to have a lesser sensitivity than indicated in other studies. This is of course a result of the lower pavement standards (moderate to high roughness levels tolerated) in the cross-section of pavements in the case study region. It was shown (Section 6.4) that the effect of roughness on NPV is more significant for smoother pavements; beyond 6 - 9 m/km IRI roughness has a reduced effect upon the NPV.

Another immediate application of the factor sensitivity results established in this study is in the area of prioritizing data collection and management resources for HDM-III application. In simplistic terms, it is obviously logical to spend the available dollars on collecting first the data items that are most sensitive to the NPV predictions.

Strictly speaking, however, factor sensitivities are not by themselves sufficient in prioritizing data collection resources. Factor sensitivities only provide a relative scale of comparing the "benefits" of collecting the individual data items. More attention should be paid to collecting/determining input factors with higher sensitivities. Compared to the impact of the less sensitive factors, the more imprecise these sensitive factors are the more unreliable are the NPV predictions.

To complete the prioritization exercise it would be necessary to have the unit costs of collecting the data items. Given the input factors data collection cost per kilometer cost-effective allocation of data collection expenditure can be recommended using, for example, the efficiency frontier. To draw the efficiency frontier of Figure 6.23 the benefit axis would make use of factor sensitivities as determined in this study.

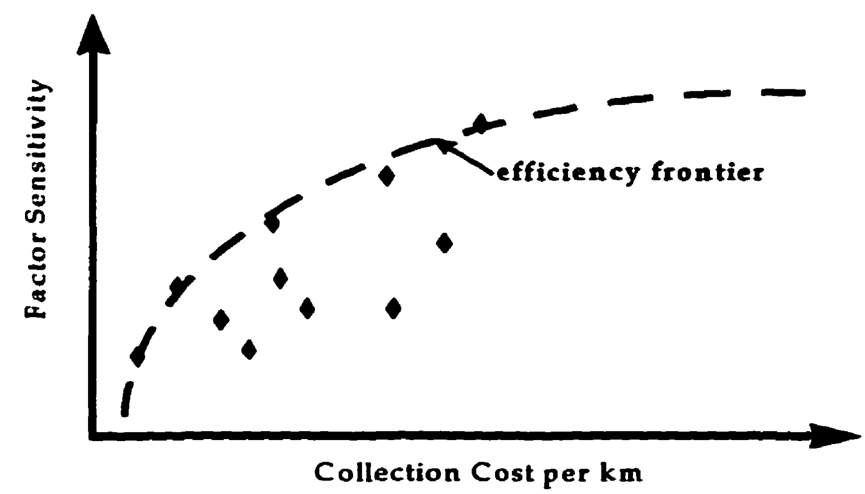


FIGURE 6.23 ***Factor sensitivities based efficiency frontier for prioritizing data expenditure***

The results given in this chapter have shown that the factor sensitivity rankings are, as expected, influenced (at least marginally) by the R&M strategies used in the investigation. Therefore, any realistic cost-effective allocation of data collection resource should be carefully planned on an application-specific basis. Such priority selection of factors should be based on sensitivities results averaged over a reasonable range of feasible strategies for the application at hand.

6.6 Summary of Chapter Conclusions

The results in this Chapter show that the most significant factors in the NPV prediction are: the rutting calibration factor (*Krp*), the pavement strength parameters (*SN, DEF*), the carriageway width (*W*), and the initial pavement distress level (*ACRA, ACRW, APOT* and *ARAV*). These first four groups of sensitive factors account for close to 64% of the total variability in the NPV.

The next most sensitive factors in the NPV are, the roughness–environmental calibration (*Kge*), the level of rutting and its variability (*RDM, RDS*), the altitude (*A*), and the pavement construction and treatment history (*AGE1, AGE2,* and *AGE3*). Road roughness (*QI*), cracking calibration factors (*Kci, Kcp*) and the base layer thickness (*HBASE*) were also found to be active in the NPV.

From the chapter findings, the least active factors to the NPV predictions from the HDM-III model are: rainfall (*MMP*), horizontal curvature (*C*), superelevation (*SP*), effective number of lanes (*ELANE*), surface layer thickness (*HSNEW, HSOLD*), the base layer compaction (*CMOD*) and the strength code. Others are, potholes and raveling calibration factors (*Kpp, Kvi*), the construction faulty code (*CQ*) and the cracking and raveling retardation factors (*CRT, RRF*). Factors that are only slightly active are: rise plus fall (*RF*), altitude (*A*), shoulder width (*WS*), subgrade strength (*SNSG*) and the previous pavement distresses (*ACRAb, ACRWb*).

The research findings also show that the NPV predictions from the HDM-III model are highly non-linear with respect to sensitive input factors and are also subject to significant factor interactions. Explanation of the NPV behavior required further investigation on the component life-cycle costs.

This chapter also developed a framework for prioritizing data collection resources with respect to HDM-III application at the network level. Once the factor sensitivities have been established, the data items to which more attention should be paid in allocating the collection dollars is determined on the basis of the factor sensitivities. Completion of the efficiency frontier for proper prioritization would require data on the costs and/or cost-effectiveness of collecting each individual data item.

Chapter 7

SIMPLIFYING HDM-III APPLICATION BY DEFAULT INPUTS

7.1 Chapter Overview

As outlined in Chapter 1 of this thesis, one immediate use of the factor sensitivity findings is to examine the viability of reducing the data requirements for the HDM-III model application in priority programming. With the results presented in Chapter 6 it is now possible to test the principal thesis hypothesis that, for a specific application an acceptable quality of output criteria could be achieved by employing relatively more default inputs (hence fewer precise inputs) than currently claimed. This chapter presents the concept of model data needs reduction by the use of surrogate default inputs and the statistical validation of such a reduced model.

The chapter first formulates a pool of default inputs for each of the life-cycle cost criteria from the ranking of active factors. Factors with main effects below a chosen cutoff point are classified as inactive factors. Typical values for these inactive factors are then assigned as default input values for subsequent model runs. Two streams of HDM-III outputs are generated by running the model over 150 data sites from the Latin hypercube design data that explores the input space as fully as possible. One output stream is based on the default inputs (*i.e.*, fixing the input values for the inactive factors constant for all validation runs). In the other output stream, all predictor variables are allowed to take on their precise values. Comparison of these two model output streams provides the statistical hypothesis testing reported here.

7.2 The Concept of Reducing HDM-III Data Needs by Default Inputs

The concept of using default inputs as a suitable framework in which the potential of the HDM-III model can be made more available to the low-income road agencies was introduced in Chapter 2. It was argued that while other approaches sound attractive, for example developing simplified algorithms (with fewer input variables), similar to [Paterson 92] work, their immediate benefit is only to those road agencies capable of developing (computer coding, *etc.*) their own analysis "engines" or entire pavement management systems, or in the very least, modifying the HDM-III computer code to make use of such simpler algorithms.

The thesis argues that with respect to most of the low-income road agencies in SSA the capability to make use of new algorithms is not forthcoming. Further, it was observed that a suitably calibrated HDM-III model is still good enough for simulating the road behavior in many tropical environments where the design standards are close to the HDM study conditions. Modifying the HDM-III computer code is not considered an important requirement in Sub-Saharan Africa, at least for now.

Given the above argument, the most appropriate approach for making the application of HDM-III more available is to streamline the data requirements while retaining the existing computer code. This approach has the advantage in that the existing HDM-III code can be retained as is, hence no further investment is required on the part of an existing user. It also allows the same simplification approach to be available to users of the forthcoming model upgrade (HDM4) since it is expected to incorporate most of the existing HDM-III technical relationships.

7.3 The Existing Link Characterization Default inputs in HDM-III

Currently, under the paved road link characterization class of inputs, the Brazil set of HDM-III relationships provide default inputs for a total of 14 input factors: altitude, superelevation, effective number of lanes, subgrade compaction, cracking and raveling retardation factors, and the seven performance calibration factors. The findings of factor sensitivities from this thesis (Chapter 6) suggest that the number of link characterization default inputs in HDM-III can be increased from the current 14 to more than 20 without a significant loss of quality of the predicted life-cycle costs and NPV. The specific number of inactive factors on per output–strategy basis is subsequently discussed in the next section.

It is also worth pointing out that the current set of default (link characterization) input factors assume values that are, of course, reflective of the uncalibrated model for Brazil technological, environmental, and economic conditions during the HDM study. The only exceptions are the effective number of lanes and the superelevation. The default value for the effective number of lanes is estimated by the model as a function of the carriageway width, whereas the superelevation is determined as a function of the horizontal curvature. The approach demonstrated in this thesis provides a mechanism of determining values of default input factors that are more reflective of the local conditions. This also applies to the less significant calibration factors: the potholes progression and the raveling calibration factors.

7.4 A Framework for Selecting the Candidate Factors for Default Inputs

7.4.1 A General Framework

Selection of the candidate input factors which can be replaced by default values (in subsequent analyses) for a given study region should be based on factor sensitivities of the model output criterion of interest. Since the sensitivity results are specific to the model output and are also dependent on the other input classes that were not investigated in this study (*e.g.*, vehicle characterization variables, strategy definition factors, *etc.*), deciding on variables to designate as default input for a given region requires a systematic investigation procedure. Figure 7.1 presents a viable framework for such an investigation which ensures that the results of the subsequent HDM-III analyses remains reliable for the pavement management decision-making. The figure shows both the investigation and the application stages for task-specific default inputs. The specific nature of the default inputs is discussed in a later subsection; the following subsection looks at an important input to the framework described above – the cutoff criterion.

7.4.2 Criteria for Choosing Candidate for Default Inputs

The immediate evidence suggested by the factor sensitivities reported in Chapter 6 is that the life-cycle costs components (of the NPV) are dominated by only a few sensitive factors. Agency life-cycle costs for the resealing strategy (STP2), for example, are dominated by the carriageway width (*W*), the cracking initiation factor (*Kci*), and the distress parameters (*ACRA, ACRW, APOT, ARAV*). For users' life-cycle costs over 98.7% of all the variability is attributed to the rise plus fall (*RF*), the cracking calibration factor (*Kcp*), the strength parameters (*SN, DEF*) and the road roughness (*QI*).

Of the 39 link characterization factors, there are only about 10 active factors that explains the variability in VOC life-cycle costs; the remaining inactive factors contribute less than 1.3%. Similarly, for the agency life-cycle costs the top 10 factors (*W, AGE1, AGE2, AGE3, Kge, Kvi, HBASE, SN* and *DEF*) accounts for 99% of the total variability in the prediction. The important implication of this finding is that the large number of insensitive factors can be trimmed from the model with practically negligible or small loss of precision in the predicted NPV.

The viability of streamlining the data requirements for applying HDM-III was examined by replacing the inactive factors in the model by constant values. The immediate question, however, is what level of factor effect should be used to designate a variable as inactive? The importance of this cutoff level criterion is that it bears a direct implication upon the prediction accuracy of the simplified model. Unfortunately it not possible to know exactly how much prediction accuracy will be compromised for any given cutoff level. This is obvious from the fact that the factor effects estimated from the stochastic approach, for example, do not account for 100% variability in the actual model outputs (see subsection 6.3.2 and Figure 6.8).

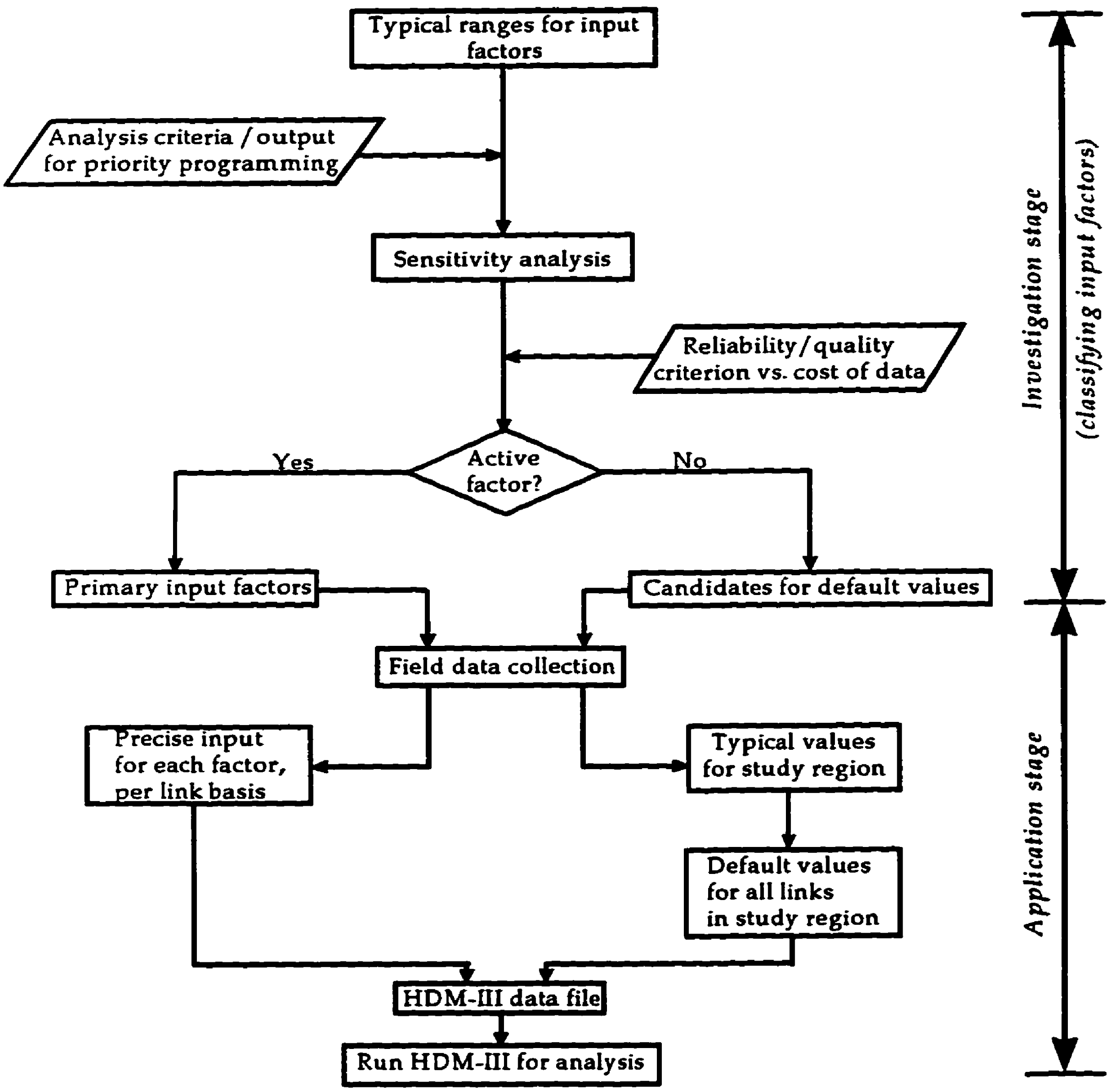


FIGURE 7.1 A framework for selecting candidate variables for default inputs

7.4.3 Specific Nature of Inactive Factors

The results from the sensitivity study strongly suggest that the factor sensitivities change slightly across treatment strategies. It was shown, for example, with respect to agency life-cycle predictions, while pavement distress parameters are active factors under strategy STP2, they are inactive under strategy STP4 (Tables 6.10 and 6.11). Similarly, the mean and standard deviation of rut depth are only active in users' costs under strategy STP4. They are inactive both in the other strategies and in agency LCC. Again, the pavement age parameters are only active in agency LCC for strategy STP4. However, with respect to the NPV, the overall change in factor sensitivity rankings is not that noticeable. It is seen from Table 6.9 that the first 8 most active factors (ranks 1 to 4) for both strategies STP3 and STP4 include the same variables (*Krp, SN, DEF, W,* and surface distresses).

From a general model building point of view, as more variables are dropped from a model, the more the estimated model parameters "absorb" the role of the dropped out variables. Therefore, the reduced model becomes less transferable to other situations.

In the case at hand, the other input factors in HDM-III that are central to R&M priority programming include R&M strategy definition attributes and unit costs and vehicle characterization variables (Figure 1.1 and Table 1.1). These later factors were kept constant at their typical values for the case study region during the course of investigation. It can only be expected that the sensitivities determined are not independent of these other base case inputs. While the results from the *ceteris paribus* (Table 6.3) are still inconclusive they point out the significant effect of some of the vehicle characterization variables. In particular, Table 6.3 shows the roughness coefficient, *CSPQI*, and the constant term in the parts – roughness equation to be extremely influential on the output NPV.

This set of affairs highlights the fact that under different levels of such other significant factors the sensitivities determined for link characterization factors are likely to change. Therefore it is recommended that default inputs be determined on application-specific basis.

7.4.4 Proposed Default Inputs for Link Characterization Factors

Findings on factor sensitivities for link characterization variables in HDM-III have been presented in Chapter 6. Tables 6.12 and 6.13 summarize the ranking of the most active factors identified in the study. The ranking results were subsequently used to determine the "inactive" model input factors that have little impact on the predicted life-cycle costs. For each type of the HDM-III outputs (agency, user's and NPV life-cycle costs) a set of candidates for default inputs was selected representing the inactive factors (those not ranked as active in Table 6.12). The values assigned as default inputs (used as constants in subsequent model runs) reflect the typical values for the factor in the case study region.

7.5 Testing the Validity of the "Defaults Based" Model

Once the candidate inactive factors to designate as default inputs in subsequent model applications have been selected, the natural question is, how valid are the model predictions based on such default inputs? Are the predictions based on the "reduced" model good enough for practical pavement management decision-making? This section discusses the question and the sample statistics which examine this key research question.

The validation of the "reduced" model relies on comparing results of the analysis performed using the "reduced" model (based on default inputs for the inactive factors) to the results from the full HDM-III model (with full range variability in all model inputs). The underlying statistical question is to test the null hypothesis, H_0 against the alternative hypothesis H_1 where,

- **H_0:** The HDM-III life-cycle costs predictions based on default inputs are significantly different from the predictions using the full set of input factors.
- **H_1:** The HDM-III life-cycle costs predictions based on default inputs are practically not different from the predictions based on full set of inputs.

If there is sufficient statistical evidence, say at 5% significance level, to reject the null hypothesis, then it will have been demonstrated that very little quality of the output criteria is lost by using default inputs for the inactive factors; that in fact, there is no statistical evidence to doubt the analysis based on default inputs as good enough for decision-making in pavement management.

The principal hypothesis stated above constitutes a general question to which it was desired to find a specific solution. Since the factor sensitivities studied in this thesis are based on life-cycle cost predictions for several R&M treatment strategies, the general hypothesis was tested at several specific levels. The specific sub-hypotheses tested are subsequently presented.

7.5.1 Specific Validation Hypotheses and Sample Statistics

To test the thesis principal hypothesis that the HDM-III model exhibits factor sparsity; that the model data needs are reducible by designating the inactive model factors as default inputs, specific life-cycle costs predictions for R&M strategies STP2 and STP4 were employed.

Apart from the principal hypothesis stated above, the study was also interested in finding out how specific the default inputs are across traffic levels and treatment strategies.

The test problem outlined above can be re-stated as an equivalent ANOVA problem. It is desirable to see if there is any real difference between the life-cycle cost predictions using full set of input data and those based on default inputs. This is a comparison of means problem where the concern is to find out whether the observed differences among the means μ_1, μ_2, ..., μ_k are significant or whether the differences are pure noise (compared to within sample variability).

In an ANOVA test the hypotheses are:

H$_0$: $\mu_1 = \mu_2 = \ldots = \mu_k$

H$_a$: $\mu_j \neq \mu_k$ for any pair (j, k) of test samples

The hypotheses stated above have been listed in specific terms in Table 7.1. The three null sub-hypotheses relevant to the theme of the thesis are subsequently summarized. Table 7.2 defines the relevant symbols used in Table 7.1. The table lists the null hypotheses, the response variable to be tested and the test criterion for each of the four model outputs investigated.

Referring to Table 7.1 hypothesis one looks at the primary interest of this thesis. It poses the question, "Can reasonable model predictions be achieved by using default values in place of the inactive factors?" Hypothesis two looks at the effect of traffic level on the default values. Traffic level was also pointed out by the *ceteris paribus* results as one of the most active factors; the concern here is whether the integrity of the model predictions based on default inputs is preserved at different traffic levels. Hypothesis three intends to find out what happens when the default inputs developed using factor sensitivities for a given strategy are used in a different R&M strategy.

Hypothesis 4 looks at users' life-cycle predictions by using default inputs. Since traffic level has a direct effect upon the VOCs, the comparison is between predictions using full data and predictions based on default inputs within the same traffic level category. The default inputs ideally formulated for ADT 500, for one R&M strategy are reused to predict life-cycle costs with a different strategy and at different traffic levels.

Part of the Latin hypercube experimental design data was used for generating the sample statistics required for hypotheses testing. As discussed earlier (see Section 5.4.3) one of the advantages of the Latin hypercube design is that it ensures that any portion of the design matrix is a fully stratified sample of the input space regardless of the size of the sample and the sample location in the matrix. For the purpose of validation testing, the first 150 data points from the modified Latin hypercube design matrix was employed. The HDM-III model was run twice on these 150 data sites, first with all the predictor variables allowed to take their values as supplied at each data site. The second run employed default inputs whereby all the inactive factors (for a given output criterion) were fixed at their mean levels for all the runs, while the active factors were allowed to vary as per the data site values. The life-cycle predictions from the two runs provided the sample data for statistical hypothesis testing performed here.

TABLE 7.1 The SpecificTest Hypotheses

Hypothesis	Null Hypothesis (H_0)	Prediction Categories
1.1 1.2	HDM-III agency life-cycle costs predictions using default inputs are comparable to predictions using full input data	$\mu_{a200}=\mu_{a202}=\mu_{a212}=\mu_{a222}=\mu_{a232}$ $\mu_{a400}=\mu_{a404}=\mu_{a414}=\mu_{a424}=\mu_{a434}$
2.1 2.2	HDM-III agency life-cycle costs predictions do not change significantly with traffic level	$\mu_{a200}=\mu_{a210}=\mu_{a220}=\mu_{a230}$ $\mu_{a400}=\mu_{a410}=\mu_{a420}=\mu_{a430}$
3.1	Swapping the default inputs from one strategy to another has no significant effect on agency life-cycle costs	$\mu_{a200}=\mu_{a204}=\mu_{a214}=\mu_{a224}=\mu_{a234}$ $\mu_{a400}=\mu_{a402}=\mu_{a412}=\mu_{a422}=\mu_{a432}$
4.1 4.2 4.3 4.4 4.5 4.6 4.7 4.8	Road Users' life-cycle costs predicted using default inputs are all equal to those predicted using full set of inputs at the same traffic	$\mu_{u200}=\mu_{u202}=\mu_{a204}$ $\mu_{a400}=\mu_{a402}=\mu_{a404}$ $\mu_{u210}=\mu_{u212}=\mu_{a214}$ $\mu_{a410}=\mu_{a412}=\mu_{a414}$ $\mu_{u220}=\mu_{u222}=\mu_{a224}$ $\mu_{a420}=\mu_{a422}=\mu_{a424}$ $\mu_{u230}=\mu_{u232}=\mu_{a234}$ $\mu_{a430}=\mu_{a432}=\mu_{a434}$

Key: See Table 7.2 for the definition of symbols (the mean values compared)

TABLE 7.2 Definition of the Mean Values Used in the Hypotheses (Table 7.1)

Description	Symbol	Life-cycle Type and Strategy Used	Set of Default Inputs Used	Traffic level of Prediction (ADT)
Full data predictions	μ_{a200}	LCC-R&M: STP2	Full data	500
	μ_{a400}	LCC-R&M: STP4	Full data	500
	μ_{u200}	LCC-VOC: STP2	Full data	500
	μ_{u400}	LCC-VOC: STP4	Full data	500
Same strategy (STP2) defaults, different traffic	μ_{a202}	LCC-R&M: STP2	STP2, ADT500	500
	μ_{a212}	LCC-R&M: STP2	STP2, ADT500	264
	μ_{a222}	LCC-R&M: STP2	STP2, ADT500	1000
	μ_{a232}	LCC-R&M: STP2	STP2, ADT500	1500
Same strategy (STP4) defaults, different traffic	μ_{a404}	LCC-R&M: STP4	STP4, ADT500	500
	μ_{a414}	LCC-R&M: STP4	STP4, ADT500	264
	μ_{a424}	LCC-R&M: STP4	STP4, ADT500	1000
	μ_{a434}	LCC-R&M: STP4	STP4, ADT500	1500
Different strategy defaults, different traffic	μ_{a402}	LCC-R&M: STP4	STP2, ADT500	500
	μ_{a412}	LCC-R&M: STP4	STP2, ADT500	264
	μ_{a422}	LCC-R&M: STP4	STP2, ADT500	1000
	μ_{a432}	LCC-R&M: STP4	STP2, ADT500	1500
Different strategy defaults, different traffic	μ_{a204}	LCC-R&M: STP2	STP4, ADT500	500
	μ_{a214}	LCC-R&M: STP2	STP4, ADT500	264
	μ_{a224}	LCC-R&M: STP2	STP4, ADT500	1000
	μ_{a234}	LCC-R&M: STP2	STP4, ADT500	1500
Same strategy (STP2) defaults, different traffic	μ_{u202}	LCC-VOC: STP2	STP2, ADT500	500
	μ_{u212}	LCC-VOC: STP2	STP2, ADT500	264
	μ_{u222}	LCC-VOC: STP2	STP2, ADT500	1000
	μ_{u232}	LCC-VOC: STP2	STP2, ADT500	1500
Same strategy (STP2) defaults. different traffic	μ_{u404}	LCC-VOC: STP4	STP4, ADT500	500
	μ_{u414}	LCC-VOC: STP4	STP4, ADT500	264
	μ_{u424}	LCC-VOC: STP4	STP4, ADT500	1000
	μ_{u434}	LCC-VOC: STP4	STP4, ADT500	1500
Different strategy defaults, different traffic	μ_{u402}	LCC-VOC: STP4	STP2, ADT500	500
	μ_{u412}	LCC-VOC: STP4	STP2, ADT500	264
	μ_{u422}	LCC-VOC: STP4	STP2, ADT500	1000
	μ_{u432}	LCC-VOC: STP4	STP2, ADT500	1500
Different strategy defaults, different traffic	μ_{u204}	LCC-VOC: STP2	STP4, ADT500	500
	μ_{u214}	LCC-VOC: STP2	STP4, ADT500	264
	μ_{u224}	LCC-VOC: STP2	STP4, ADT500	1000
	μ_{u234}	LCC-VOC: STP2	STP4, ADT500	1500

Key: *LCC-R&M = agency life-cycle costs, LCC-VOC = users' life-cycle costs*

7.5.2 Statistical Assumptions for the *t*-test (or ANOVA)

In paired responses situations statistical comparison is normally investigated using the simple two sample *t*-test. The investigation would, for example, perform comparison of pairs of streams HDM-III life-cycle predictions, one using a full set of inputs, and the other based on default inputs for the inactive factors for a specific output. The one way analysis of variance (ANOVA) is the equivalent *t*-test for more than two samples.

The key statistical assumptions under which the *t*-test (and the ANOVA) can be applied are:

(1) The two (*k* for ANOVA) samples or populations are approximately normally distributed.

(2) The samples all have the same variance (homogeneity of variance).

(3) The samples are independent of one another.

The *t*-test (and ANOVA) is known to be robust with respect to moderate violations of these assumptions. However, the test(s) cannot be applied where the assumptions are highly violated. In other words, the conclusions reached using the *t*-test may be misleading if the assumptions for its application are highly violated.

An examination of the HDM-III life-cycle costs predictions indicated that agency costs for the same strategy have approximately the same variance irrespective of the set of the default input or full data used and is also independent of the traffic level used. For the users' (VOC) life-cycle costs, the variance seems to be approximately equal for all strategies at any given traffic level. As long as the VOC life-cycles are compared for the same traffic level, the assumption of equal variance does not seem to be questionable, whereas for agency life-cycle costs, the assumption seems to be met even when traffic level is disregarded as long as the comparison is done for the same R&M treatment strategy.

7.5.3 Normality of the HDM-III Life-Cycle Cost Predictions

Stem and leaf and box plots are commonly used to show the distributional characteristics of a data set. Both locational and spread aspects of data as well as skewness are best viewed using these statistical tools. Such visual display provides a first indication of the normality or non-normality of the data.

Another common tool for testing normality is the normal probability plot. By plotting the sorted observations against their cumulative expected standard score a straight line plot indicates the data is normal. The more the plot deviate from a straight line, the more non-normal the data is.

Figure 7.2 presents stem and leaf, boxplots and normal probability plots for selected response variables among the large number of HDM-III life-cycle predictions discussed in Chapter 7.

Both the steam and leaf and normal probability plots show that the assumption of normality is more than moderately violated for the HDM-III life-cycle costs predictions. The predictions are generally enormously skewed and the tails are much heavier than the Gaussian distribution.

A formal statistic commonly used for testing the assumption of normality is the Shapiro-Wilk [Cody 91]. The Univariate procedure in SAS®[8] produced the Shapiro-Wilk statistic values typically in the range of 0.93 to 0.94. The corresponding *p*-values testing the null hypothesis that the life-cycle predictions are normally distributed were typically less than 0.0001. That is, there is a strong evidence that the HDM-III life-cycle predictions are not Gaussian.

Several attempts were made to transform the life-cycle predictions into approximately normal. None of the common transformations provided any measurable improvement around the dilemma of the normal assumption. It was therefore, concluded that the hypothesis testing based on ANOVA technique are questionable unless we can validate them using other robust testing techniques.

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[8] *SAS is a registered trademark of SAS Institute Inc., Cary, North Carolina.*

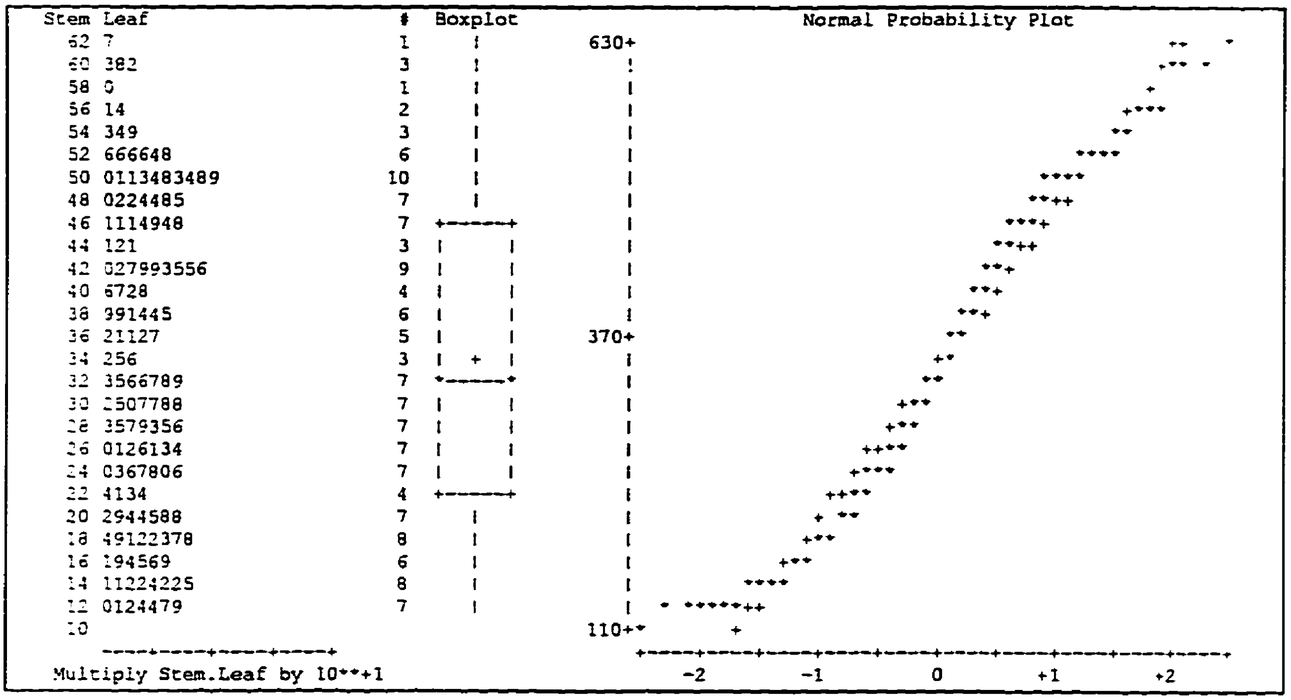

FIGURE 7.2 (a) Agency life-cycle costs for strategy STP2 at ADT 500 using full input data (μ_{u200})

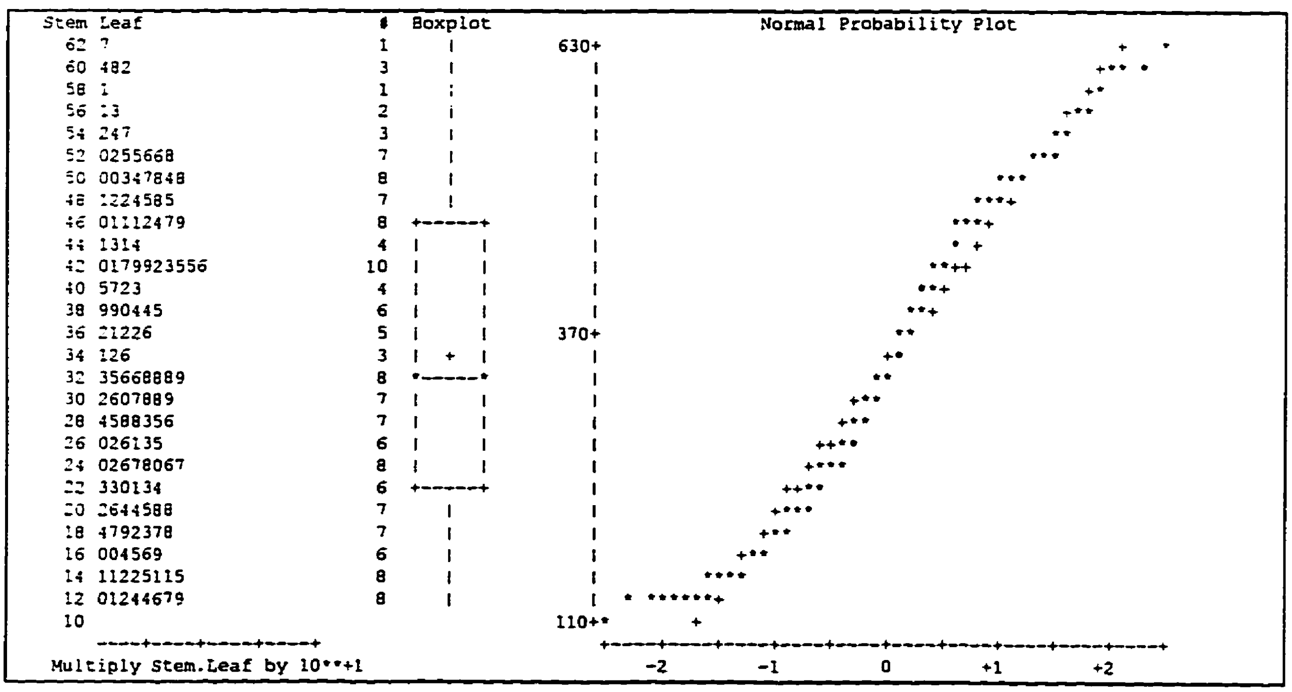

FIGURE 7.2 (b) Agency life-cycle costs for strategy STP2 at ADT 500 using STP2-defaults (μ_{u202})

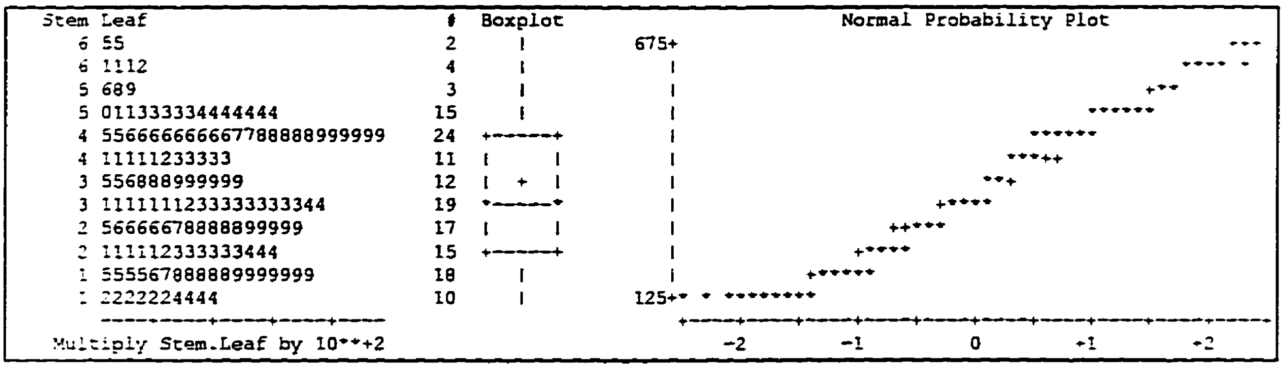

FIGURE 7.2 (c) Agency life-cycle costs for STP2 at ADT 1500 using STP4-default inputs (μ_{u234})

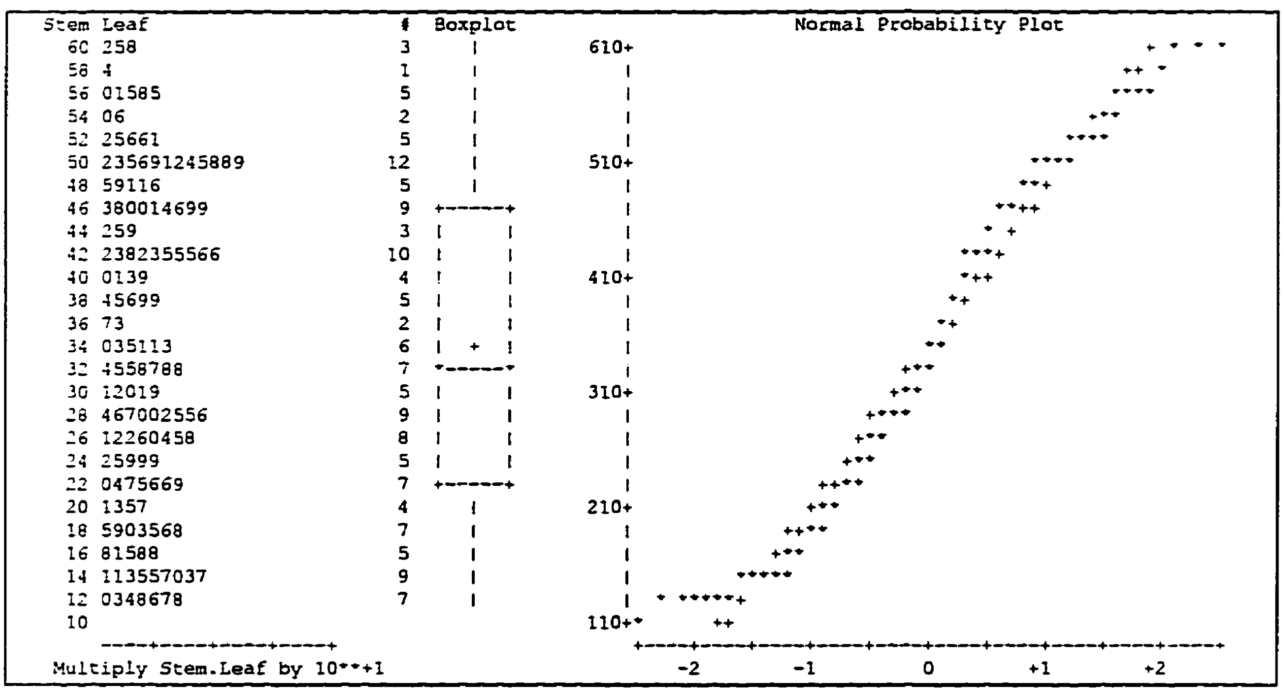

FIGURE 7.2 (d) Agency life-cycle costs for STP2 at ADT 1000 using full input data (μ_{u220})

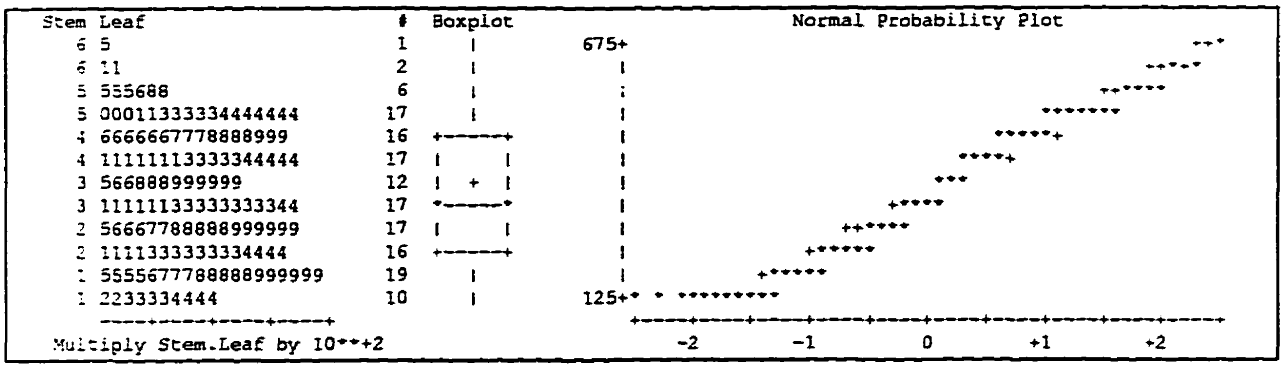

FIGURE 7.2 (e) ***Agency life-cycle costs under STP2 at ADT 1000 using STP2-default inputs (μ_{u222})***

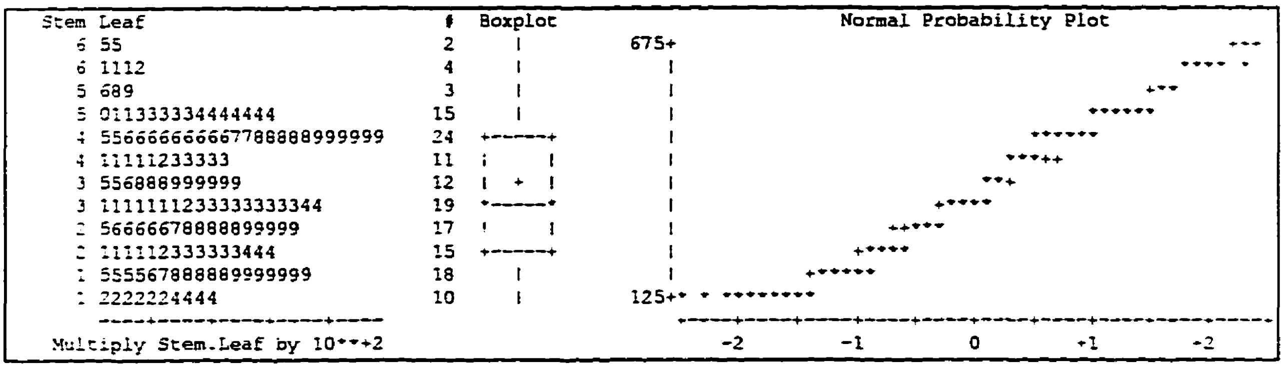

FIGURE 7.2 (f) ***Agency life-cycle costs for strategy STP2 at ADT 1000 using STP4-default inputs***

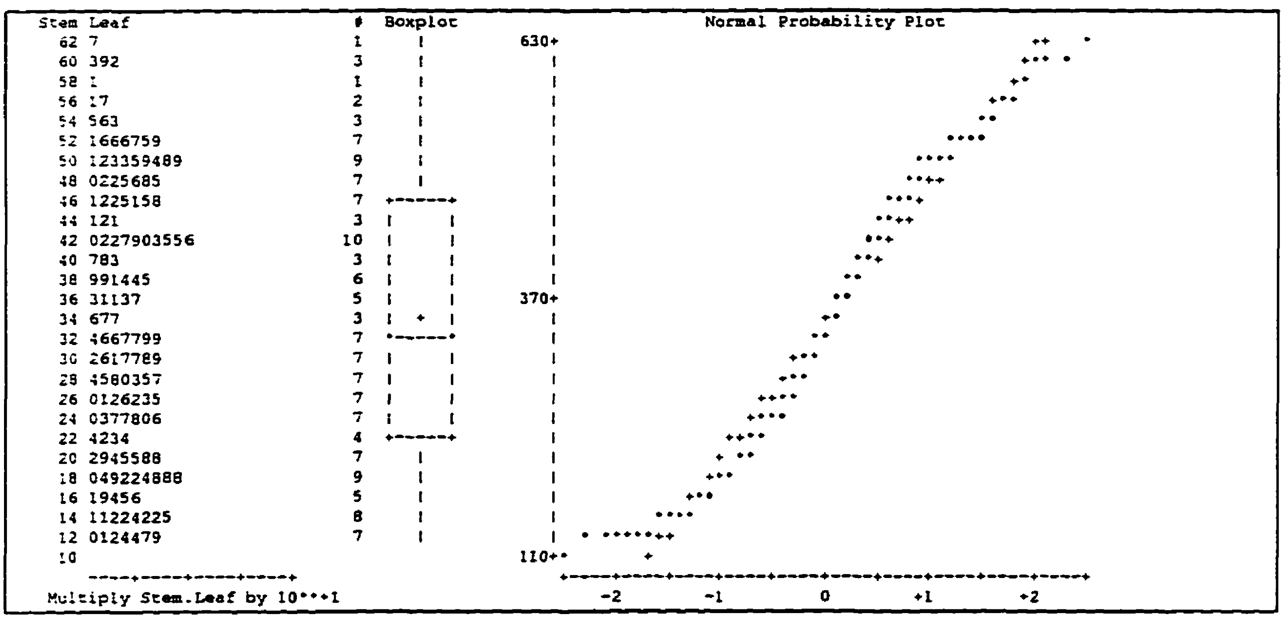

FIGURE 7.2 (g) ***Agency life-cycle costs for strategy STP2 at ADT 1500 using full input data***

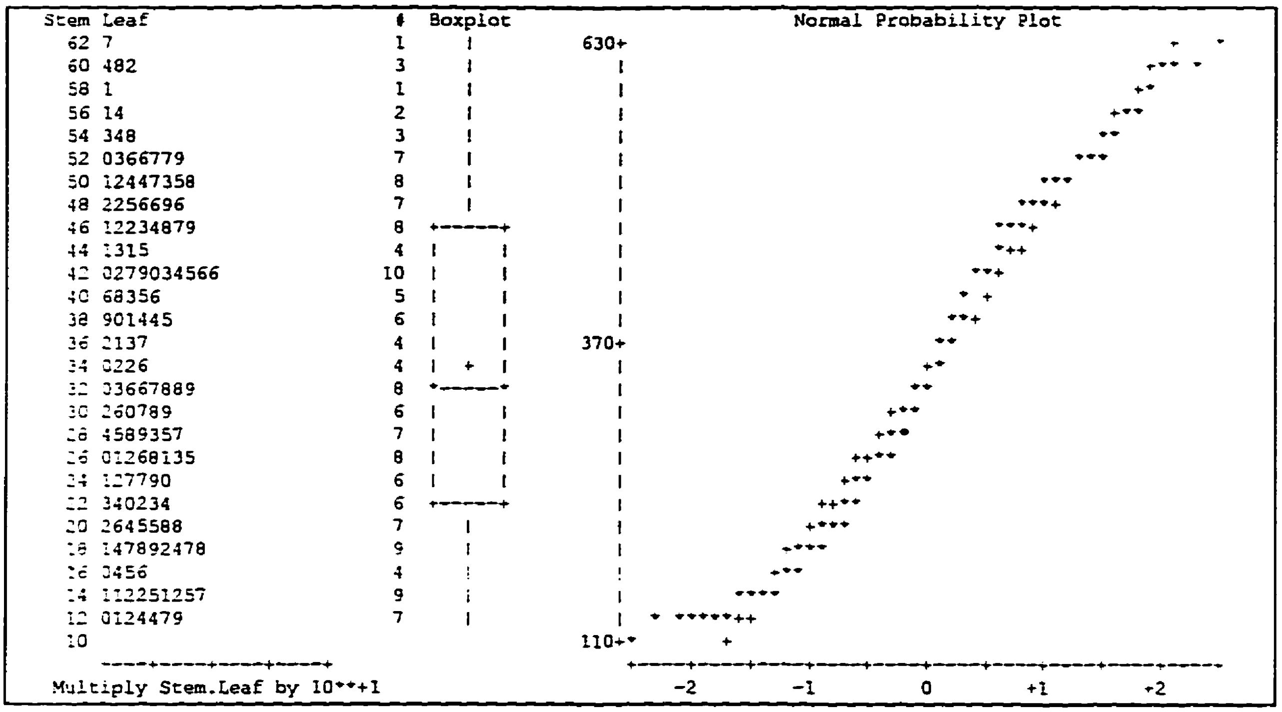

FIGURE 7.2 (h) Agency life-cycle costs for strategy STP2 at ADT 1500 using STP2-defaults (μ_{u232})

7.5.4 Non-parametric Tests Comparing "Default-Based" and Full Data HDM-III Life-Cycle Predictions

Non-parametric tests refer to a class of methods of statistical inference that do not require us to know the form of the probability distribution of the sample data. Methods such as based on signs of differences or ranks of measurements *etc.*, do not depend or rely on the precise shape of the distribution, or the explicit parameters of such a distribution.

Kruskal-Wallis test is the equivalent non-parametric of one way ANOVA for comparing three or more samples. Below we present the schematic plots of the test treatments and then carry out the formal Kruskal-Wallis test for each of the test hypotheses. But before that, we re-state the hypotheses given in Chapter 7 in a more convenient form for this test, and define the relevant symbols.

7.5.4.1 Schematic Plots

Figure 7.3 shows schematic plot (for hypothesis 1.1) comparing the HDM-III predictions for R&M strategies STP2 and STP4. The plots show rather strongly that the life-cycle predictions from default input data are extremely close to those based on full data. What is more interesting is that the default inputs seem to produce fairly good agency costs predictions even under different strategy and different traffic level.

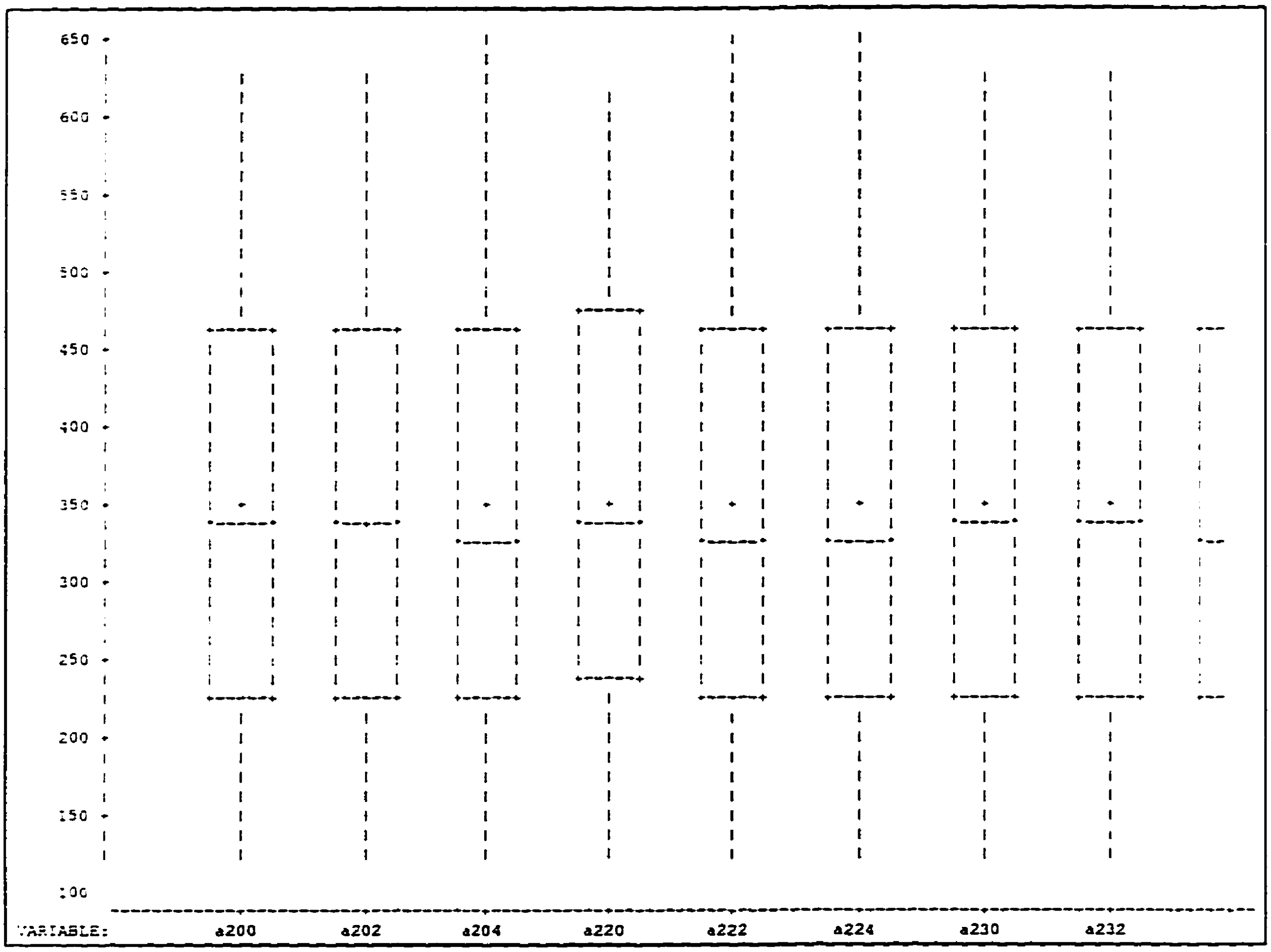

FIGURE 7.3 (a) Schematic plots of agency life-cycle costs for STP2

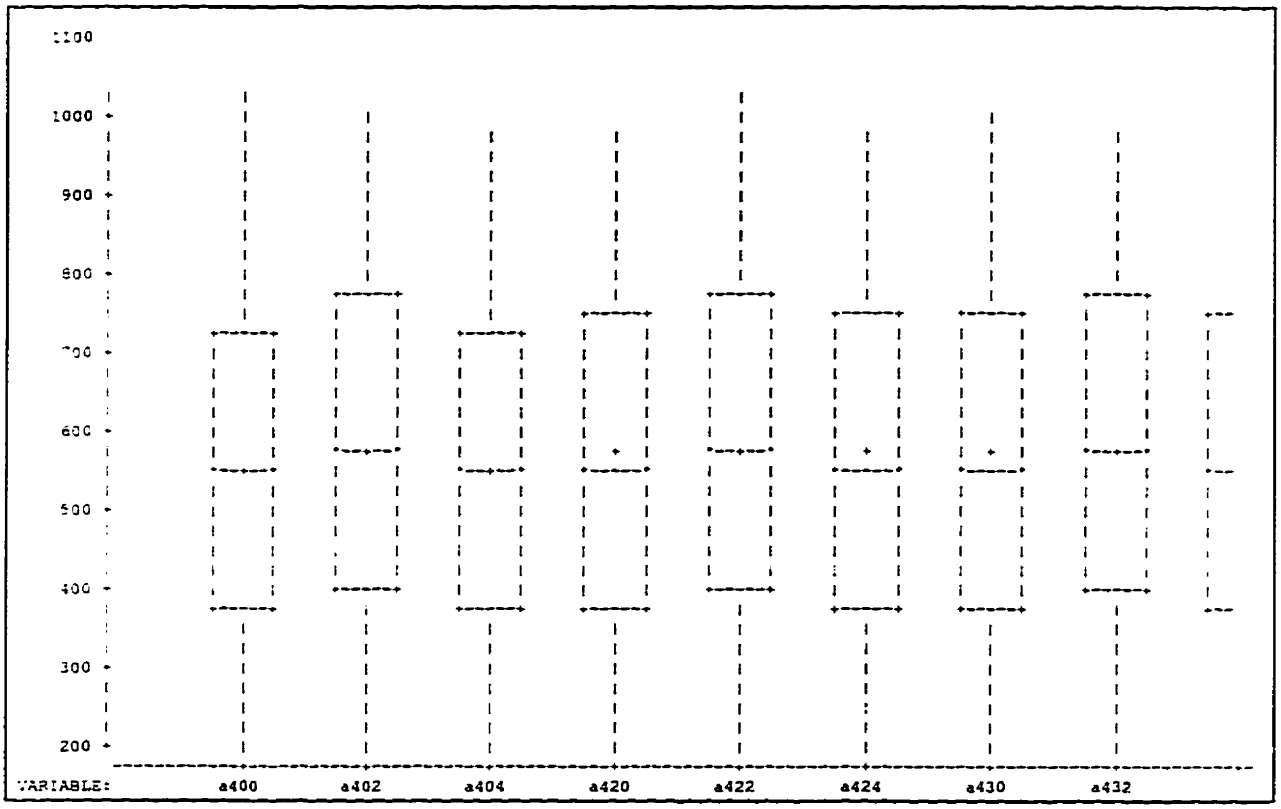

FIGURE 7.3 (b) Schematic plots of agency life-cycle costs for STP4

7.5.4.2 Kruskal-Wallis Test

The Kruskal-Wallis test statistic is based on comparing the average rank of the observations in the i-th sample with respect to the grand or overall average rank of all the observations. The sum of all the ranks is equal to $N(N+1)/2$ where N is the total count of all the observations in the s treatments to be compared. Therefore, the grand average of all ranks is given by,

$$R_{..} = \frac{\left(R_{11}+\ldots+R_{1n_1}\right)+\ldots+\left(R_{k1}+\ldots+R_{kn_k}\right)}{N} = \frac{N+1}{2} \qquad \ldots(7.1)$$

where, R_{ij} stands for the rank of i-th observation in the j-th sample or treatment.

The Kruskal-Wallis statistic is a measure of the overall closeness of the R_i to the grand average rank, $R_{..}$ It is based on the weighted sum of the squared differences $\{R_i - ½(N+1)\}^2$. Thus, the statistic is defined as:

$$K = \frac{12}{N(N+1)} \sum_{i=1}^{k} n_i \left(R_i - \frac{N+1}{2} \right)^2 \qquad ...(7.2)$$

where, R_i is the i-th treatment average rank.

K is zero when the R_i are all equal, and is large when there are substantial differences among the treatments. The null hypothesis is rejected for large values of K, corresponding to a given significance level. The critical values corresponding to the upper tail significant levels (α) are approximated by the Chi-square distribution with the degrees of freedom, $d.f. = s - 1$. For example, if 3, 4, and 5 treatments are to be compared each of which has 150 observations, the approximate critical values, K_c at an α level of 0.05 are: 6.0, 7.8, and 9.6 respectively (Table I and J, [Lehmann 75]).

The Kruskal-Wallis test results for the hypotheses defined in Table 7.1 are summarized in Table 7.3. The SAS® NPAR1WAY procedure was used. The table shows the sample statistics are all consistent with the null hypotheses given in Table 7.1. There is no evidence to reject the null hypotheses. The small magnitudes of the Chi-Square values indicates how close the default-based cost predictions are to the full data predictions.

TABLE 7.3 Kruskal-Wallis Test Results

Hypothesis Number	d.f.	Chi-Square (χ^2_{obs}) Approximation	Upper Tail Chi-Square	Decision value: χ^2_{crt} (Reject H_0 if $\chi^2_{obs} > \chi^2_{crt}$)
1.1	4	0.0695	0.9994	9.6
1.2	4	0.0797	0.9992	9.6
2.1	3	0.2232	0.9738	7.8
2.2	3	0.1463	0.9857	7.8
3.1	4	0.1636	0.9968	9.6
3.2	4	0.1999	0.9953	9.6
4.1	2	0.7918	0.6731	6.0
4.2	2	0.1199	0.9414	6.0
4.3	2	0.1625	0.9219	6.0
4.4	2	0.0566	0.9721	6.0
4.5	2	0.1398	0.9325	6.0
4.6	2	0.1367	0.9339	6.0
4.7	2	0.1314	0.9364	6.0
4.8	2	0.1117	0.9457	6.0

Since the null hypotheses 1.1, 2.1, and 3.1 (1.2, 2.2, and 3.2) states the equality of the default-based life-cycle cost predictions to the same full data predictions at 500 ADT, we conclude that for the same R&M strategy either set defaults inputs produce sufficiently accurate agency life-cycle predictions for all the traffic levels investigated. That is, we could in fact test the null hypothesis:

$$H_0: \quad \mu_{a200}=\mu_{a202}=\mu_{a212}=\mu_{a222}=\mu_{a232}=\mu_{a210}=\mu_{a220}=\mu_{a230}=\mu_{a204}=\mu_{a214}=\mu_{a224}=\mu_{a234} \qquad \ldots(7.3)$$

against the alternative,

H_a: $\mu_j \neq \mu_k$ for any pair (j, k) of full data/default-input-based predictions.

The analysis of variance procedure in SAS® produced the ANOVA table (Table 7.4) for the R&M strategy STP4 predictions for a similar null hypothesis to Equation (7.3). The F statistic obtained shows that, in fact, the between groups variation is much smaller than the within-group variation in life-cycle cost predictions. The average predictions are therefore fairly close for all the different set of default and full input data.

TABLE 7.4 ANOVA Table for the Agency LCC: Strategy STP4

Source	DF	Sum of Squares	Mean Square	F Value	p value
Model	11	28611.028	2601.003	0.05	1.000
Error	1768	94260701.385	53314.876		
Corrected Total	1779	94289312.413			

7.5.4.3 Simple Scatter Plots

The schematic plots as well as the Kruskal-Wallis tests focus at testing the overall distribution of the stream of values, *i.e.*, they compare the typical or mean measures of the distributions. Scatter plots, on the other hand, provide a simple yet powerful technique of visualizing the closeness (or lack of it) of the individual values in a pair of responses.

Figure 7.4 shows the scatter plots for a selected pair of default-based and full-data-based streams of agency and users' life-cycle predictions. Figure 7.4 (a) shows the agency life-cycle costs based on default inputs are extremely close to those based on full-data at all traffic levels and strategies investigated. Part (b) of the figure shows that the users' life cycle cost predictions are also very close for both strategies and at all the traffic levels investigated.

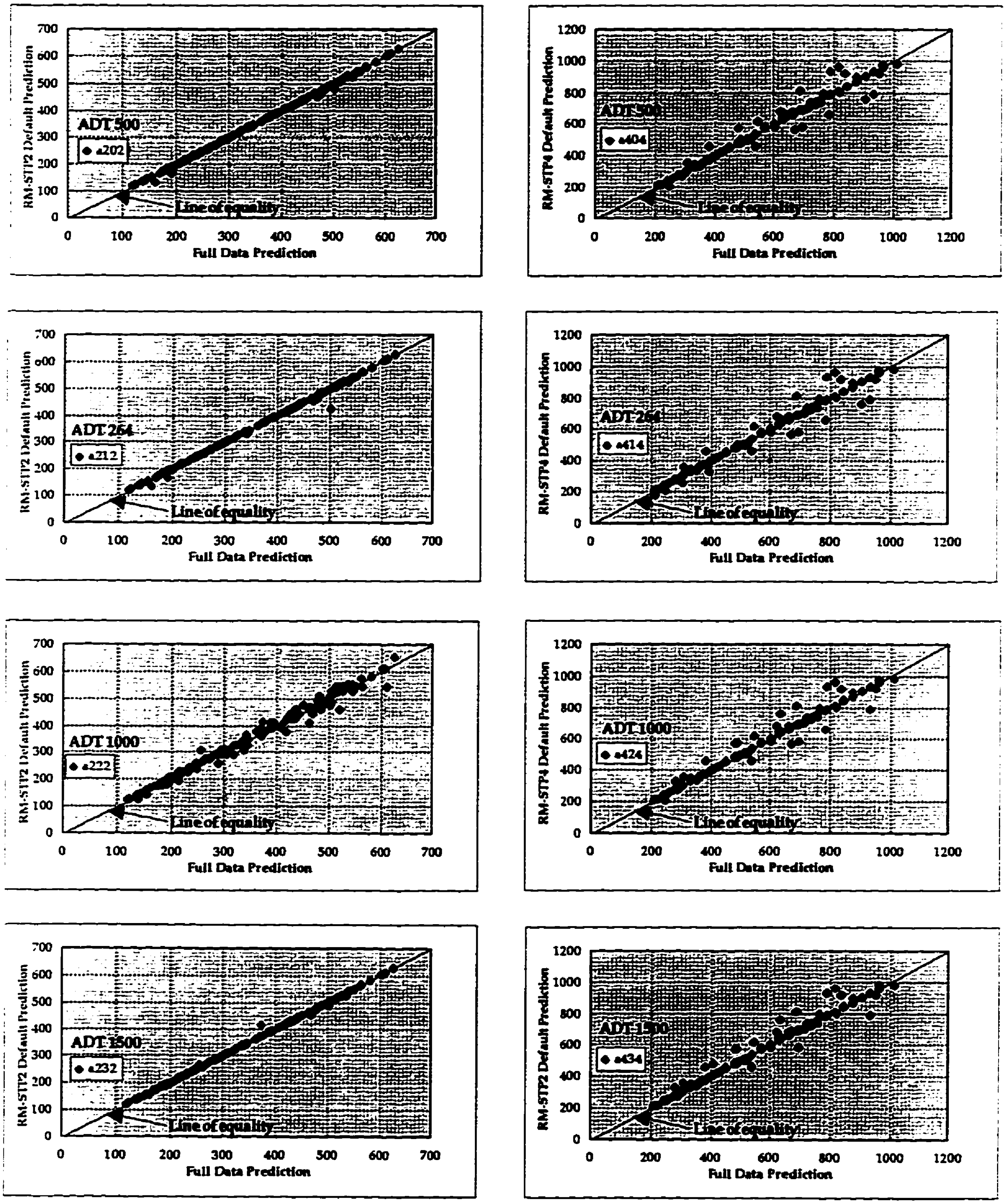

FIGURE 7.4 (a) ***Default-based agency life-cycle costs predictions versus the full data predictions***

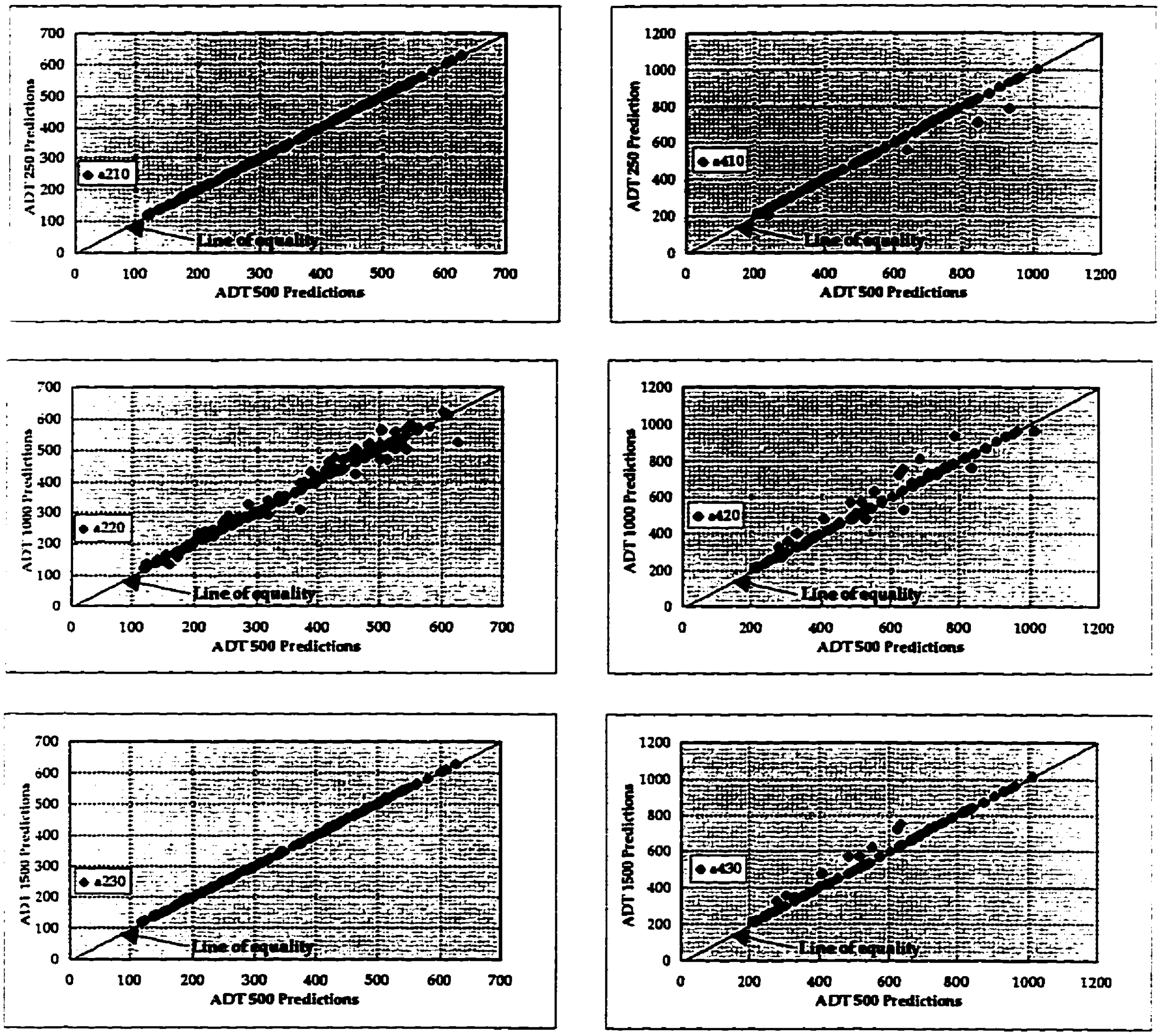

FIGURE 7.4 (b) Comparing agency life-cycle cost predictions at varying traffic levels

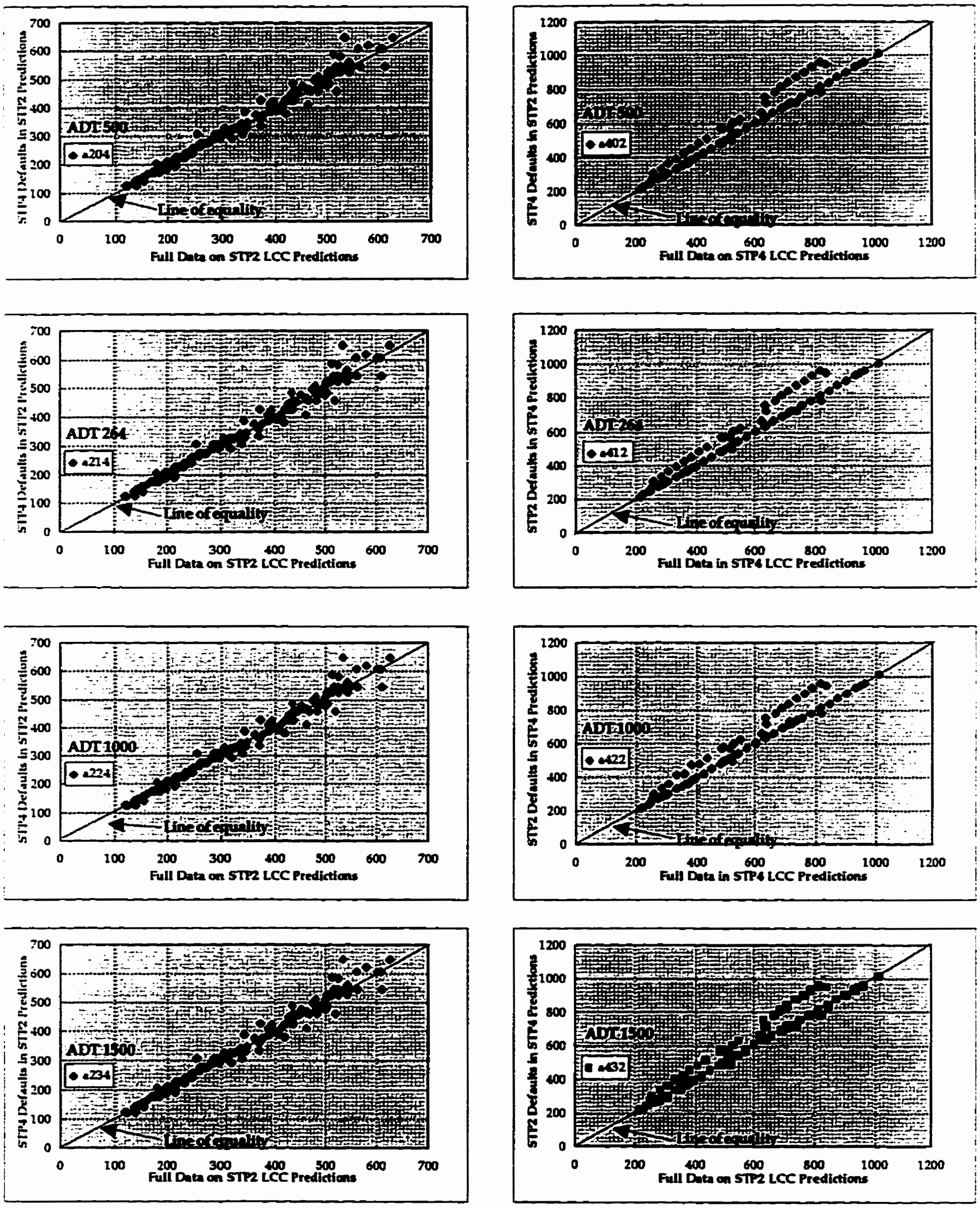

FIGURE 7.4 (c) Agency life-cycle costs predictions based on defaults for different strategy

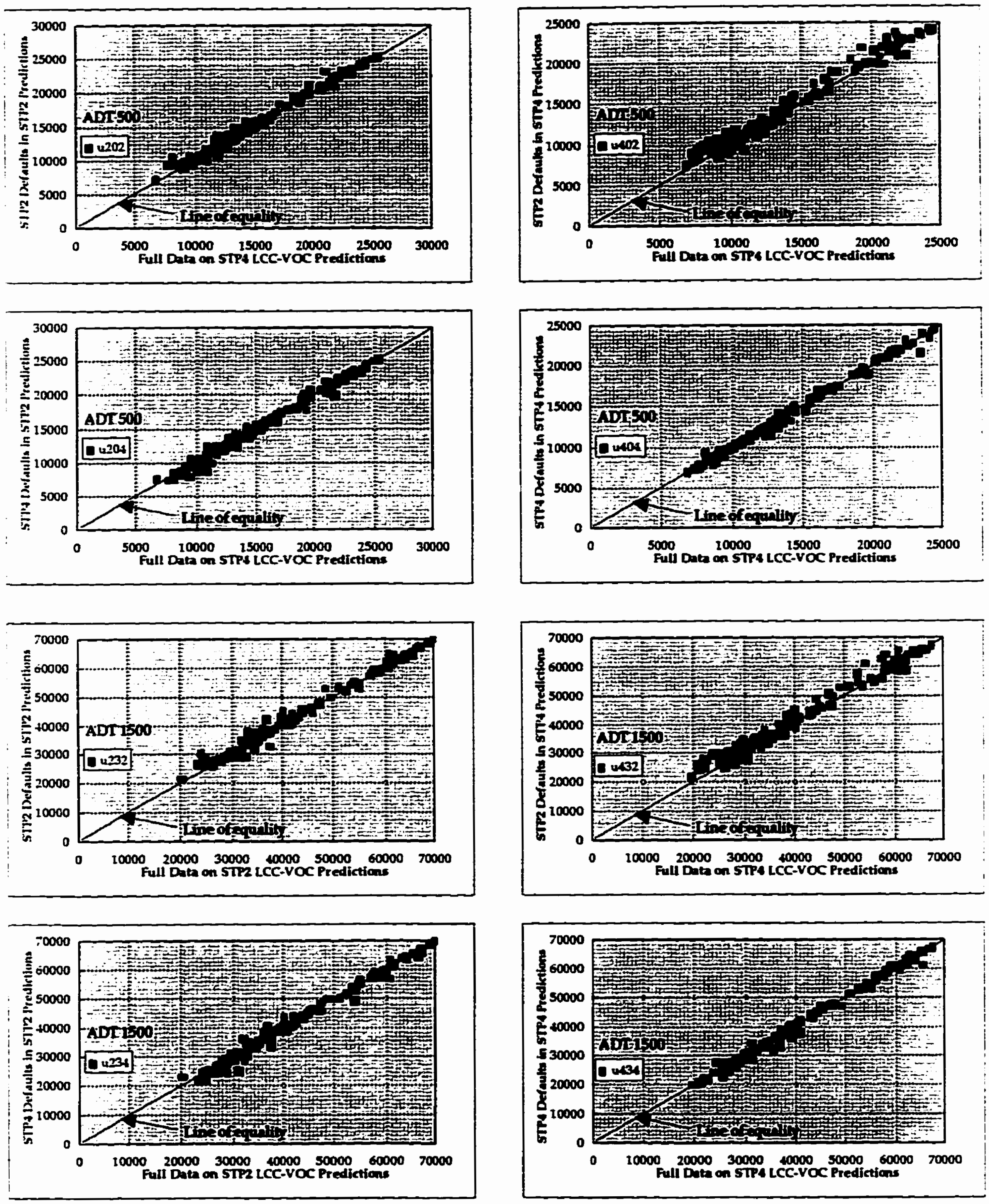

FIGURE 7.4 (d)   Users' life-cycle costs predictions based on defaults for different strategy

7.6 Default-Based NPV Predictions

The comparisons presented so far have dealt with the component agency and users' life-cycle costs. The NPV predictions based on default inputs for the inactive factors determined in Chapter 6 (see Section 6.6) were investigated. The default-based predictions were generated by using typical values for the least active factors determined in Chapter 6. A total of 22 factors was assigned default values. The least active factors to the NPV predictions which were assigned default values for the comparison presented here are: rainfall (*MMP*), horizontal curvature (*C*), superelevation (*SP*), effective number of lanes (*ELANE*), surface layer thickness (*HSNEW, HSOLD*), compaction of the base layer (*CMOD*), and the strength code. Others are, the potholes and raveling calibration factors (*Kpp, Kvi*), the construction faulty code (*CQ*), and the cracking and raveling retardation factors (*CRT, RRF*). Also, default values were used for the slightly active factors – the rise plus fall (*RF*), the altitude (*A*), the shoulder width (*WS*) and the subgrade strength (*SNSG*).

Figure 7.5 shows the scatter plots comparing individual NPV predictions (default-based versus full data based) at each of the 150 data points. The figure shows that the individual default-based NPV predictions are reasonably close to the predictions based on full data.

7.7 Chapter Conclusion

The statistical tests presented in this chapter show that default-based model reduction is viable. The results from the Kruskal-Wallis tests (Table 7.3), the schematic plots (Figure 7.3) and the scatter plots (Figure 7.4), all demonstrate that the default-based life-cycle cost predictions are very close to full data-based predictions.

The results from the hypothesis testing, the schematic plots and scatter plots, have effectively demonstrated that life-cycle costs predictions remain fairly accurate once the active factors are accurately specified. The inactive factors can be assigned default values with practically negligible compromise to the quality of predictions.

NPV predictions based on default inputs also reproduce fairly well the predictions based on full data.

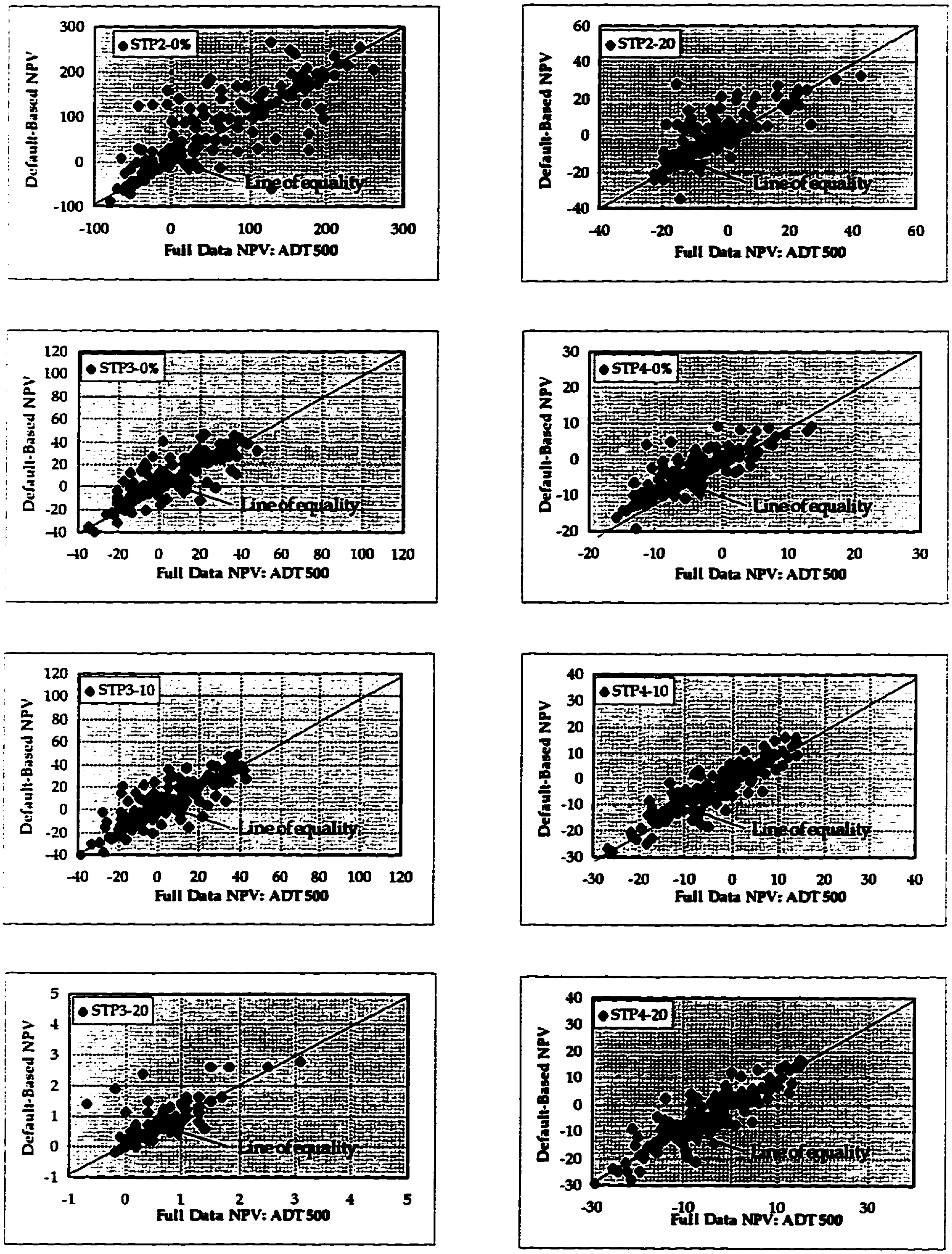

FIGURE 7.5 (a) ***Defaults-based versus full data NPV predictions at ADT 500***

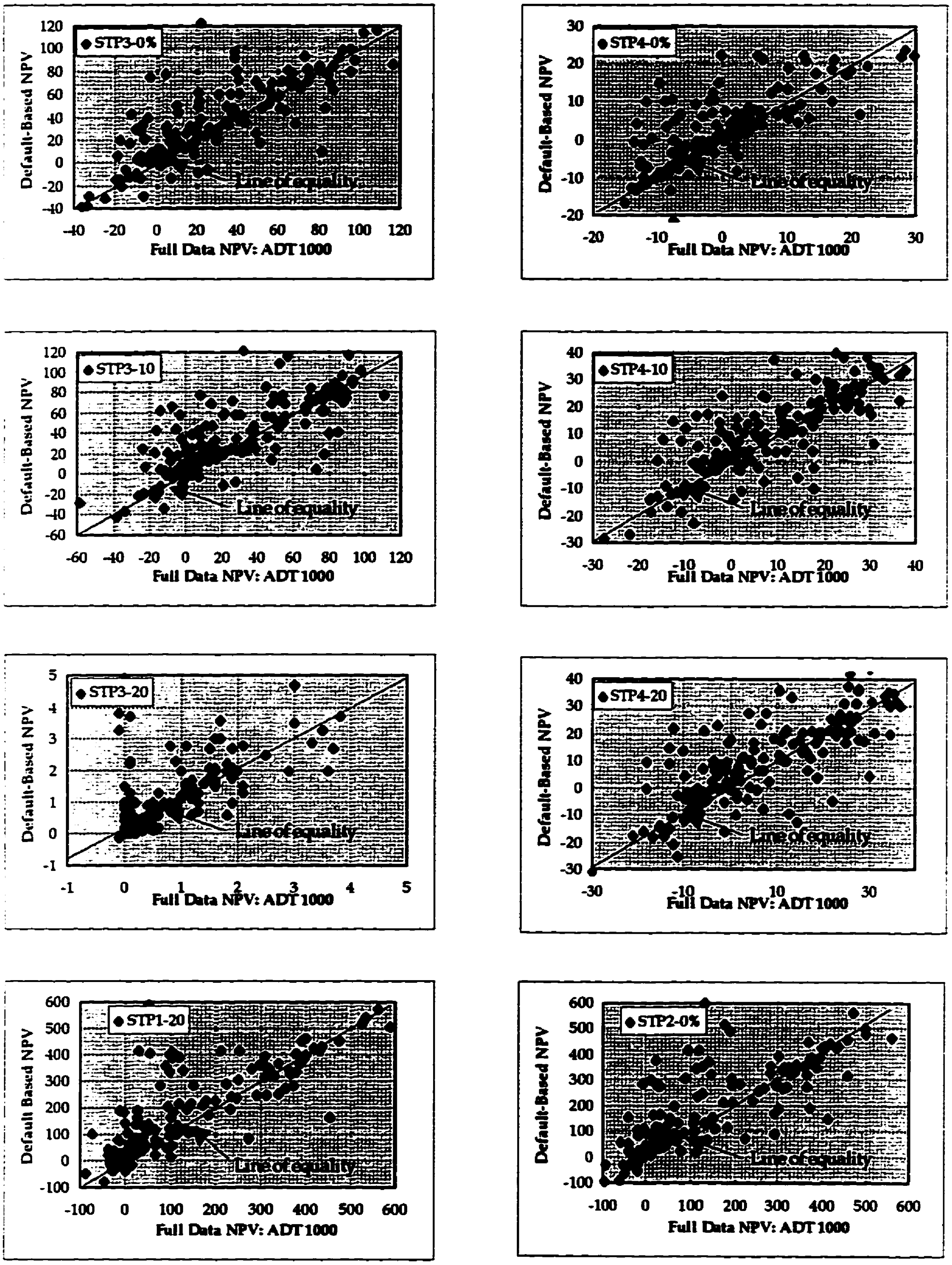

FIGURE 7.5 (b) Defaults-based versus full data NPV predictions at ADT 1000

Chapter 8

CONCLUSIONS AND RECOMMENDATIONS

The purpose of this chapter is to highlight some of the principal findings of this research, point out some implications with respect to HDM-III application in priority programming, and suggest areas requiring further research on the subject matter. The objective of this research was to explore the possibility of streamlining the HDM-III model for application as an analysis engine in pavement management. Comprehensive approaches to factor sensitivity analysis were developed and applied to determine the effect and behavior of input factors upon the common criteria used in priority programming based on the HDM-III model life-cycle predictions.

8.1 Conclusions

The priority analysis function in the context of a network level pavement management system provides the mechanism by which economic criteria are applied to evaluate and compare project alternatives to identify a set of optional choices for implementation. Among the several analysis tools available to low income road agencies, the HDM-III model is the most widely recommended choice.

Data deficiency was recognized as the most serious constraint in low-income road agencies, and probably one of the major disincentives of widespread application of the HDM-III model. Other constraints pointed out as potentially discouraging routine uses of the model at the network level are the lack of a comprehensive guide for end-users' with respect to, low, medium and high priority input factors, and the lack of practical guidelines on region or application-specific calibration.

A review of the practice in network level priority programming indicated that there are diverse schools of thought as to what criterion should be used for ranking or selecting project alternatives. Criteria based on life-cycle costs (for example, the internal rate of return (IRR), the net present value (NPV), *etc.*) have been widely used in developing countries where it is more desirable to compare alternatives on the basis of total societal costs. The findings in this thesis show that, among the various HDM-III predictions, the NPV index is the most suited for ranking and prioritizing maintenance and rehabilitation programs. Compared to the IRR, the NPV is consistently predicted for all link-alternatives in the analysis problem. This is of particular practical advantage when the model is applied in the context of larger suites of pavement management analysis. Control of the flow of information in the shared environments becomes easier.

The Latin hypercube experimental design [McKay 79] was shown to provide a sound methodology for efficiently exploring factor sensitivities over the entire desired input space. In particular, this design is favored for its ability to uniformly and completely explore each factor's (practical) range in a multi-dimensional problem without a prior assumption of factors' role.

Out of the various possible methods of analyzing the post-experimental data in a Latin hypercube model investigation, the use of regression approach in conjunction with the stochastic predictor approach proposed by [Sacks 89a] was shown to be a justifiable and practical choice. The analysis presented in Chapter 6 shows that the standardized coefficients of a suitably selected linear-additive model can provide initial estimate of life-cycle factor sensitivities. However, a more reliable factor sensitivity ranking must be corroborated by an estimation technique in which factor interactions can be identified. The stochastic model provided a useful tool for this purpose. The maximum likelihood procedure for estimating the stochastic model parameters is computationally intensive. As a result, only a small number of response variables could be studied by this method.

The most interesting findings of this research are the factor sensitivities of the HDM-III predictions with respect to the link characterization inputs. The most significant factors in the NPV prediction were found to be: the rutting calibration factor (*Krp*), the pavement strength parameters (*SN, DEF*), the carriageway width (*W*), and the initial pavement distress level (*ACRA, ACRW, APOT* and *ARAV*). These first four ranking significant factors account for close to 64% of the total variability in the NPV.

The next most sensitive factors in the NPV are, the roughness–environmental calibration (*Kge*), the level of rutting and its variability (*RDM, RDS*), the altitude (*A*), and the pavement construction and treatment history (*AGE1, AGE2,* and *AGE3*). Road roughness (*QI*), cracking calibration factors (*Kci, Kcp*) and the base layer thickness (*HBASE*) were also found to be active in the NPV.

The research findings show that the NPV predictions from the HDM-III model are highly non-linear with respect to sensitive input factors and are also subject to significant factor interactions. Explanation of the behavior of the NPV required further investigation on the component agency and users' life-cycle costs.

The component agency and users' life-cycle costs were shown to be dominated by different factors. Interestingly, some of the most active factors for both are those not directly influenced by R&M treatments. The agency life-cycle costs component was found to be highly sensitive to the carriageway width. More than 96% of the total variability in the input space investigated is explained by the width factor.

The next active factors below the dominant width (*W*) factor in the agency life-cycle costs were found to vary according to the R&M strategy. For resealing and similar R&M treatments, the next most sensitive factors to the agency life-cycle cost are the cracking calibration factor and the initial pavement distress level. For overlaying strategies, the next active factors are the pavement roughness level, the rutting calibration factor, the pavement construction and treatment age and the roughness-calibration factor (*Kge*). The observed factor sensitivities for asphalt concrete on granular base were found to be relatively comparable to those obtained for surface dressing on soil cement pavements.

The users' (VOCs) life-cycle cost component was shown to be dominated by the rise plus fall (*RF*) variable. Again, more than 95% of the total variability on VOC life-cycle costs is explained by the *RF* factor. Similar to the pattern in agency life-cycle costs, the remaining (less than 5%) variability is explained by different factors for different R&M strategies. The ranking of active factors was shown to vary from one R&M strategy to the next.

One important implication of the sensitivity findings is in the area of re-calibration priority of the HDM-III pavement performance relationships. The sensitivity results (Chapter 6) indicate that, for the class of pavements investigated, the rutting calibration factor (*Krp*) and the cracking calibration factor (*Kci, Kcp*) call for the highest calibration priority. The next most sensitive calibration factors are: the roughness-environmental-age factor (*Kge*) and roughness progression (*Kgp*). According to the findings, the ravelling calibration (*Kvi*) and the pothole progression (*Kpp*) should be given the least priority in re-calibration.

In Chapter 7 the research investigated the viability of expanding the scope of default inputs in the current HDM-III model. It was demonstrated that, given the factor sparsity exhibited by the component agency and users' life-cycle costs, the data requirements can, in fact, be streamlined without significant compromise in the quality of life-cycle cost predictions. The investigation demonstrated that for practical network applications the present pool of default inputs under link characterization factors can be at increased from the current 14 to about 20-22.

The least active factors to the (HDM-III) NPV predictions are: rainfall (*MMP*), horizontal curvature (*C*), superelevation (*SP*), effective number of lanes (*ELANE*), surface layer thickness (*HSNEW, HSOLD*), compaction of the base layer (*CMOD*) and the strength code. Others are, the pothole and raveling calibration factors (*Kpp, Kvi*), the construction faulty code (*CQ*), and the cracking raveling and retardation factors (*CRT, RRF*). The following factors were shown to be only slightly active: rise plus fall (*RF*), altitude (*A*), shoulder width (*WS*), subgrade strength (*SNSG*) and the previous pavement distresses (*ACRAb, ACRWb*).

8.2 Recommendations

In the thesis research, an exhaustive investigation of input factor sensitivities of the HDM-III model using the Latin hypercube experimental design was demonstrated. Given the promising results achieved in this study, the following areas are recommended for further research:

1. The investigation presented looked only at two types of pavement (surfacing-base pairs). Future research work should look at other common pavement types.

2. The scope of the research in this thesis focused only on a few most common R&M strategies: patching, resealing and overlay. The intervention criteria reflected the low standards typical in Tanzania (and other low-income Sub-Saharan African countries). Further work is recommended to study other strategies at higher policy standards.

3. Since a substantial proportion of the road networks in low income countries consists of unpaved roads, it would worthwhile to extend the investigation to this class of roads. A starting point would be the link characterization factors and typical R&M treatment strategies for unpaved roads.

4. Further investigation could also be carried out to include other factors relevant to R&M priority analysis. The vehicle characterization factors would be of particular interest. Although inconclusive, the *ceteris paribus* results presented in Chapter 6 suggest that some of the factors in this class are potentially very sensitive to the life-cycle predictions.

5. The research in this thesis investigated the application of HDM-III for the low-income road agencies of Sub-Saharan Africa (SSA). The demonstration was based on a case study from a typical country in SSA. The prevailing vehicle technology, fiscal or macro-economic factors, input prices and policy standards, all have a bearing on the results presented. It should be particularly noted that in Tanzania, wage rates are relatively low in relation to vehicle inputs and prices. Also, road design standards are generally low (modified structural number of 3.5 to 4.5). Furthermore, intervention levels tend to fair conditions tolerating higher average roughness (mean IRI = 5.5 m/km). Further research is needed to investigate higher pavement design standards and intervention policies.

6. Section 6.5 developed a framework for prioritizing data collection resources with respect to network level application of the HDM-III model. Once the factor sensitivities have been established, then the data items to which more attention should be paid in allocating the collection dollars are determined on the basis of the factor sensitivities. An important prerequisite for this framework for prioritizing data collection resources is costs and/or cost-effectiveness of collecting such data. The literature is lacking on this relevant area of costs and benefits of collecting data for pavement management. This is an area that warrants a future study.

7. The methodology of this research should benefit the upcoming upgrade of the HDM-III model. Since the HDM4 [ISOHDM 94] is expected to include several enhancements and additions or improvements of the technical relationships in HDM-III, further research is recommended to investigate factor sensitivities in the upcoming HDM4 model. Such a study could provide extremely useful contribution, for example, in a comprehensive user guide on low and high input data priorities, approaches to local calibration, and on region-specific applications of the new model.

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APPENDICES

APPENDIX A

Tanzania: The Context of the Case Study Country

A.1.0 Background

The purpose of this appendix is to give a brief profile of the case study region. The role of data in this research, and the basics of the design and implementation of the data collection work were discussed in Chapter 4 (see Section 4.6). Given that the transferability of the sensitivity findings in the study are critically influenced by the base case factors employed, it was considered worthwhile to provide the context in which the study was conducted.

Most of the material summarized in this appendix are based on a report [Mrawira 95a] submitted to the Ministry of Works, Communication and Transport (MWCT) of the United Republic of Tanzania as final product from the field research. Only the bare skeleton is given here; detail discussion would be found in the cited report.

A.2.0 Executive Summary

The Ministry of Works, Communication and Transport, (MWCT) of the United Republic of Tanzania, through financial arrangements from the USAID Agricultural Transport Assistance Project (ATAP), retained the services of Mr. M. D. M. Mrawira, a consultant engineer with the National Construction Council and currently a Ph.D. scholar at the University of Waterloo, Canada, as an independent researcher to conduct a study towards calibrating HDM-III to Tanzanian conditions.

The primary objective of the study was twofold. First, to develop and compile a database of input data required for application of the World Bank's Highway Design and Maintenance Standards Model (HDM-III) in priority programming for the trunk and regional road networks in Tanzania. Second, the study was expected to provide a standard guide to the problem of calibrating the HDM-III model to suit local conditions in Tanzania.

A major part of this report discusses the data collection exercise, and highlights the study achievements and shortcomings with respect to the original scope. The study succeeded in compiling a substantial amount of the input data required for HDM-III application to network-level works programming. The collected data are presented in the appendices (bound separately) to the report. The complete volume of the study database was submitted on floppy diskettes (two 3.5" HD) to the Ministry of Works (MWCT) in both *dBASE-IV* and *Microsoft Assess* file format.

It must be cautioned that the study success rate in terms of data actually acquired was not one hundred percent of the target scope; some gaps still exist in the study database. In particular, data relating to rates of road deterioration, and rates of resource consumption (in vehicle operating costs estimation) for different makes of vehicles was hard to come by. Such data required historical records taken periodically for the same subjects over time. Almost all REO's do not maintain any such records. The MWCT has yet to identify the need for such data, and therefore, no effort has ever been committed to acquire such systematic data in Tanzania. The report [Mrawira 95a] points out areas in the study database that need further improvements.

Roughness data is also a major deficiency in most REOs. The report recommended a road roughness evaluation protocol based on the TRRL vehicle-mounted Bump Integrator (BI) calibrated by a *MERLIN* as an appropriate methodology in Tanzanian settings. To improve the quality of roughness results, the report recommends a number of precautions and techniques of calibrating the Bump Integrator.

Other areas recommended for improvements are the condition survey protocols. The current MWCT guidelines on condition survey, based on OECD approach, are inadequate. The rating determined by this approach is an arbitrary index that does not bear a direct functional relationship with the extent of road surface distresses. Condition survey data of this form have limited usefulness as a source of HDM-III input data. The traffic data also are deficient in quality and consistency; there is a need for updating and improving the current traffic counting protocols. Axle load surveys should be introduced as a standard part of traffic counting. Also, more counting stations should be introduced so that any given road link has at one or two traffic counting stations.

A.3.0 Country Profile

A.3.1 Location and Demographics of the Study Area

Tanzania is located in Eastern Africa, bordering the Indian Ocean between Kenya and Mozambique. It also borders Uganda to the north, Rwanda, Burundi and Zaire to the west. Zambia and Malawi complete the borders on the South-West. Figure A.1 shows territorial boundaries of the country; the insert on the map shows the location of Tanzania on the African continent.

Tanzania has a large territory (slightly smaller than France and Spain combined). Its total area of 945,090 square km (land area 886,040 sq. km) is slightly larger than twice the size of California. The population was estimated at 28 million (in 1994) with demographic density concentrated on its geographic periphery. The population growth rate over the last 20 years has been about 2.6 to 3.2%.

The climate varies from tropical along the coast to temperate in the North-East and South-West highlands. The terrain consists of coastal low plains at 0 to 250 m above sea level, an expansive central plateau ranging from 300 m to 800 m above sea level and highlands in the North-East and South-West rising from the Plateau to a series of mountain ranges well above 1500 - 2000 m. Mount Kilimanjaro, the highest peak in Africa at about 5895 m (19 340 ft) above sea level marks the terrain in the north.

Land use statistics estimate the arable land as only 5% of the total land. Permanent cropping is exercised over a meager 1% of the land. Irrigated farming was estimated (1989) as totaling only 1,530 sq. km. Other land use are: meadows and pastures 40%, forest and woodland 47%, and others 7%.

A.3.2 Macro Economic Context

Tanzania is one of the poorest countries in the world. The economy is heavily dependent on agriculture which accounts for about 60% of GDP, provides 85% of exports and employs 90% of the work force. Industry accounts for 8% of GDP and is mainly limited to processing agricultural products (sugar, beer, cigarettes, sisal twine) and light consumer goods. The economic recovery program announced in mid-1986 has generated notable increases in agricultural production and financial support for the program by bilateral donors. Growth in 1991-93 featured a pickup in industrial production and a substantial increase in output of minerals led by gold.

National domestic product (GDP) – purchasing power equivalent – was estimated in 1993 at $16.7 billion. From these World Bank's estimates the national product per capita for 1993 was about $600. National product real growth rate for the same year was estimated at 3.2%. The industrial production growth rate in 1990 was 9.3%. Mining also plays a strong role in the industrial produce, the dominant being diamond and gold mining. Other industries are: oil refinery, shoes, cement, textiles, wood products and fertilizer.

Topography and climatic conditions (frequent draughts) limit cultivated crops to only 5% of land area. Important cash crops include: coffee, sisal, tea, cotton, pyrethrum (insecticide made from chrysanthemums), cashews, tobacco and cloves (Zanzibar). Significant food crops are: corn, wheat, cassava, bananas, fruits, vegetables; small numbers of cattle, sheep and goats.

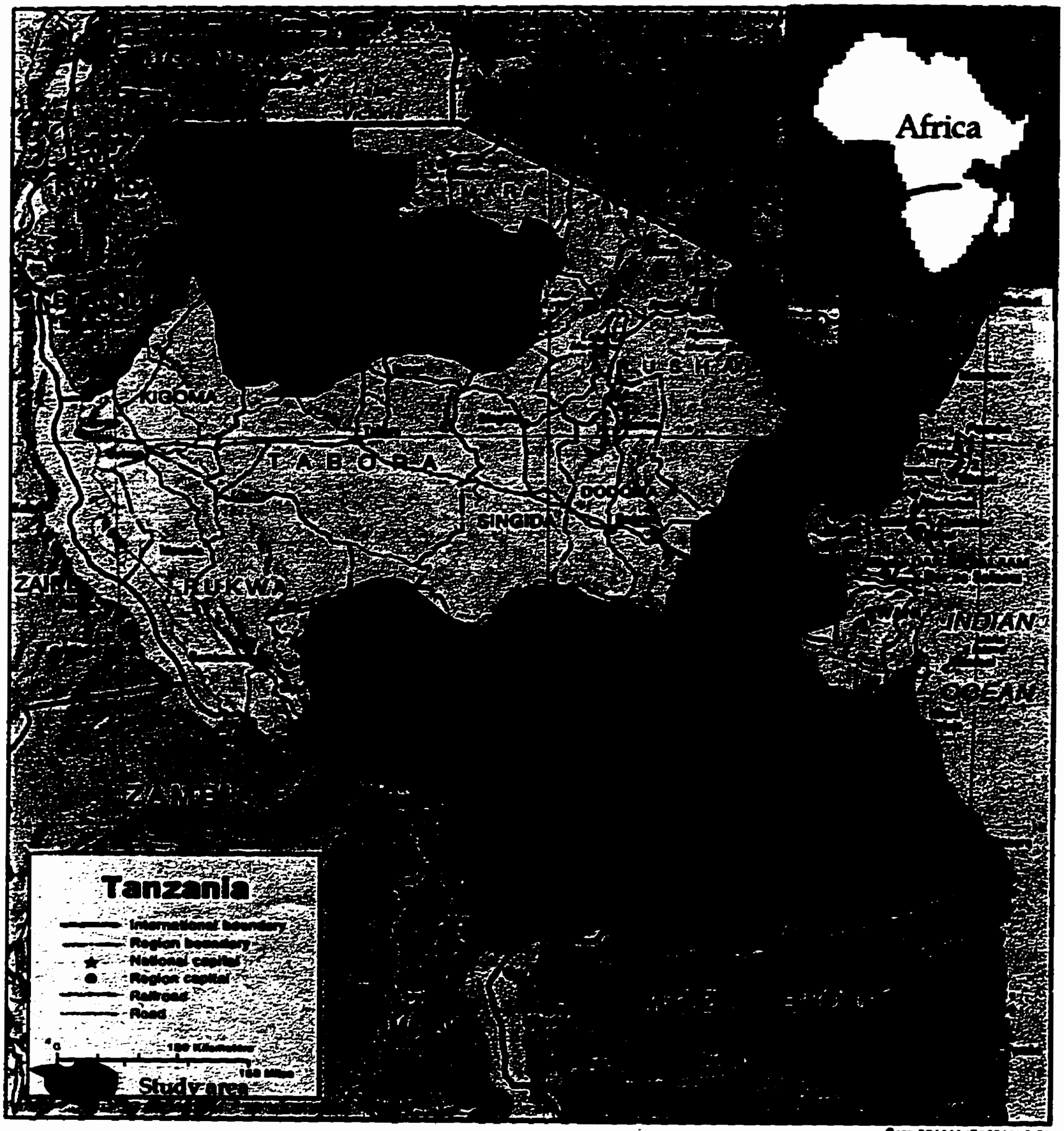


FIGURE A.1 ***Geographical location of the study area***

Most of the agricultural output is produced by small farmers scattered in small rural communities, while the major markets and processing centers for crops, as well as the distribution points for agricultural inputs and fuel, are concentrated in urban centers located at considerable distances from each other and from major coastal sea ports.

A.3.3 The Transportation System

Because of this spatial distribution of human settlements and of production, transportation and communication assume an extraordinarily important role in Tanzania's economic development. In addition to its role of integrating domestic markets, Tanzania's transport system provides an outlet to the sea for the land locked countries of Malawi, Zambia, Burundi, Zaire and Uganda. In recent years, after coffee, the transport sector was the second largest earner of foreign exchange.

Sector Summary

The Tanzanian transportation system consists of:

- A road network totaling about 88,000 km.
- Two railway systems – the Tanzania Zambia Railway (TAZARA) which links Dar Es Salaam with Zambia and the Tanzania Railway Corporation (TRC) which serves the central and northern regions and provides transit to Zaire, Rwanda, Burundi and Uganda.
- Four ocean ports of Dar Es Salaam, Zanzibar, Tanga and Mtwara, and two inland ports of Mwanza and Kigoma. Inland waterways account for cargo and passenger movements in Lake Tanganyika, Lake Victoria and Lake Nyasa.
- A civil aviation sub-sector consisting of Air Tanzania Corporation, several small airlines, two international airports and more than 60 smaller domestic airports and air strips. Twelve airports have permanent surface runways; only 4 of these have runways over 1250m long.
- A fleet of road vehicles of more than 100 000, and
- A 982 km pipeline (crude oil) from Dar Es Salaam to Ndola, Zambia.

The Road Network

The road network is by far the most dominant mode of transport accounting for more than 60% of the total internal traffic flows. The network consists of about 3 800 km of paved trunk roads, 6 500 km of gravel trunk roads, 17 750 km of regional roads and an estimated 30 000 km of district and feeder roads, mostly improved and unimproved gravel roads. In addition, there are about 30 000 km of unclassified roads which are managed by parastatals, national parks and village councils.

By mid the 1980's the road network had become severely deteriorated as a result of inadequate maintenance over several years. It was estimated that only 15% of the trunk and 10% of the rural roads were in good condition at the start of the Integrated Roads Project (IRP-I) in 1990. As a result of the World Bank funded IRP-I project the proportion of trunk and rural roads in good condition has increased by at least 100 and 50% respectively at the start of this field work (1994).

Vehicles and Trucking Capacity

There is limited available data on the size of and characteristics of the vehicle population in the country. However, the best available estimates suggest a total fleet size of more than 100 000, of which, 47% are private cars and pickups, 40% commercial vehicles, 7% buses and taxis and the rest special purpose vehicles. In terms of ownership, the private sector dominates the markets for both freight and passenger services. The are no regulatory barriers to market entry and markets have been decontrolled. However, for intra-regional traffic, tariffs are still being established thorough a process of negotiation between operators and the Regional Transport Coordinating Committees. Similarly in Dar Es Salaam, bus tariffs are negotiated between the Ministry of Works, Communication and Transport (MWCT) and private and public operators. Inter-urban and intra-urban (apart from Dar Es Salaam) passenger transportation is provided entirely by the private sector at market rates.

A.4.0 The Field Work Design and Context

A.4.1 Scope of the Study

The scope of this study was to compile all the basic input data required to apply HDM-III in maintenance and rehabilitation programs formulation. Two categories of data were envisaged. The first category was the type of data required for calibration of the pavement deterioration and vehicle resource consumption relationships in HDM-III. The intention was to construct time series sampling records from existing data that could be used to model pavement performance and VOC trends. The second category constitutes the bulk of HDM-III input data proper. This category was dealt with using a questionnaire survey intended to capture cross-sectional data of the regional road networks.

The study area covered the trunk and regional roads of eleven administrative regions. The study regions were Morogoro, Iringa, Mbeya and Ruvuma along the TANZAM and Southern Corridors (see Figure A.1). Others are Tanga and Kilimanjaro on the North Eastern, and Shinyanga, Mwanza and

Kagera on Central and Lake circuit. And finally, Lindi and Mtwara along the Southern Coastal corridor. The shaded area in Figure A.1 shows the geographical distribution of the study regions.

The selection was not entirely arbitrary. Most of these regions fall in the so called "core rural regions" (under IRP-I); and incidentally all had some Technical Assistance activities going on. It was considered that this sample will be manageable and yet wide enough to include all the important geographical, geological and climate as well as economical variations prevailing in Tanzania.

The data compiled constitute very detailed information ranging from road link characterization attributes (*e.g.*, alignment, environmental factors, current pavement condition, *etc.*), to maintenance standards and policies, traffic volumes and growth patterns, and vehicle fleet characteristics and vehicle operating costs (VOC) data. Appendix B (Study Questionnaire) illustrates the level of detail desired on each individual data item.

Road roughness data was attached a special interest in this study. The justification was that roughness values used in most studies, consultants' reports and in regional action plans have historically been either purely subjective estimates or measured using an inappropriate approach. An example at hand is the recent study on TANZAM Highway Feasibility and Pavement Management [DCIL 92], where the consultant used HDM-III to provide economic evaluation of *R & M* needs. A vehicle-mounted bump integrator was used to measure road roughness on the said project; however, it is considered that the calibration of this roughness equipment was not properly performed.

A.4.2 Respondents' Profile

A total of 13 questionnaires were completed, one each for the 11 study administrative regions, and two for the two independently managed highway units (TANZAM and Songea – Makambaku Highways). A total of 45 respondents were consulted in person (by the researcher) to complete the 13 questionnaires. Table A1 shows a profile and distribution of the respondents. As seen in the table, the number of respondents ranged from 2 to 7 for the regional questionnaires and 2 and 1 for the TANZAM and Songea – Makambaku highway units respectively. The engineering experience of the respondents varied from 3 to more than 10 years, most of whom were graduate engineers.

TABLE A.1: Profile of the Questionnaire Respondents

Region / Corridor	Question -naire #	Name and Designation of Respondent	Number of Respondents	Experience/ Education
Morogoro	01	Farisi (Asst. PLE), Gumbi (Asst. RRE), Myovelwa (ME)	4	3 - 10 years, Adv. Diploma, B.Sc.
Iringa	02	A. Andreski (TA -REO), Shaun Kennedy (TA), Mtigumwe (Asst. RRE), Byabato (RE)	5	5 - 10 years, B.Sc., M.Sc.
Mbeya	03	Mlaponi (PLE), Kitali (ME), Kisaini (Asst. RRE), Kalitwa, (Asst. PLE), Kissanga (RRE), Massaba (TRE), Kipande (RRE)	7	3 - 10 years, B.Sc.
Ruvuma	04	Mac Mbwira (PLE), Chambo (RRE), S. Mwasindila (RRE)	3	5 - 10 years, B.Sc., M.Sc.
Songea - Makambako	05	S. N. Jackson (Unit TRE), C. B. Ayo (Ass. TRE)	2	3 to 5 years, M.Sc.
Kilimanjaro	06	O. C. Machange (Asst. TRE), Laizer (TRE), Harrison (TA to REO), Mkuzu, Asst. RRE)	4	5 to 10 years, B.Sc. M.Sc.
Tanga	07	Lyakurwa (TRE), Isige (PLE), Beda (RRE), Lyimo (RRM)	4	3 to 5 years, B.Sc.
Shinyanga	08	Mhauka (PLE), G. A. Urio (RRE), E. S. Makundi (TRE)	3	5 - 10 years, B.Sc.
TANZAM Highway	09	Kabaka (TRE- Morogoro)	1	5 - 10 years, B.Sc.
Mwanza	10	Damus P. M. Nakei (PLE), Ronald Lwakatare (Asst. RRE), D. Whatley (TA-REO)	3	3 - 5, 10+ years, B.Sc. M. Sc.
Kagera	11	Kyaruzi (Asst. RRE), – (TRE)	2	3 - 5 years, B.Sc.
Mtwara	12	Kyomo (TRE), H. Swalehe (Asst. RRE), Nkine (ME), Masele (PLE)	4	3 - 5 years, Adv. Diploma, B.Sc.
Lindi	13	Kulaya (Asst. TRE), J. M. Byemerwa (RRE), Chekachene (TRE)	3	3 - 5 years, B.Sc.

Key: ME = Materials Engineer. PLE = Planning Engineer. RE = Regional Engineer. RRE = Rural Roads Engineer. TRE = Trunk Road Engineer. Asst. = Assistant. TA–REO = Technical Assistance to the Regional Engineer's office.

A.4.3 Statistics of the Key Data

Link characterization data compiled in the study covered a total of 66 paved road links constituting a total of 2750 km of roads. Table A2 shows a summary distribution of the paved road characterization data. Out of the 66 total links, 48 links (1671 km) were roads under REOs' jurisdictions and 18 links (1083 km) were under the two independent highway units. The table also shows that the principal pavement types in the study regions are surface dressing (61%) and asphalt concrete (39%).

A.4.3.1 Profile of the Link Characterization Data

TABLE A.2 Paved Link Summarized by Region

Region / Corridor	Number of Links	Total Length (km)	Mean (weighted) Width (m)	Mean (weighted) Shoulder (m)	Surface Type %SD	%AC
Kagera	1	33	6.5	1.5	100	
Kilimanjaro	12	306	6.0	1.0	100	
Lindi	3	90	6.5	0.5	100	
Mbeya	8	106	6.7	1.3	4	96
Morogoro	2	262	6.7	1.5	100	
Mtwara	2	112	6.5	1.0	100	
Mwanza	8	164	6.0	1.3	98	2
Ruvuma	1	20	6.5	1.5	100	
Shinyanga	3	197	6.5	1.4	100	
Songea - Makambaku	3	295	6.5	1.2	100	
Tanga	8	381	6.0	0.9	50	50
TANZAM Highway	15	788	6.8	1.5		100
Total or Average	**66**	**2754**	**6.46**	**1.25**	**60.7**	**39.3**

Key: TANZAM = Tanzania – Zambia Highway, SD = surface dressing, AC = asphalt concrete.

TABLE A.3 Unpaved Links Summarized by Region

Region	Number of Links	Total Length (km)	Mean (weighted) Width (m)	Mean (weighted) Gravel Layer (mm)
Iringa	33	1352	4.9	55
Kagera	19	1226	5.4	25
Kilimanjaro	21	490	4.9	130
Lindi	14	982	5.6	100
Mbeya	43	1332	5.3	110
Morogoro	39	1071	5.2	120
Mtwara	22	1106	4.6	140
Mwanza	60	1300	4.7	50
Ruvuma	35	1571	4.5	65
Shinyanga	22	790	6.4	40
Tanga	26	966	5.1	80
Total or Average	**334**	**12186**	**5.1**	**80**

A.4.3.2 Summary of the Roughness Data

Roughness data was measured on a sample basis from all the eleven study regions. As shown in Table A3 a total of 2488 km of roads were measured at an overall sampling rate of 82%. The table summarizes the distribution of the roughness measurements over the study region. It also shows the weighed average link roughness values for the study regions. Table A4 shows the mean, the standard deviation and the 95% confidence interval of the roughness observations on the paved road links.

TABLE A.3 Roughness Measurements Distribution Over the Study Area

Link	Paved Length (km)	Total Length (km)	Sampling Rate	Mean Roughness (BI mm/km)
Kagera	0.0	90.50	89%	6449.74
Kilimanjaro	177.2	238.20	69%	3574.72
Lindi	63.4	288.60	68%	6364.59
Mbeya	25.0	308.40	100%	7532.30
Mtwara	100.5	277.50	66%	5292.42
Mwanza	95.0	237.00	64%	5124.13
Shinyanga	136.5	173.50	59%	5124.13
Tanga	32.5	96.00	100%	5160.47
Tanzam Highway (Dar - Iyayi)	714.5	714.50	100%	2131.75
Total (or Weighted Mean)	**1344.6**	**2424.2**	**82%**	**4483.94**

TABLE A.4 Summary of Paved Links Roughness Data

Link	Roughness (BI mm/km)		Range (95% Confidence)	
	Mean	STD. DEV.	Lower	Upper
Isaka - Bukombe - Lusahunga Road (1/4)	3597.7	368.3	2875.9	4319.5
Isaka - Bukombe - Lusahunga Road (2/4)	2582.4	207.5	2175.8	2989.1
Isaka - Bukombe - Lusahunga Road (3/4)	3506.5	473.5	2578.5	4434.6
Isaka - Bukombe - Lusahunga Road (4/4)	4306.2	628.1	3075.1	5537.3
KMT (Arusha Rd. jctn.) - Machame Road	4456.0	1113.6	2273.3	6638.8
Masasi - Naganga (Lindi brd) (1 of 2)	2757.1	713.9	1357.8	4156.4
Masasi - Naganga (Lindi brd) (2 of 2)	2640.7	360.5	1934.1	3347.4
Mingoyo - Masasi Road (1 of 2)	2647.2	394.0	1875.0	3419.5
Mingoyo - Masasi Road (2 of 2)	2902.4	817.7	1299.7	4505.2
Mkomazi - Same - Himo Jctn (1 of 2)	3907.6	763.2	2411.6	5403.5
Mkomazi - Same - Himo Jctn (2 of 2)	2376.5	423.1	1547.3	3205.7
Mtwara - Lindi Road (1/2)	4738.7	1263.9	2261.4	7216.0
Mtwara - Lindi Road (2/2)	3457.0	997.0	1502.9	5411.2

TABLE A.4 Summary of Paved Links Roughness Data (continued)

Link	Roughness (BI mm/km)		Range (95% Confidence)	
	Mean	STD. DEV.	Lower	Upper
Musoma - Mwanza (1/2)	3444.9	330.9	2796.4	4093.4
Tanga - Segera - Chalinze Rd (1 of 2)	1341.4	742.5	775.0	2796.6
Tanga - Segera - Chalinze Rd (2 of 2)	1577.9	212.5	1161.5	1994.4
Tanzam Highway (Dar Es Salaam to Iringa)	1855.5	1629.0	780.0	5048.3
Tanzam Highway (Iringa to Iyayi)	2786.5	1119.2	915.1	4980.1
Tanzam Highway (Uyole to Mbeya)	2052.9	210.6	1640.3	2465.6
Tanzam Highway (Tunduma to Mbeya)	1752.9	165.2	1429.1	2076.7
Uyole to Ibanda (Malawi Road)	1752.9	165.2	1429.1	2076.7
Minimum Link mean value	**1341.4**	**165.2**	**775.0**	
Maximum Link mean value	**4738.7**	**1629.0**		**7216.0**

A.4.3.3 Summary of Vehicle Operation Cost Survey

The vehicle data was collected from eight regions (see Table A5) and consisted of a total of 44 records ranging from 3 to 13 vehicle class types per region surveyed. Table A5 also shows that data collected ranged from 2 to 14 per vehicle class. Tables A6 and A7 present summaries of the key vehicle operating data by vehicle model and by MWCT vehicle classification respectively.

TABLE A.5 Distribution of VOC Data Respondents

	Number of Respondents per Vehicle Class							
Region	Car	Pickup	L. Bus	S. Truck	L. Truck	Semi Trailer	Full Trailer	Total
Morogoro	2	1	1		2		1	7
Iringa	1	1	1		2	7	1	13
Mbeya					2		1	3
Ruvuma					3		1	4
Shinyanga		1			3			4
Mwanza		4		3				7
Kagera		1		2				3
Mtwara					2		1	3
Total	**3**	**8**	**2**	**5**	**14**	**7**	**5**	**44**

Key: L = large; S= Small = less than 25 passengers(bus)/ less than 5 tons (truck)

TABLE A.6 Summary of the Vehicle Operating Costs Data

Vehicle Model	Payload	No. of Axles	Tires	VKmT	Rates of Consumption			Source Firm
					Fuel	Lubricants	Tires	
BENZ 2624 V8	38	6	22	80,000	0.400	0.0056	0.0055	M/S F. M. ABR
Benzi 2628	40	6	22	50,000				M/S S. T. ABRI
Comet 16-14	10	2	6	19,300	0.330		0.0003	SHIRECU
DAF AVM 2100	10	2	6	34,000	0.240		0.0002	SHIRECU
DAF FA 1600	8	2	6	43,700	0.270		0.0002	SHIRECU
GORICA	9			72,000				IRINGA RETC
GORICA	15	3	12					MBEYA RETC
HINO FF173K	7	2	6	100,000				IRINGA RETC
HINO FF173K	7	2	6		0.350	0.0085	0.0003	MBEYA RETC
Isuzu CVR 11K	10	2	6		0.420	0.0047	0.0002	KAURU (Ruvu
Isuzu FTR	8	2	6	36,000	0.450		0.0002	Mtwara RETC
Isuzu FTR 11K	8	2	6		0.420	0.0053	0.0002	KAURU (Ruvu
Isuzu FTR, 11K	8	2	6	31,500	0.400	0.0105	0.0000	Moretco
Land Rover 10		2	4	60,000				Msuya garage/
MITSUBISHI F	30	5	18	46,400	0.900	0.0023	0.0009	Moretco
Mitsubishi FV 4	30	6	22		0.470	0.0124	0.0002	KAURU (Ruvu
Mitsubishi FV 4	30	3	10	54,000	0.700		0.0003	Mtwara RETC
MITSUBISHI F	15	6	22		0.900	0.0206	0.0009	MBEYA RETC
MITSUBISHI F	15	5	18	72,000				IRINGA RETC

TABLE A.6 Summary of the Vehicle Operating Costs Data (continued)

Vehicle Model	Payload	No. of Axles	Tires	VKmT	Rates of Consumption			Source Firm
					Fuel	Lubricants	Tires	
Nissan CKB 31	10	2	6	48,000	0.550		0.0002	Mtwara RETC
Nissan CKB 31	10	2	6		0.470	0.0049	0.0001	KAURU (Ruvu
NISSAN CKB 3	10	2	6		0.500	0.0109	0.0003	MBEYA RETC
NISSAN CKB3	10	2	6	108,000				IRINGA RETC
Nissan OKB31	10	2	6	46,000	0.500	0.0013	0.0002	Moretco
Peogeot 404		2	4	225,000				Msuya garage/
Peogeot 504		2	4					Mindu Tours (Ir
Peogeot 504		2		225,000				Msuya garage/
SCANIA 93	40	6	22	40,000				M/S S. T. ABRI
SCANIA 113E	42	6	22	60,000	0.600	0.0058	0.0055	M/S F. M. ABR
SCANIA 143	50	6	22	40,000				M/S S. T. ABRI
SCANIA F93H	11	2	6	150,000				M/S COMFOR
Scania HR63 F		2	6	208,000				Hood Bus Serv
Toyota L/C HJ7		2	4	70,000	0.127		0.0001	SHIRECU
VOLVO	50	5	18	50,800		0.0018		M/S S. T. ABRI
VOLVO N12, V	50	6	22	60,000	0.700	0.0082	0.0055	M/S F. M. ABR
Mean value	20		11	78,065	0.485	0.0073	0.0010	

TABLE A.7 Vehicle Operating Costs Data Summarized by Vehicle Type

MoW VehType	Payload	Num of Axles	Ann Hrs Driven	Fuel Rate	Engine Size	Lubricants rate	SourceCompany
0							
	9						IRINGA RETCO
	15	3					MBEYA RETCO
	12	3					
1							
		2	2,400		1,680		Msuya garage/ Mara T
		2	2,400		1,680		Msuya garage/ Mara T
		2			1,971		Mindu Tours (Iringa0
		2	2,400		1,777		
2							
		2	2,000		2,000		Msuya garage/ Mara T
		2		0.127	3,980		SHIRECU
		2	2,000	0.127	2,990		
4							
		2	2,770		9,000		Hood Bus Services Ltd.
	11	2	2,250		9,800		M/S COMFORT LTD
	11	2	2,510		9,400		

TABLE A.7 Vehicle Operating Costs Data Summarized by Vehicle Type (continued)

MoW VehType	Payload	Num of Axles	Ann Hrs Driven	Fuel Rate	Engine Size	Lubricants rate	SourceCompany
6							
	7	2		0.350	6,443	0.0085	MBEYA RETCO
	7	2			6,400		IRINGA RETCO
	8	2		0.450	5,785		Mtwara RETCO
	8	2		0.420	5,785	0.0053	KAURU (Ruvuma Retc
	8	2		0.400	5,785	0.0105	Moretco
	8	2		0.270	6,000		SHIRECU
	10	2			11,600		IRINGA RETCO
	10	2		0.240	6,571		SHIRECU
	10	2		0.500	11,670	0.0109	MBEYA RETCO
	10	2		0.550	11,670		Mtwara RETCO
	10	2		0.500	11,670	0.0013	Moretco
	10	2		0.420		0.0047	KAURU (Ruvuma Retc
	10	2		0.470	11,670	0.0049	KAURU (Ruvuma Retc
	10	2		0.330	6,571		SHIRECU
	9	**2**		**0.408**	**8,278**	**0.0066**	
7							
	38	6		0.400		0.0056	M/S F. M. ABRI
	40	6			9,000		M/S S. T. ABRI
	40	6	1,400				M/S S. T. ABRI
	42	6		0.600		0.0058	M/S F. M. ABRI

TABLE A.7 Vehicle Operating Costs Data Summarized by Vehicle Type (continued)

MoW VehType	Payload	Num of Axles	Ann Hrs Driven	Fuel Rate	Engine Size	Lubricants rate	SourceCompany
	50	5	1,300			0.0018	M/S S. T. ABRI
	50	6		0.700		0.0082	M/S F. M. ABRI
	50	6					M/S S. T. ABRI
	44	**6**	**1,350**	**0.567**	**9,000**	**0.0053**	
8							
	15	5			16,000		IRINGA RETCO
	15	6		0.900	16,031	0.0206	MBEYA RETCO
	30	3		0.700	14,886		Mtwara RETCO
	30	5		0.900	14,886	0.0023	Moretco
	30	6		0.470	16,031	0.0124	KAURU (Ruvuma Retc
	24	**5**		**0.742**	**15,567**	**0.0118**	
Grand Means:							
	20	3	2,074	0.485	8,637	0.0073	

APPENDIX B

The Field Study Questionnaire

QUESTIONNAIRE FOR UPDATING TRUNK (& REGIONAL) ROAD INVENTORY DATA FOR PLANNING REQUIREMENTS

Region or Office: ______________________________

Persons Interviewed: ______________________________

Interviewer: ______________________________

Date: ______________________________

Questionnaire ID ______________

INTRODUCTION:

Thank you for agreeing to be one of our valuable respondents to this questionnaire survey to establish road maintenance and inventory data.

This research is being undertaken jointly between the Ministry of Communication and Works, National Construction Council (NCC) and the University of Waterloo in Canada. Although it is primarily part of a PhD thesis research by Mr Mrawira, it is also a response to one of Ministry's immediate research needs, particularly under the current Management Action Group (MAG) objectives. The purpose of the study based on this questionnaire is to compile updated road network characteristics and inventory data required for planning and programming maintenance and rehabilitation investments. The target roads are the trunk and regional networks.

The primary objective of the overall research is to calibrate a simplified methodology based on the World Bank's HDM-III model for the specific application in maintenance options analysis in Sub-Saharan Africa. The research will, in essence, attempt to develop sets of default input parameters for the HDM model that can eventually be used to speed up the process of input files preparation for maintenance and rehabilitation needs analysis. It is anticipated that such an approach will make the HDM model more easily adaptable in day to day planning, programming and budgeting applications for Regional Engineers as well as Ministerial needs, and therefore offer a valuable improvement in pavement management technology in, not only Sub-Saharan Africa but in all low-income countries.

Given the above research goal, the use of the data collected in this effort is considered very central to both the success of the research itself and the validity of the simplified model for your region. We therefore request you to provide the information asked in this questionnaire as carefully and as accurate as possible. In case you are not able to provide an answer based on records to any given question, please provide an estimate and mark it as personal estimate.

Part 1 **ROAD CHARACTERISTICS AND LINK DEFINITION**

1. A *link* is defined as a road length with the uniform traffic throughout its entire length; whereas a *section* of a link has uniform road geometry, pavement type, climate and condition.

   1.1 **Paved Roads Link Characteristics:** For the main trunk/ regional roads, provide the following information for each individual road *link*; attach more sheets if necessary.

Information	Road Link (give origin and destination for each)					
	O:					
	D:					
Traffic volume (AADT)						
Road Length (km)						
Average rainfall (mm/yr)						
Rise plus fall (est.)						
Horizontal curvature (est.)						
Carriageway width (m)						
Shoulder width (m)						
Surface type[1]						
Thickness of surface layer[2] (mm)						
Thickness of old surf. layer[3] (mm)						
Thickness of base layer(s)[4] (mm)						
Subgrade CBR (or strength est.)						
Structural number, SN						
Benkelman deflection (link ave) (mm)						
Year of last Deflection measurement						
Area cracked (%)						
Area ravelled (%)						
Area pothole (%)						
Mean rut depth (mm)						
Likely error in rut depth (%)						
Year last constr or overlay						
Year last resealed						
Roughness (or riding quality est.)[5]						
Roughness Unit						

[1] *Surface treatment, hot rolled asphalt, etc.*

[2] *If the road has been resurfaced, please give the most recent layer thickness.*

[3] *This represents a situation where the original surface have been resurfaced or overlaid.*

[4] *In a situation where a base layer plus another (sub-base) layer of lower quality material may have been used.*

[5] *If actual number is available, like International Roughness Index (IRI) it can be used; otherwise a subjective estimate of very good, good, fair, poor or very poor can be used.*

1.2 **Unpaved Roads Link Characteristics:** **For trunk or regional roads network, please provide the following information for each individual road *link*; attach more sheets if necessary.**

Information	**Road Link (Origin and Destination)**					
	O:					
	D:					
Traffic volume (AADT)						
Road Length (km)						
Average rainfall (mm/yr)						
Rise plus fall (est.)						
Horizontal curvature (est.)						
Carriageway width (m)						
Shoulder width (m)						
Gravel type (volcanic/lateritic)						
Gravel thickness (mm)						
Initial roughness[6]						
Roughness Unit						
Material properties of surface gravel: Perc. passing at sieves: 2.0 mm 0.425 mm 0.075 mm						
Plasticity index						
Minimum and maximum roughness[7]						
Material properties of base gravel: Perc. passing at sieves: 2.0 mm 0.425 mm 0.075 mm						
Plasticity index						
Minimum and maximum roughness[7]						
Mechanical compaction? (Y or N)						
Year last constr. or regravelled						
Year last reshaped (deep grading)						
Subgrade CBR (or strength est.)						

[6] *see footnote 5 under question 1.1.*

[7] *The roughness and range of roughness of the surface is function of for example material properties, give the possible range of values for the material.*

1.3 The following questions relate to your answers to 1.1 and 1.2 above. Please mark [with ×] the most appropriate response:

1.3.1 How was the horizontal curvature for each link obtained?
[A] personal estimate or guess
[B] from design drawings or construction records
[C] other (please specify) ______________________________

1.3.2 How were the pavement layer thicknesses estimated?
[A] personal estimate or guess
[B] from design drawings or construction records
[C] core drilling, dynamic sounding, or other non-destructive method.

1.3.3 Does your agency conduct regular visual inspection to estimate pavement condition (cracking, ravelling, damaged area, pot-holing, etc.) ☐ Yes ☐ No

If yes to 1.3.3 then, answer sub-questions 1.3.3.1 to 1.3.3.4; otherwise skip.

1.3.3.1 Which paved road pavement distresses are normally evaluated. Mark [×] all applicable.
[A] cracking [B] ravelling [C] potholes [D] rut depth [E] area damaged.

1.3.3.2 Which unpaved road distresses are normally evaluated? Mark [×] all applicable.
[A] gravel loss [B] corrugations [C] dusting
[D] rutting [E] general damage [F] potholes
[G] comfortable speed [H] other (specify) ____________________

1.3.3.3 How frequent are the road inspections? Mark [×] the most appropriate.
[A] never [B] for rehabilitation design only
[C] once biannually or less [D] once annually or more.

1.3.4 How often does your agency conduct pavement strength evaluation (*e.g.*, deflection)?
[A] never [B] for overlay or other rehabilitation design only
[C] once biannually or less [D] once annually or more.

1.3.5 Does your agency conduct pavement riding quality or roughness evaluation? ☐ Yes ☐ No

If yes to 1.3.6 then answer sub-questions 1.3.5.1 and 1.3.5.2, otherwise skip.

1.3.5.1 State the equipment used for roughness measurement: ____________________

1.3.5.2 What is the frequency of roughness measurements:
[A] never [B] for overlay /other rehabilitation design
[C] once biannually or less [D] once annually or more.

Part 2 MAINTENANCE STANDARDS, POLICIES AND UNIT COSTS

2.1 Please provide the most recent unit costs of individual road maintenance operations or tasks (based on, for example, contract bids or force-account rates). Attach more pages if necessary.

Maintenance Operation or Work Type	Applicable Surface Type(s)	Application Criterion Frequency	Unit Cost of the Maintenance Operation by			
			Unit of Measure	Economic[8]	Financial[9]	Foreign Exchange
Cold/hot mix patching			Tsh/sq. m.			
Slurry seal, reseal?			Tsh/sq. m.			
Single surface dressing (8..12mm)			Tsh/sq. m.			
Double surface dressing (20..30mm)			Tsh/sq. m.			
Hot mix asphalt overlay 25mm			Tsh/sq. m.			
Hot mix asphalt overlay 40mm			Tsh/sq. m.			
Hot mix asphalt overlay 50mm			Tsh/sq. m.			
Routine maintenance (incl. signs, vegetation, drainage, roadside, etc.)			Tsh/km/yr.			
Light grading gravel rd ((2.5 m^3/m)			Tsh/km			
Heavy grading gravel rd ()2.5 m^3/m)			Tsh/km			
Regravelling 50mm			Tsh/km			
Regravelling 75mm			Tsh/km			
Regraveling 100mm			Tsh/km			
Spot regravelling			Tshs/m^3			
Light grading earth roads			Tsh/km			
Heavy grading earth roads			Tsh/km			
Other (specify)						

2.2 A maintenance standard is defined as a set of operations with definite intervals or other criteria to determine when to carry them out. What are the most common criteria in your agency?
[A] fixed time interval [B] deterioration level [C] weighted by traffic
[D] cumulative axle load ESAL [E] other (specify) ___________

2.3 What is the total number of kilometres of road (by class or surface type) under your jurisdiction?
[A] Paved trunk roads ___________ [B] Unpaved trunk roads _________
[C] Paved regional roads ___________ [D] Unpaved regional roads _________

2.3.1 What is the minimum annual level of road maintenance funds requirements for your region?

____

[8] *Economic costs represent the value of goods or services when the wider social sacrifices or opportunities foregone to deliver the goods or services are considered.*

[9] *As opposed to economic costs financial costs reflect the actual money paid in return for goods or services, whether taxes, duties are applicable or not.*

2.3.2 How far is your region's annual maintenance budget needs are normally met?
[A] 50% or less [B] 60 to 80% [C] 80% or more

2.3.3 Does your agency keep any cost records for completed and or ongoing maintenance and rehabilitation works? ☐ Yes ☐ No

2.4 Does your office maintain construction costs data, and vehicle operating costs database (initiated in IRP-II)? ☐ Yes ☐ No

Part 3 TRAFFIC VOLUME AND GROWTH CHARACTERISTICS

3.1 For each road link provide the most recent traffic data in terms of annual average daily traffic (AADT) classified into the following vehicle types (attach extra sheet if necessary):

Road Link		Average Daily Traffic for vehicle type:							
Origin	Destination		Pickup L/R	Bus <25p	Bus >25p	Trucks <5t	Trucks >5t	Semi Trailer	Full Trailer

3.2 What is the likely traffic growth trends in your region for the next 20 years? In the table below give growth projections indicating the periods with different growth rates.

Traffic Growth Period	Traffic Growth Rates (in %) for vehicle type:							
	Car	Pickup L/R	Bus <25p	Bus >25p	Truck <5t	Truck >5t	Semi Trailer	Full Trailer
Growth Period 1 (0 - 5 years)								
Growth Period 2 (5 - 10 years)								
Growth Period 3 (10 - 15 years)								
Growth Period 4 (15 - 20 years)								

3.3.1 How often does your agency conduct traffic surveys?
☐ never ☐ for rehabilitation or new road design only
☐ once biannually or less ☐ once annually or more

3.3.2 **What is the common method of traffic survey?**
[A] 12-hours 7-days spot counts
[B] 12-hours 3-days spot counts
[C] 16-hours 7-days spot counts
[D] 16-hours 3-days spot counts
[E] Other methods (please specify) ____________________________

3.3.3 Does your traffic data include observation of seasonal variation? ☐ Yes ☐ No

3.3.4 Are axle loadings data collected as part of your traffic surveys? ☐ Yes ☐ No

3.3.5 What will you estimate as the accuracy of the traffic (AADT) data?

☐ 10% or less error ☐ 10 - 20% error ☐ 20 - 40% error ☐ 40% or more error

3.3.6 How accurate would you put the traffic growth rates at?

☐ 30% or less error ☐ 30 - 60% error ☐ 60% or more error

Part 4 VEHICLE FLEET CHARACTERISTICS AND UNIT COSTS[10]

4.1 For each of the main corridors or road classes in your region give your estimate of the average characteristics of a typical vehicle in each class below.
Firm / organisation ____
Applicable road classes or corridors ______________________________________

[10] *This section would ideally be addressed to respondents from local transporting companies, e.g., taxi operators, 'daladala' owners, trucking firms, etc. If however, the Regional Engineers Office cannot advice the interviewer of reputed transport firms in the region, then it is requested to provide estimated response to this section.*

Vehicle Characteristic	Vehicle Type or Class							
	Car	Pickup L/R	Bus <25p	Bus >25p	Trucks <5t	Trucks >5t	Semi-Trailer	Full Trailer
Maximum engine power (metric HP)								
Gross vehicle weight (tonnes)								
Number of axles (or tires)								
Average Axle or (axle-group loads for each vehicle class								
Financial Unit Costs:								
Cost per new vehicle								
Cost per new tire								
Vehicle repair labour cost per hour								
Driver & crew salary per hour								
Annual overhead/standing cost								
Interest rate on new vehicles								
Gasoline price per litre								
Diesel price per litre								
Lubricants cost per litre								
Cargo delay charges per veh-hour								
Annual kilometres driven per veh								
Estimated vehicle life in years								
Hours driven per year								
Number of passengers per vehicle								
Economic Unit costs:								
Cost per new vehicle								
Cost per new tire								
Vehicle repair labour cost per hr								
Driver & crew salary per hour								
Annual overhead/standing cost								
Interest rate on new vehicles								
Gasoline price per litre								
Diesel price per litre								
Lubricants cost per litre								
Cargo delay charges per veh-hour								
Annual kilometres driven per veh								
Estimated vehicle life in years								
Hours driven per year								
Number of passengers per vehicle								
Choose the appropriate vehicle usage: Constant kilometres driven per year Constant hours of use per year	Km							
	Hr							

APPENDIX C

The Pre-processor Flow Chart and Source Code (C++)

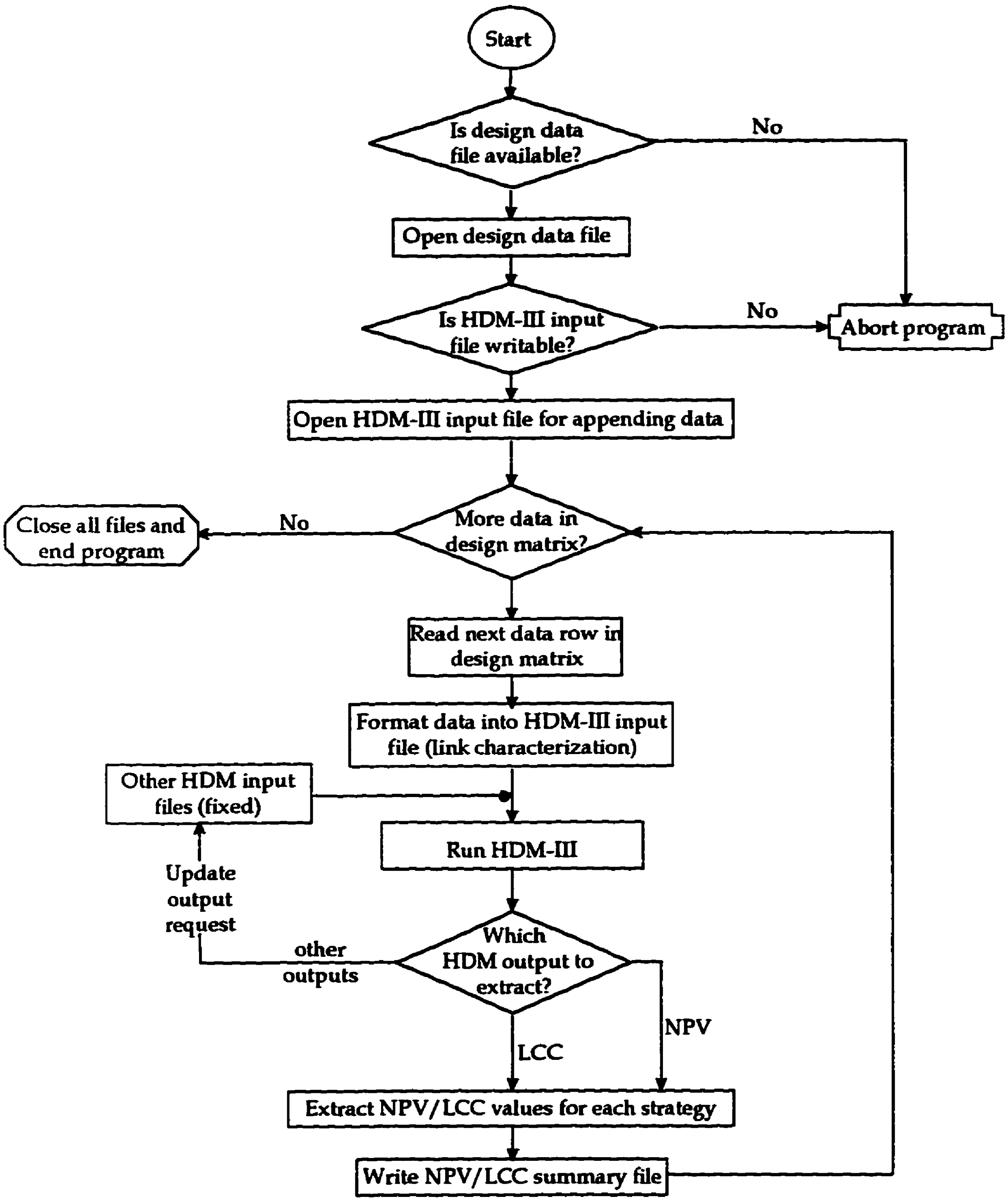


FIGURE C.1 ***The pre-processor (for computing the design data through HDM-III) flow chart***

The Pre-processor C++ Source Code

```
/* REVISED April 19, 1996. By Donath Mrawira */
/* This Program is a Preprocessor for Series A, HDM-III Model input file */
/* The program reads from a file "SOURCE.DAT" an array of 39 values */
/* Arranged in 7 columns times 6 rows where the first value is used as a label */
/* The program writes out the formatted file "PAVEOA.TXT" and then calls the */
/* Model by a batch call "runhdm.bat < run.txt". Both RUNHDM.BAT and RUN.TXT */
/* Have to be in same directory. Also, the other 6 HDM-III input files (listed */
/* in run PAVEOR.TXT file) must be present. */
/* The program next reads the HDM-III output file "REPORT.OUT */
/* First it extracts Undiscounted Economic Cost Totals Under "Cap+Rec", Existing */
/* VOCs" and "Total Econ. Costs". The values are written to file: "CONDITN.DAT */
/* Then it extract NPV values to another file: OUTPUT.DAT. */
/* Note that if the files CONDITN.DAT and OUTPUT.DAT exit they will be appended. */
/* For each new run of an experimental batch, the user has to move or rename */
/* the files SOURCE.DAT, CONDITN.DAT and OUTPUT.DAT */
/* This version assumes (base, surface) combination: (1, 2), i.e. */
/* Asphalt Cement (AC) on Granular base */
/************************************************************************ */

#include <stdio.h>
#include <math.h>
#include <string.h>
#include <stdlib.h>
#include <conio.h>
#include <process.h>

void    cost_sum(int case_num);
void    extract(int case_num);
void    main()
{
        FILE *fp_data;                  /* pointer for the Series A source data */
        FILE *fp_format;        /* pointer for the formatted Series A data */
        char input_str[1000];   /* pointer for reading one line of input */
        char temp_input[300];
        float xf[39];     /* an array variable for breaking down the line string into ind. values */
```

```
        char temp_str[20];
        int count,loopvar;          /* counter variable */
        int num_lines=0;

        fp_data=fopen("source.dat","r");
        if (fp_data==NULL)
                {
                 printf("Error. Cannot open the input data file\n");
                 printf("Exiting\n");
                 abort();
                }
       while ((fgets(input_str,500,fp_data))!=NULL)
                {
        /* Get a string of data */
        /* And the next six lines as well, because one set of data is in a 7 lines */
for (loopvar=1;loopvar<7;loopvar++)
                {
                fgets(temp_input,300,fp_data);
                strcat(input_str,temp_input);
                }
        /* Now break the data down into individual floating point numbers */
                strcpy(temp_str,strtok(input_str," \n"));
        /* throw the first item out. It is a line identifier */

for (count=0;count<39;count++)
                {
                strcpy(temp_str,strtok(NULL," "));
                xf[count]=atof(temp_str);
                }
        /* Now write the data to file */
                fp_format=fopen("pave0a.txt","w");
       if (fp_format==NULL)
                 {
                fclose(fp_data);
                printf("Error cannot open the output file for writing the formatted data\n");
                printf("Exiting\n");
                abort();
                }
```

```
        fprintf (fp_format, "LINK T703Nyanguge - Magu 1 A101 \n");
        fprintf (fp_format, "SECTION 1 26.0 A102 \n");
        fprintf (fp_format, " SECTION DATA P ALL A201 \n");

 /* now lets write in HDM format the read variables into the file "pave1a.txt" */
        fprintf (fp_format, " ENVIRONMENT %6.4f %6.1f A202 \n",xf[0]/1000.,xf[1]);
        fprintf (fp_format, " GEOMETRY %6.1f %6.1f%6.3f%6.2f%6.4f%6.4f A203

        \n",xf[2],xf[3],xf[4],xf[5],xf[6],xf[7]);
        fprintf (fp_format, " SURFACE PAVD 2 1 1%6.1f%6.1f A204 \n",xf[8],xf[9]);
        fprintf (fp_format, " BASE/SUBGRADE 1%6.2f 1%6.1f%6.1f%6.1f A205

        \n",xf[10],xf[11],xf[12],xf[13]);

 /* select strength code: and insert corresponding values of SN or DEF */
if (xf[14] == 1)
        {
        fprintf (fp_format, " STRENGTH PARAMETERS 1 %6.4f %6.2f A206\n", xf[15],
        xf[16]);
        }
else
        {
if (xf[14] == 2)
        {
        fprintf (fp_format, " STRENGTH PARAMETERS 2 %6.4f A206\n", xf[15]);
        }
else
        {
        fprintf (fp_format, " STRENGTH PARAMETERS 3 %6.2f A206\n",xf[16]);
        }
        } /* end if for strength code */

fprintf (fp_format, " DETERIORATION FACTORS %6.3f%6.3f%6.3f%6.3f%6.3f %6.3f
%6.3f A208\n",xf[17],xf[18],xf[19],xf[20],xf[21],xf[22],xf[23]);
fprintf (fp_format, " CONDITION %6.1f%6.1f%6.1f%6.1f%6.1f%6.2f%6.3f%i
A209\n",xf[24],xf[25],xf[26],xf[27],xf[28],xf[29],xf[30],(int)xf[31]);
fprintf (fp_format, " HISTORY %6i%6i%6i%6.2f%6.2f%6.1f%5.1f A210\n", (int)xf[32],
(int)xf[33], (int)xf[34], xf[35],xf[36], xf[37], xf[38]);
fprintf (fp_format, "END LINK A211 \n");
```

```
        fprintf (fp_format, "END SERIES A212 \n");
                fclose(fp_format);

/* Now call the HDM-III program by DOS Command. Note that the batch file */
/* RUNHDM.BAT must be in the same directory as this code. The batch file is also */
/* modified to supply the run control file by adding the line "C:\PATH\HDM1.EXE <RUN.TXT"; */
/* Where "RUN.TXT" is another text file with filename for */
/* run control; and PATH = directory of HDM executable files. */

if (system("runhdm")==-1)
        {
         printf("cannot run hdm\n");
         printf("Exiting\n");
         exit(0);
        }
         /* Now call the codes which extracts the data from the results file */
        printf("Number of runs so far:%i\n",++num_lines);
        cost_sum(num_lines);
        extract(num_lines);
                } /* end while loop */
 fclose(fp_data);
 fclose(fp_format);
 exit(0);
return;
} /* end main */
 /* The following code extracts the undiscounted Cost Summary for "Report.out" file */
void    cost_sum (int case_num)
{
 FILE *fp,*fp3;
 char inp_str[150];
 float trf[50];
 char tmp_str[20];
 int count=0;
 int found;
 int linkid=0;

 fp=fopen("report.out","r");
 fp3=fopen("conditn.dat","a+");
```

```
 if (fp==NULL)
              {
              printf("Error! Cannot Open Results File!!\n");
              abort();
              }
 if (fgets(inp_str,500,fp)==NULL)
              {
              fprintf(fp3,"Case #%i NA NA NA NA NA NA NA NA", case_num);
              fprintf(fp3," NA NA NA NA NA NA NA NA NA NA NA NA\n");
              fclose(fp3);
              fclose(fp);
return;
              }
for (linkid=0;linkid<5;linkid++)
              {
              found=0;
              while (found==0)
                     {
                     fgets(inp_str,120,fp);
                     strcpy(tmp_str,strtok(inp_str," \n"));
                     if (strcmp(tmp_str,"ECONOMIC:")==0) found=1;
                     }
              for (count=0;count<8;count++)
                     {
                     strcpy(tmp_str,strtok(NULL," "));
                     trf[count] = atof(tmp_str);
                     }
              fprintf(fp3,"%9.3f %9.3f %9.3f",trf[0]+trf[1],trf[2],trf[7]);
              }
 fprintf(fp3,"\n");
 fclose(fp3);
 fclose(fp);
return;
}/* end extract Cost Summary Routine */

/* The following code extract NPV values from the HDM report file: "REPORT.RPT" */
void    extract (int case_num)
 {
```

```
 int count=0;
 int num_so_far=0;
 FILE *fp,*fp2;
 int found=0;
 char input_str[300];
 char temp_str[20];

 fp=fopen("report.out","r");
/* the HDM-III Output (report #11) must be in file named REPORT.OUT */
 fp2=fopen("output.dat","a+");
/* NPV values will be stored in a file named OUTPUT.DAT */
if (fp==NULL)
        {
 printf("Error!! Cannot open results file\n");
 printf("Exiting\n");
 exit(1);
        }
if (fgets(input_str,500,fp)==NULL)
 {
 fprintf(fp2,"Case #%i NA NA NA NA NA NA NA NA", case_num);
 fprintf(fp2," NA NA NA NA NA NA NA NA NA NA NA NA\n");
 fclose(fp2);
 fclose(fp);
return;
        }
 /*Now throw out all the irrelevant lines in the file */
 found=0;
 while (found==0)
        {
 fgets(input_str,500,fp);
 strcpy(temp_str,strtok(input_str," "));
 if (strcmp(temp_str,"T703")==0) /* The code expects the link code used to be T703 */
        found=1;
        }
/* Now get the NPV values. There should be 20 of them */
/* throw out the next line. */
 fgets(input_str,500,fp);
while ((fgets (input_str,500,fp))!=NULL)
```

```
        {
        strcpy (temp_str,strtok (input_str," "));
        for (count=1;count<14;count++)
         strcpy (temp_str,strtok(NULL," ")); /* get the 14th item, net pres val */
if (strcmp (temp_str,"\0")!=0)
         {
         fprintf (fp2,"%7.2f ", atof (temp_str));
         num_so_far++;
        }
        if (num_so_far==4)
        {
         found=0;
         num_so_far=0;
         while ((found==0)&& ((fgets (input_str, 500, fp))!=NULL))
        {
         strcpy (temp_str,strtok (input_str," "));
         if (strcmp (temp_str,"T703")==0)
                found=1;
        }
        }
        Fgets (input_str,500,fp); /*throw out every 2nd line */
        }
 fprintf (fp2,"\n");
 fclose (fp);
 fclose (fp2);
        } /* End extract NPV values Routine */
```

APPENDIX D

Diagnosis of the Stochastic Predictor: Cross Validation Residual Plots

Figure D.1 The predicted NPV (ADT 264) versus the predictor variables

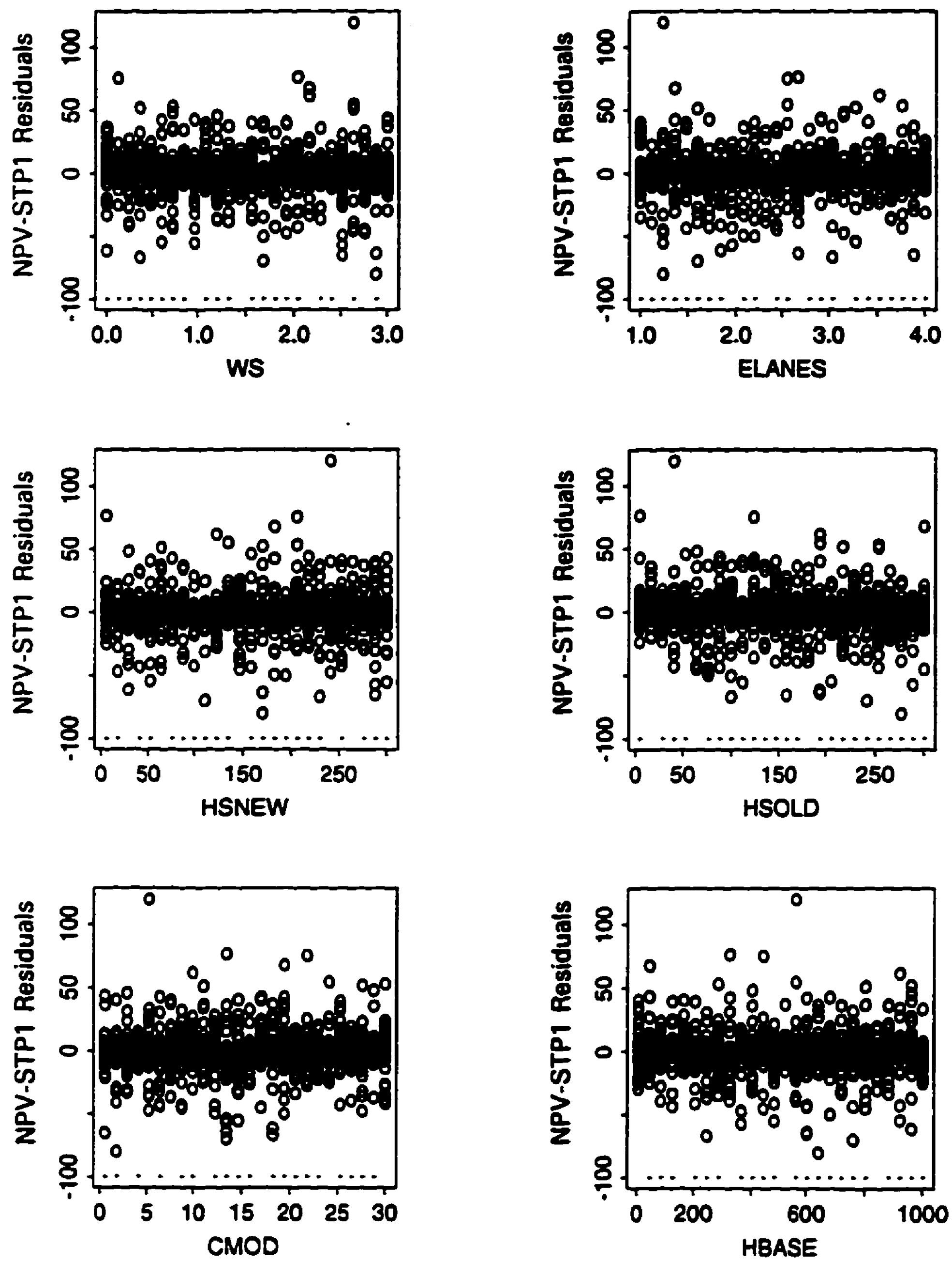
(See Section 6.3.2.1 and Figure 6.8)

Figure D.2 The predicted LCC-VOC (ADT 1000) versus the predictor variables

(See Section 6.3.2.3)

Key: NPV = net present value of the total life cycle costs savings of the R&M strategy STP1 over STP0; pavement type: asphalt concrete (AC) on granular base; traffic: 264 ADT; discount rate = 10% per year.

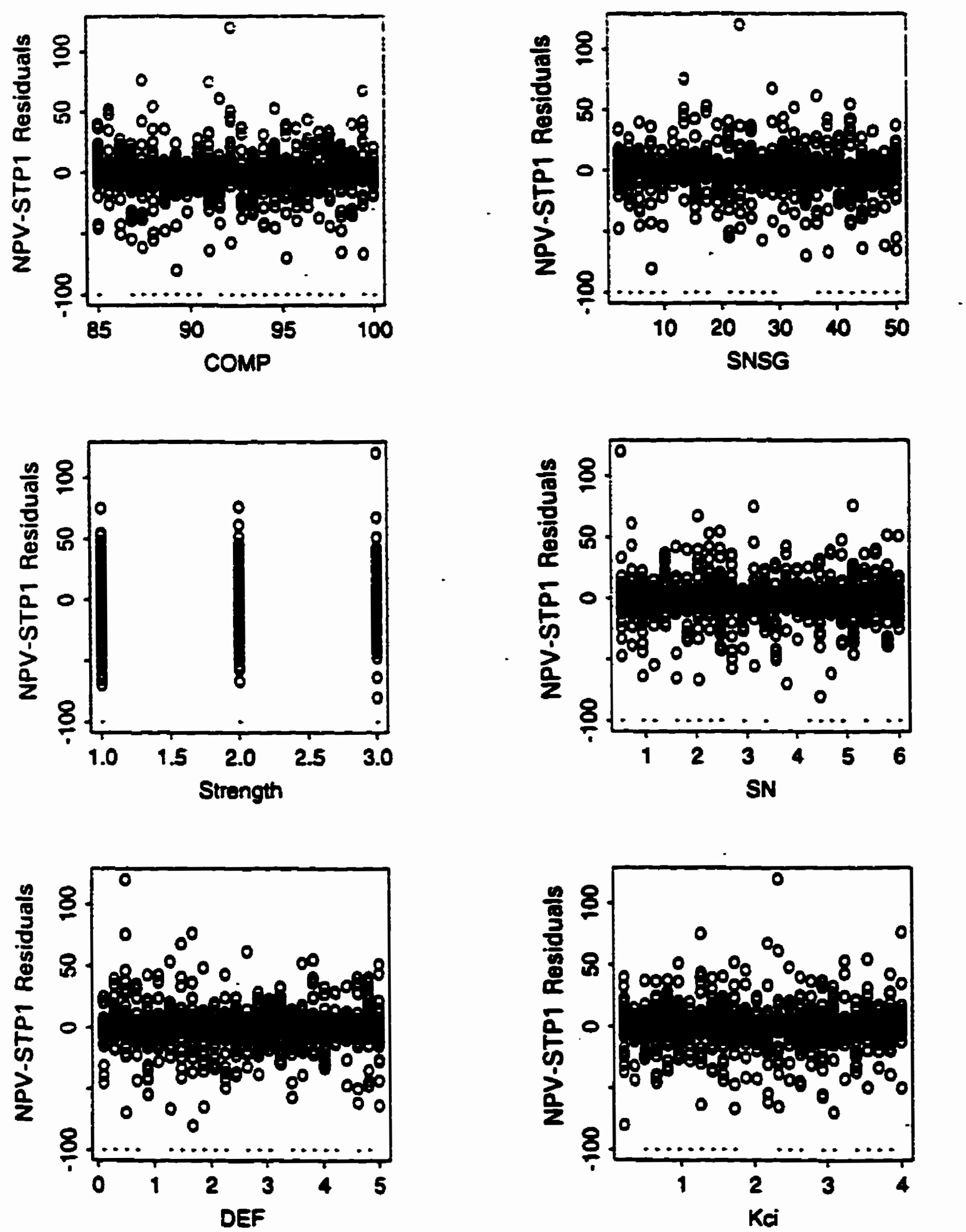
LCC-VOC = users' (VOC) life-cycle costs for the R&M strategy STP4; pavement type: asphalt concrete (AC) on granular base; traffic: 1000 ADT



(a)

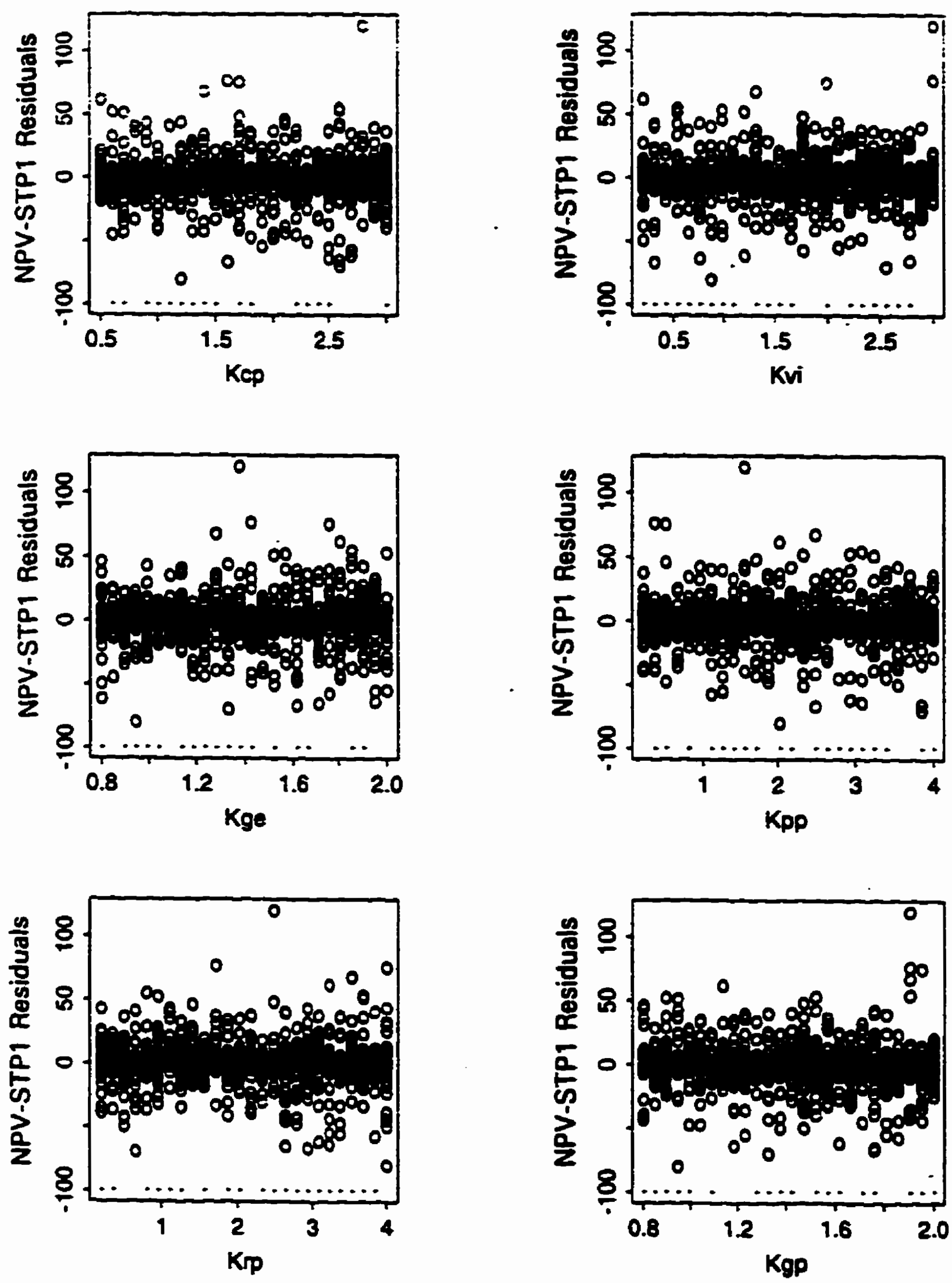
FIGURE D.1 ***Cross validation residuals: NPV against predictor variables***

(Symbols according to the Glossary)



(b)

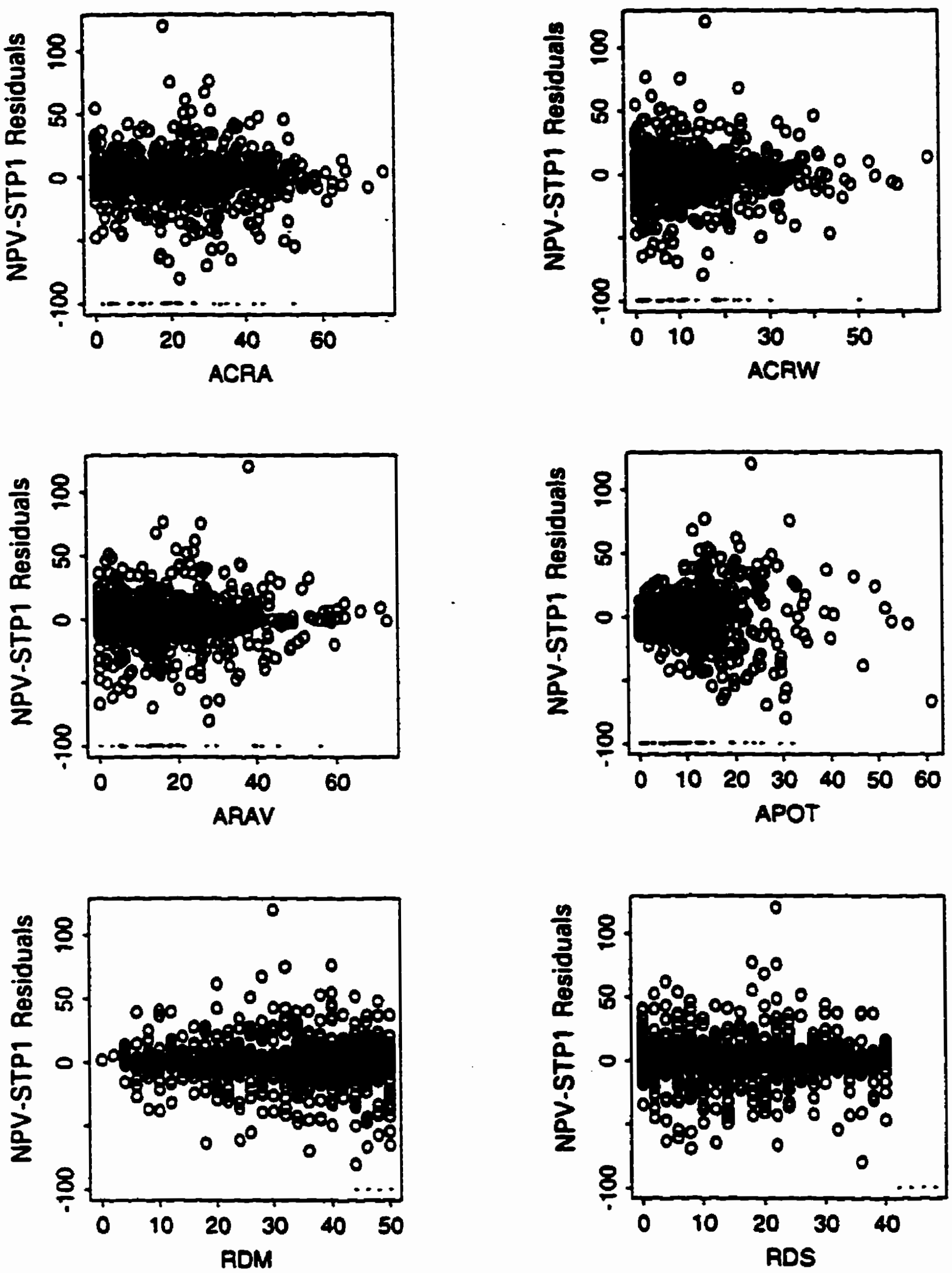
FIGURE D.1 ***Cross validation residuals: NPV against predictor variables (cont.)***
(Symbols according to the Glossary)



(c)

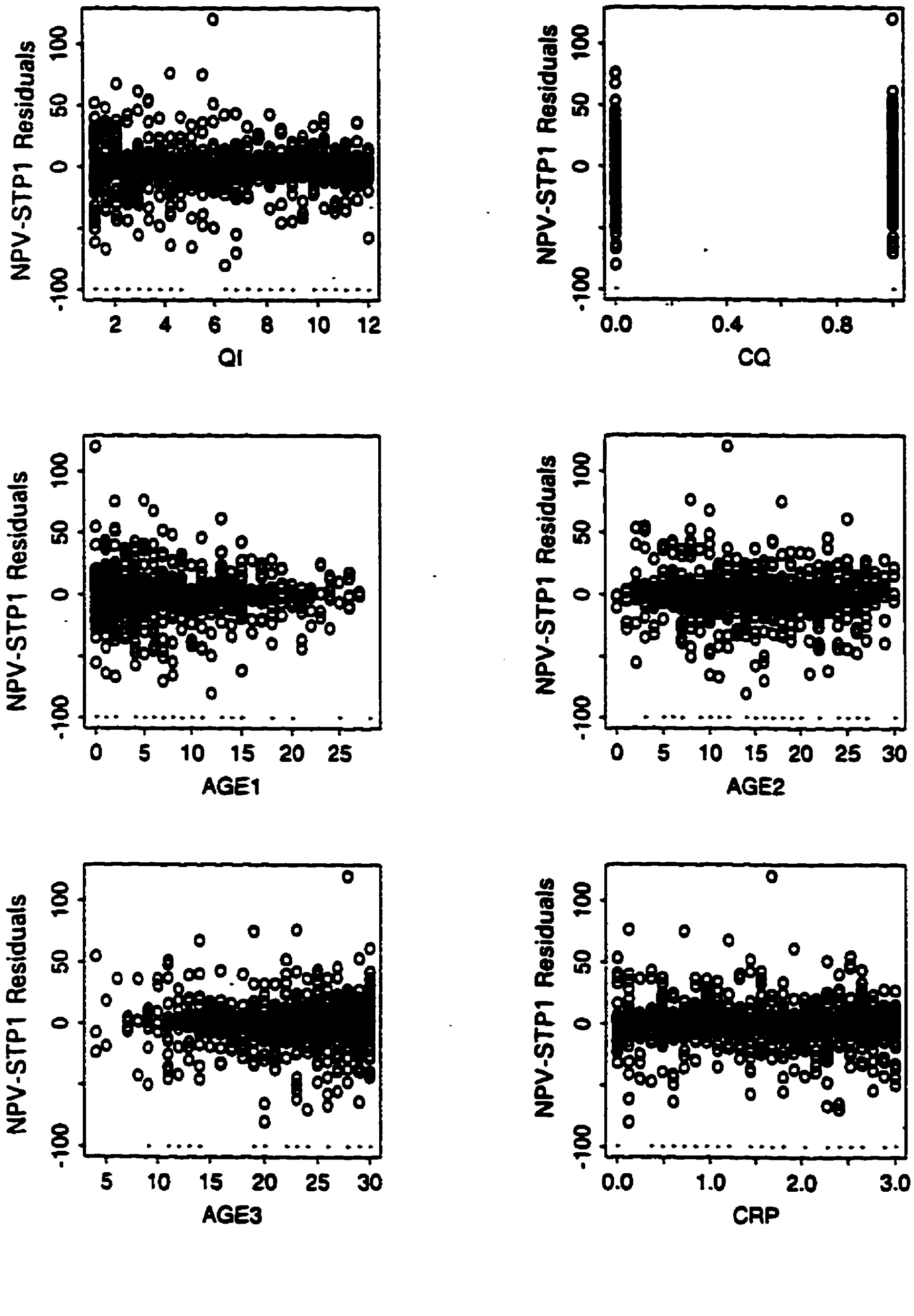
FIGURE D.1 **Cross validation residuals: NPV against predictor variables (cont.)**

(Symbols according to the Glossary)



(d)

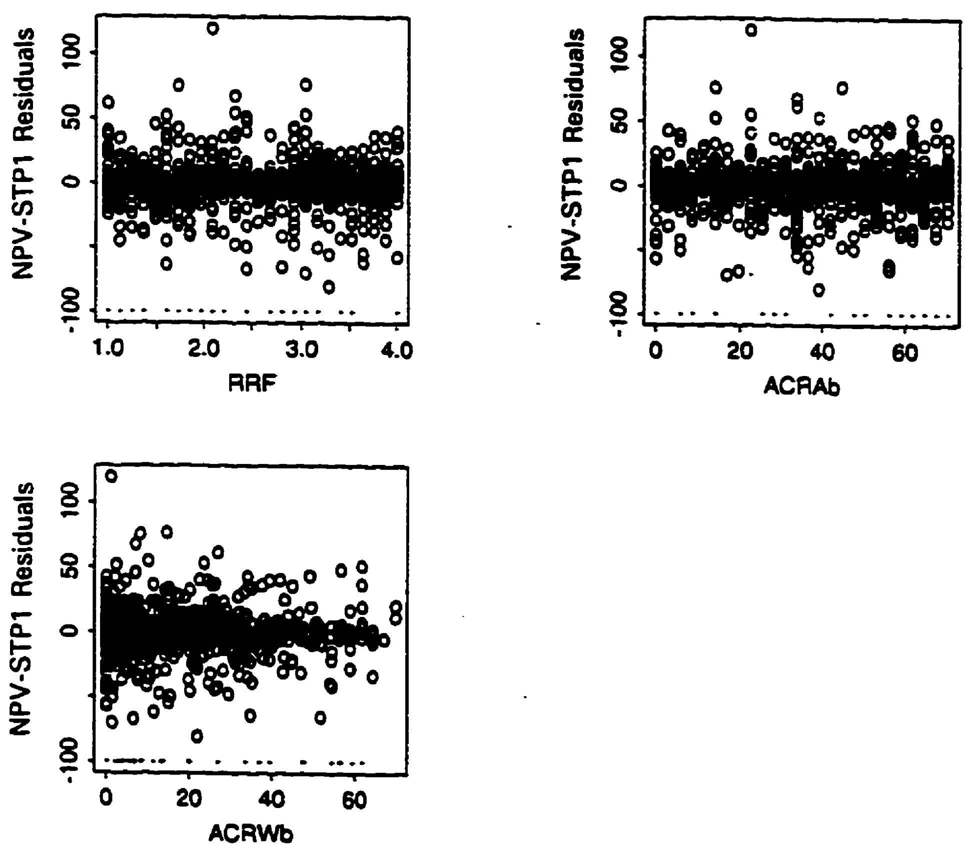
FIGURE D.1 ***Cross validation residuals: NPV against predictor variables (cont.)***
(Symbols according to the Glossary)



(e)

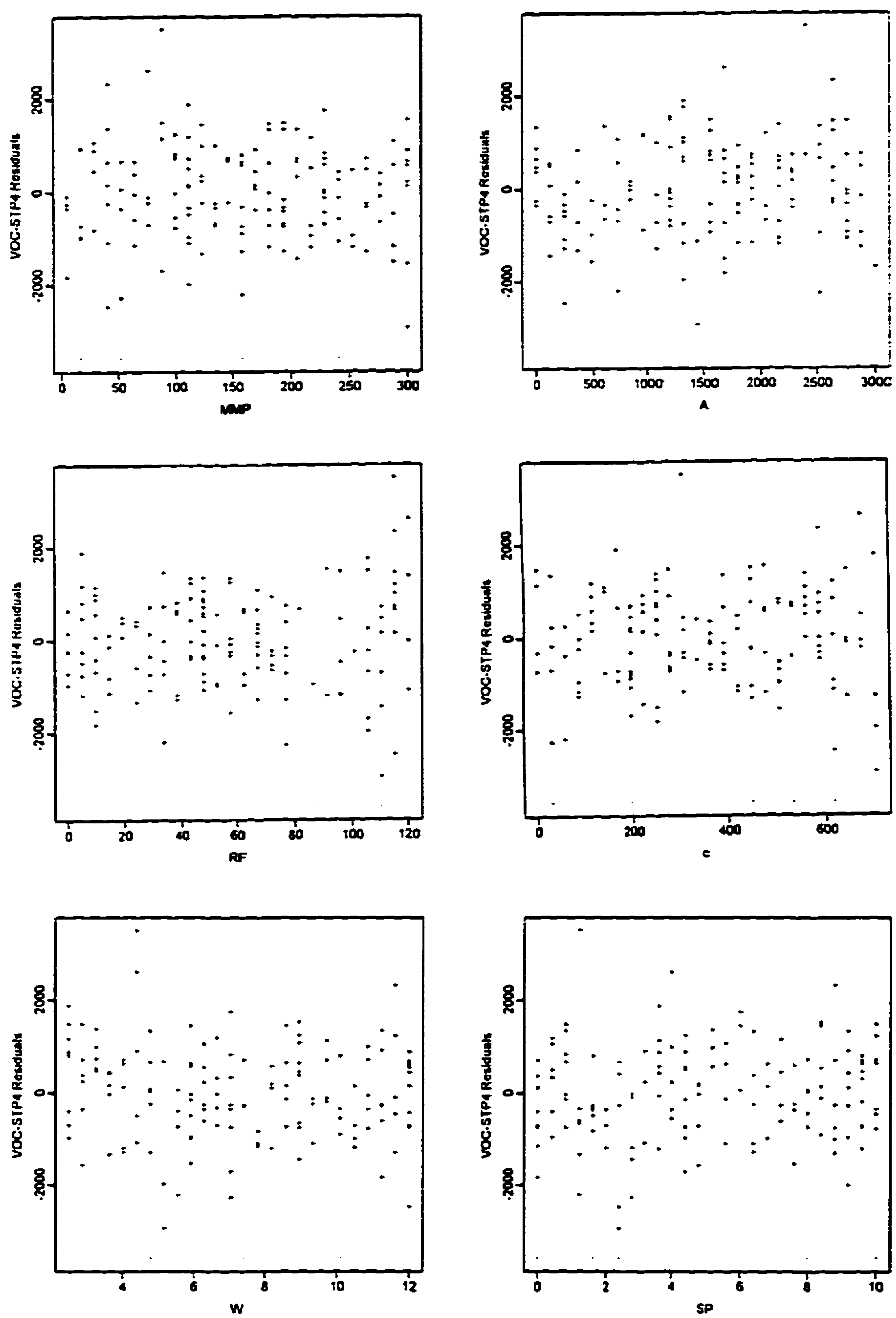
FIGURE D.1 ***Cross validation residuals: NPV against predictor variables (cont.)***

(Symbols according to the Glossary)



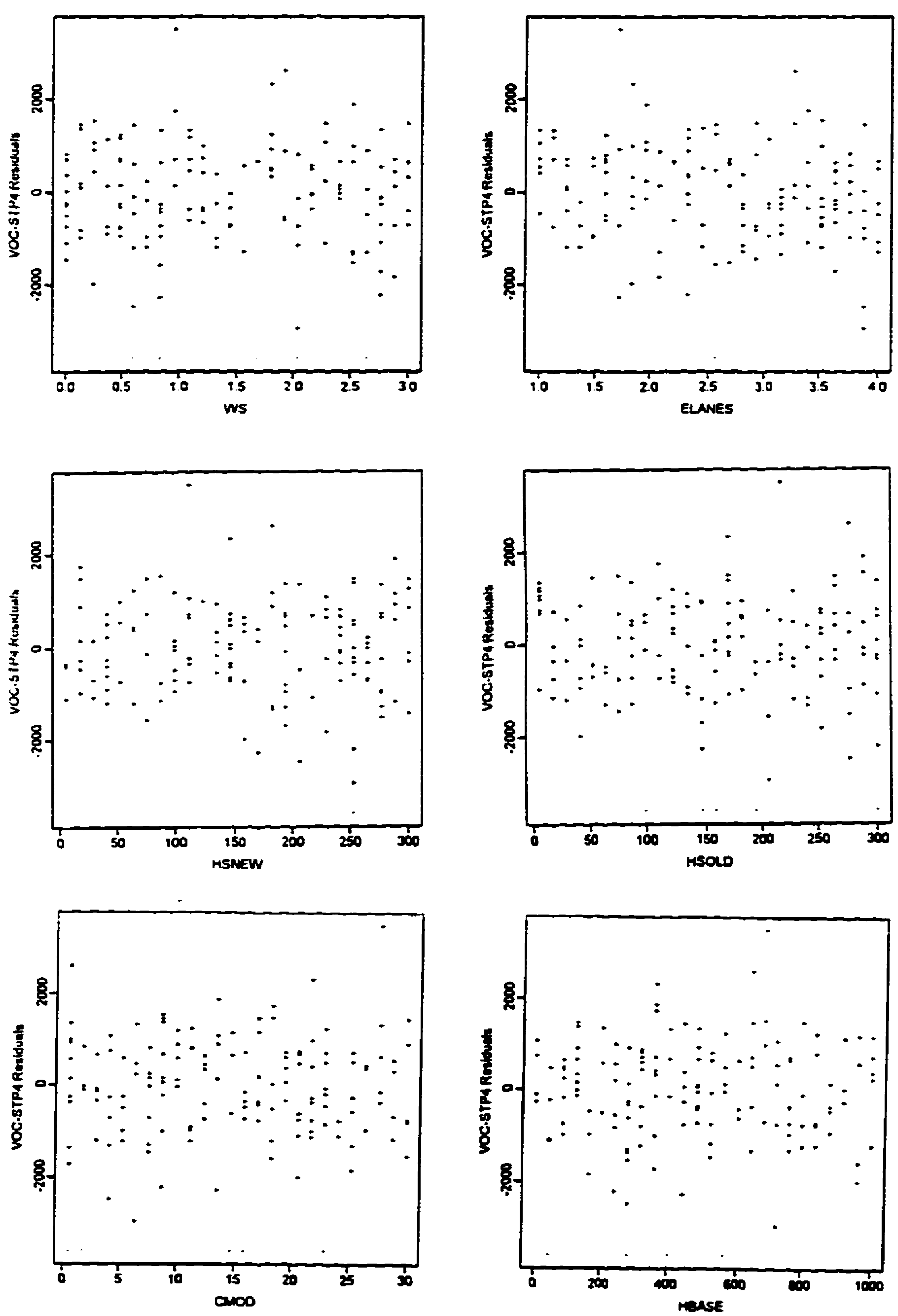
(f)

FIGURE D.1 ***Cross validation residuals: NPV against predictor variables (cont.)***
(Symbols according to the Glossary)



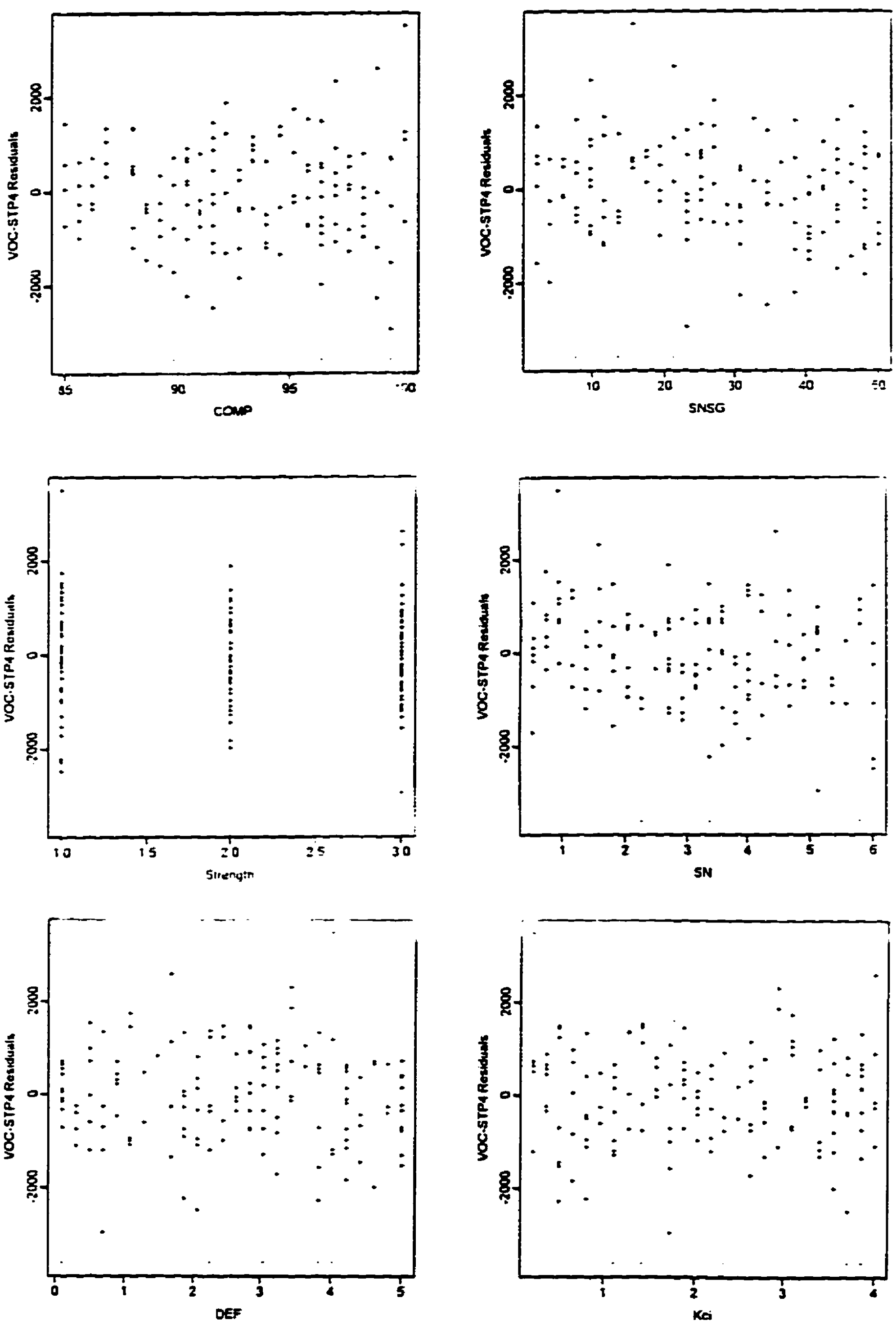
(a)

FIGURE D.2 ***Cross validation residuals: LCC-VOC against predictor variables***
(Symbols according to the Glossary)



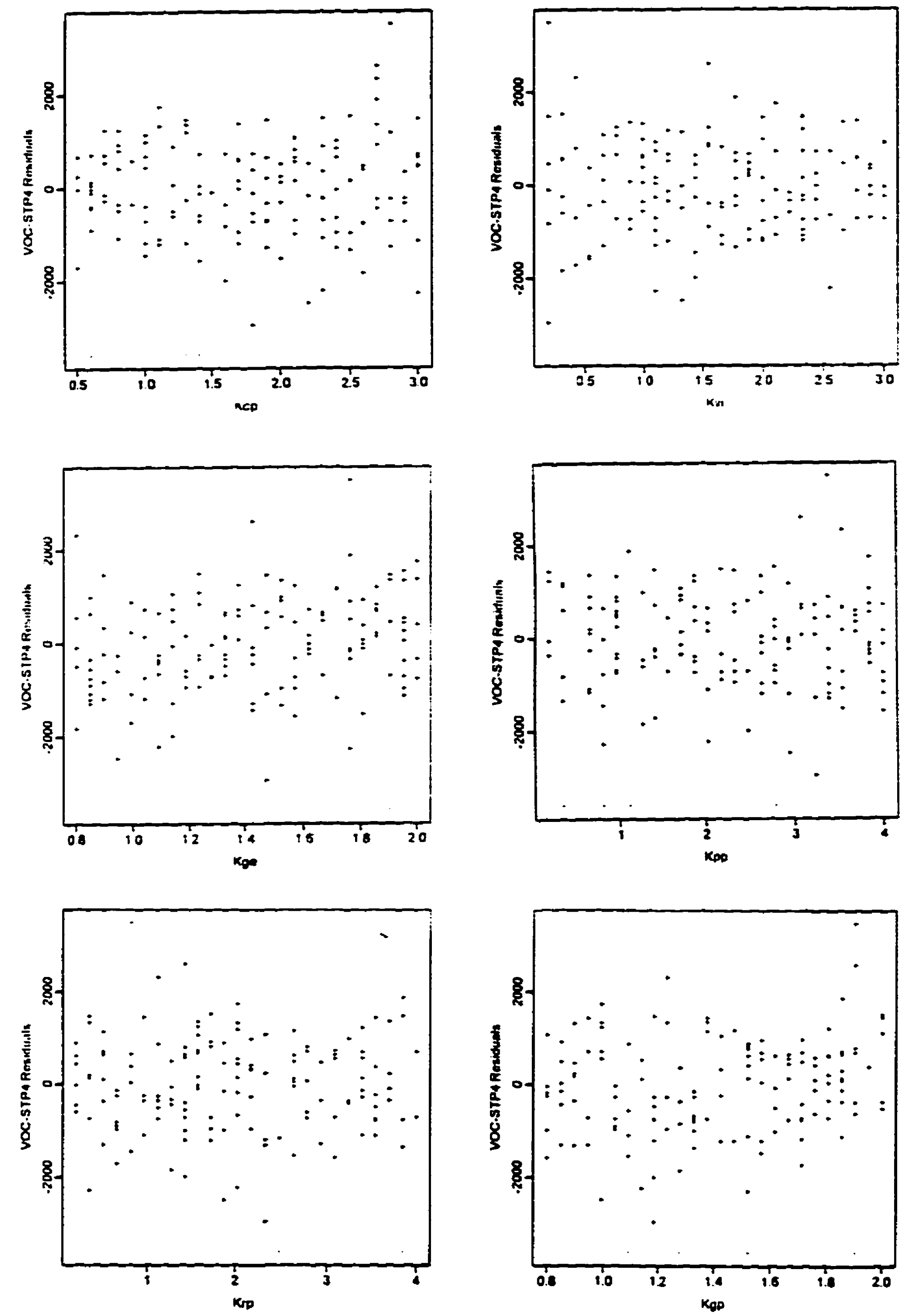
(b)

FIGURE D.2 ***Cross validation residuals: LCC-VOC against predictor variables (cont.)***
(Symbols according to the Glossary)



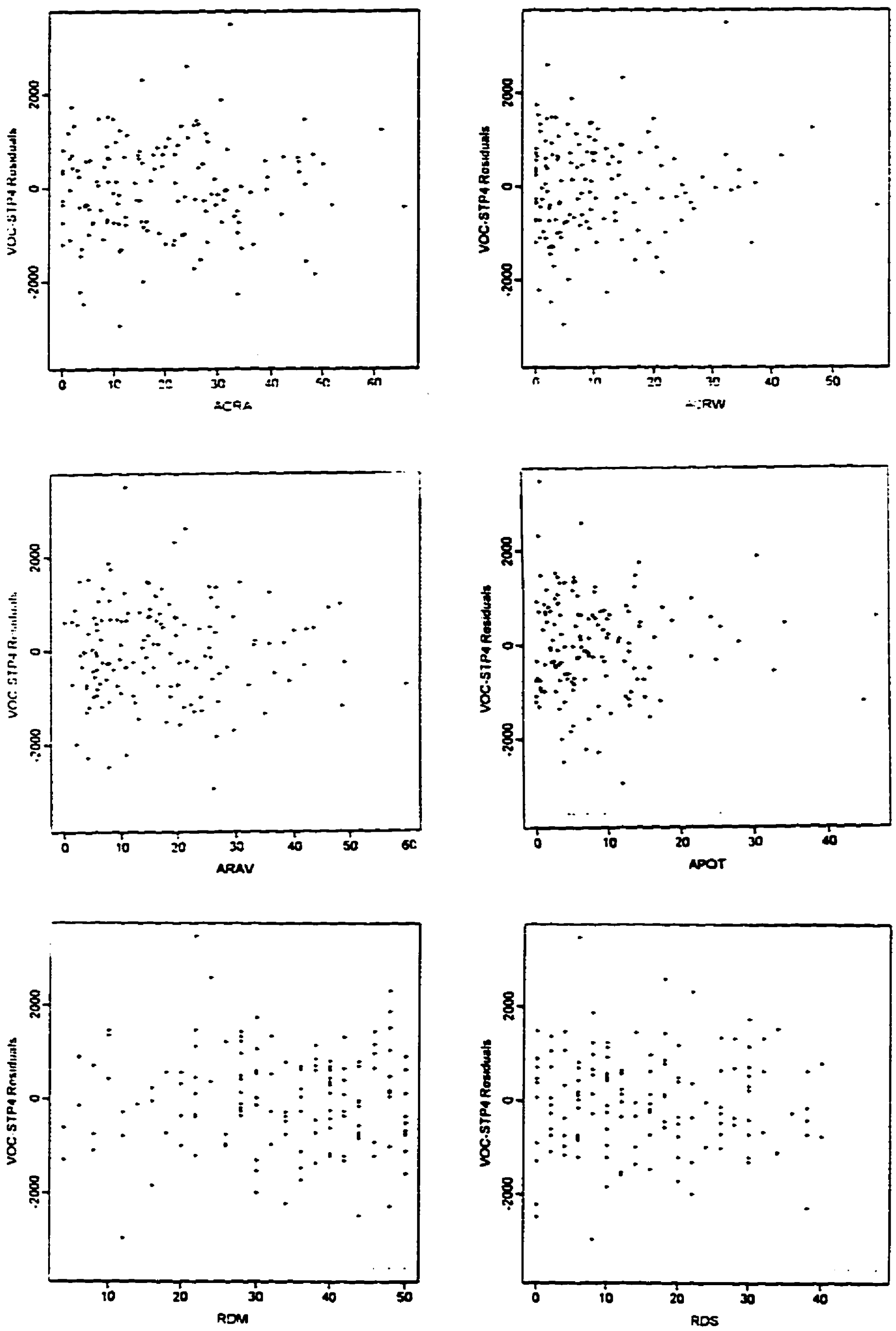
(c)

FIGURE D.2 **Cross validation residuals: LCC-VOC against predictor variables (cont.)**
(Symbols according to the Glossary)



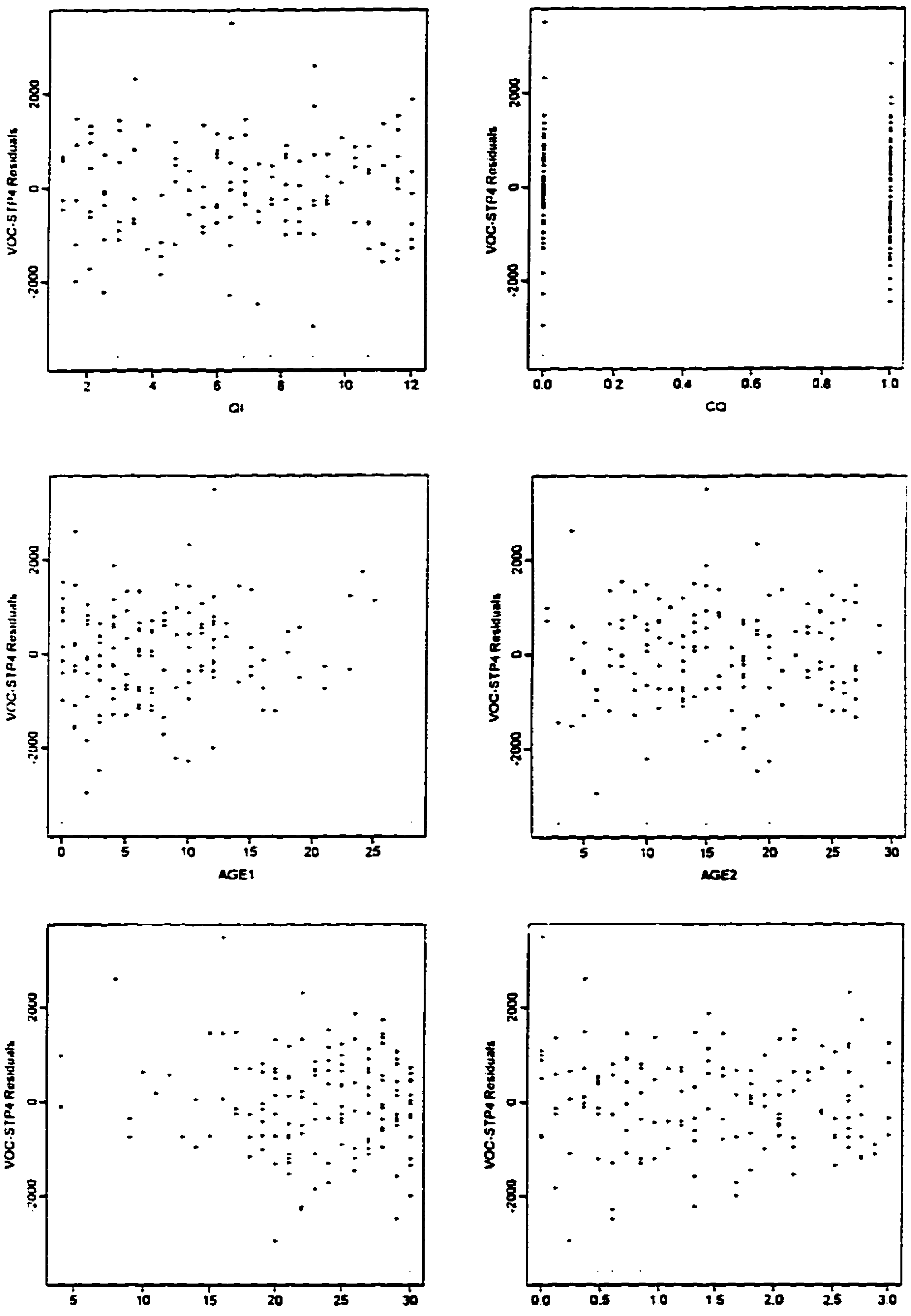
(d)

FIGURE D.2 ***Cross validation residuals: LCC-VOC against predictor variables (cont.)***
(Symbols according to the Glossary)



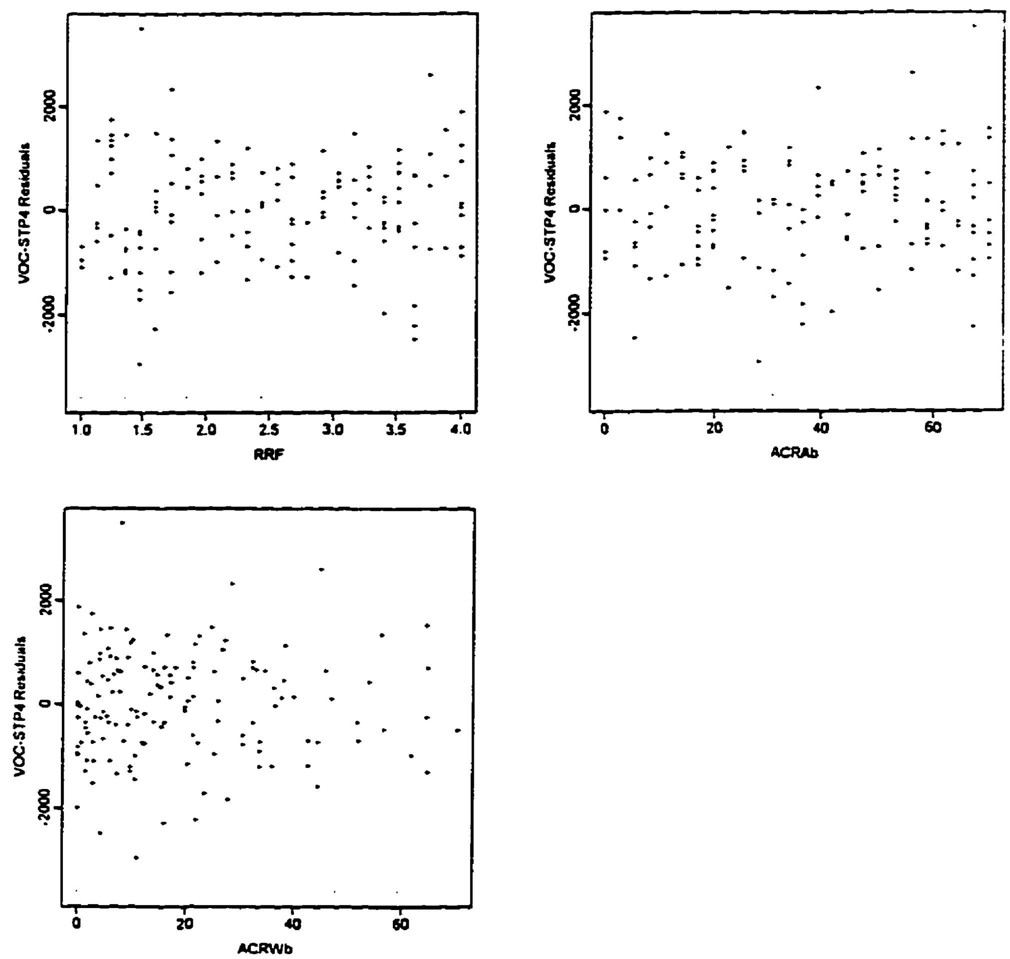
(e)

FIGURE D.2 ***Cross validation residuals: LCC-VOC against predictor variables (cont.)***
(Symbols according to the Glossary)



(f)

FIGURE D.2 Cross validation residuals: LCC-VOC against predictor variables (cont.)
(Symbols according to the Glossary)



(g)

FIGURE D.2 ***Cross validation residuals: LCC-VOC against predictor variables (cont.)***
(Symbols according to the Glossary)

GLOSSARY

AC	Asphalt concrete; hot rolled asphalt mix pavement wearing course.
AC/GB	Asphalt concrete on granular base pavement.
ADT (AADT)	Average Daily Traffic (Annual Average Daily Traffic).
ASCII	American Standard Code for Information Interchange; 256 character set also called plain text
BI	Bump Integrator, the TRRL's fifth wheel Towed Bump Integrator Index of Roughness.
BLUP	Best linear unbiased estimator (predictor).
CPU	Central processing unit.
CBR	California Bearing Ratio.
DOS	Disk operating system.
EBM	Expenditure Budgeting Model [Watanatada 87b].
ESAL	Equivalent Standard Axle load. The 8.2 ton (18 000 lb), dual wheel axle load equivalent.
HDM-VOC	The HDM-III Vehicle Operating Cost Model; a limited version of HDM-III model.
HDM4	The forthcoming upgrade of HDM-III [ISOHDM 93].
HDM-III	The Highway Design and Maintenance Standards Model [Watanatada 87a].
HDM-PC	The micro-computer (DOS) version of the HDM-III model [Bank 89].
IRI	International Roughness Index; unit of road roughness.
IRR	Internal rate of return.
ISOHDM	International Study on Highway Development and Management tools [ISOHDM 93].
LCC	Life-cycle costs; LCC-VOC: users' life-cycle costs; LCC-R&M: agency life-cycle costs.
MoW	Ministry of Transportation, Communication and Works, Tanzania.
MLE	Maximum likelihood estimator (estimation).
NPV	Net present value (worth).
pdf	probability density function.
PMS	pavement management system.
R&M	rehabilitation and maintenance; road preservation activities.
RODEMAN	Road Deterioration and Maintenance Effects Model. A limited version of HDM-III model.
RONIS	Road Network Improvement System [Turay 90, 91].
RTIM3 (RTIM2)	Road Transport Investment Model; version 3 (2) [TRRL 86, Cundill 95].
SD	Surface (double) dressing, also called surface (double, triple) treatment.
SD/CB	Surface dressing on cement stabilized base pavement.
SD/GB	Surface dressing on granular base pavement.
SSA	Sub-Saharan Africa. The Africa region south of the Sahara excluding the South Africa.
STP0 (... STP4)	Codes for paved road R&M treatment strategies, also called maintenance alternatives.
VOC	Vehicle Operating Costs.

Link Characterization Variables

A	Altitude [above mean sea level] (m).
ACRA	Area of all cracks (%).
ACRAb	Area of previous all cracks (%).
ACRW	Area of wide cracks (%).
ACRWb	Area of previous wide cracks (%).
AGE1	Age of preventive treatment (years).
AGE2	Age of surfacing (years).
AGE3	Age from last re-construction (years).
APOT	Area of potholes (%).
ARAV	Area raveled (%).
C	Horizontal curvature (degrees/km).
CMOD	Resilient modulus of soil cement (GPa).
COMP	Relative compaction (%).
CQ	Construction faulty code [yes /no].
CRP	Cracking retardation time (years).
DEF	Benkelman beam deflection (mm).
ELAN	Effective number of lanes.
HSNEW	Thickness of new surface layers (mm).
HSOLD	Thickness of old surface layers (mm).
Kci	Cracking initiation calibration factor (dimensionless).
Kcp	Cracking progression calibration factor.
Kge	Roughness-age term calibration factor.
Kgp	Roughness progression calibration factor.
Kpp	Pothole progression calibration factor.
Krp	Rut depth progression calibration factor.
Kvi	Raveling initiation calibration factor.
MMP	Average monthly rainfall (mm).
QI	Roughness (IRI m/km, other units: BI mm/km and QI km^{-1}).
RDM	Mean rut depth (mm).
RDS	Standard deviation of rut depth (mm).
RF	Rise plus fall (m/km).
RRF	Raveling retardation factor.
SN	Structural number.
SNSG	Subgrade strength in CBR (%) [=California bearing ratio].

SP	Superelevation (%).
W	Carriageway width (m).
WS	Shoulder width (m).

Vehicle characterization variables

AKM_0	vehicle base annual utilisation.
ALPHA1	Unit fuel efficiency factor.
BETA	Weibul shape parameter.
C0LH	Constant term in the *LH* - *PC* equation.
C0SP	Constant term in the exponent of the *QI* - *PC* equation.
C0TC	Constant term in the tire wear equation.
CLHPC	The PC exponent in the LH - PC equation.
CLHQI	QI factor in the exponent of the *LH* - *PC* equation.
CRPM	Calibrated engine speed (rpm).
CSPQI	Roughness coefficient in the exponent of the *QI* - *PC* equation.
CTCTE	Tire wear coefficient.
EVU_0	Base elasticity of vehicle annual utilisation.
GVW	Gross vehicle weight (metric tons).
HPDRIVE	Usable driving power (metric horse power, HP).
HRD_0	Base number of hours driven per year.
HPRAKE	Usable braking power (HP).
PAYLOAD	Payload (metric tons).
QI0SP	Limiting *QI* at which the *QI* - *PC* equation becomes linear.
VDESIROPV	Limiting desired speed for paved road (m/s).